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REEXAMINING RELATIVE BAR PERFORMANCE AS A FUNCTION OF NON-LINEARITY, HETEROSCEDASTICITY, AND A NEW INDEPENDENT VARIABLE

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ABSTRACT

One might believe that a law school's graduates doing better on the bar exam than their matriculating credentials predicted must be primarily attributable to the teaching ability and performance of the institution's faculty. Some scholarship makes such a claim. However, it is empirically untrue. Prestidigitation rather than legal pedagogy yields such superficial results. Law schools manipulating their matriculant pools via academic attrition and transfer is the sleight-of-hand that improves their graduates' bar-performance rates. This article reveals the math behind the magic.

This article demonstrates that effective pedagogy may not be the only driver of a law school's students overperforming on the bar examination. Statistical analysis supports such an assertion by revealing the model misspecification of linear regression upon which previous studies rely. We wrote original code for the program Mathematica to generate regression equations which clearly illustrate the error of previous studies that applied linear regression to heteroscedastic, non-linear data. Linear regression

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of such data creates bias in favor of schools that matriculated students who have mid-range UGPAs and LSAT scores.

We demonstrate mathematically that academic attrition and net-transfer rates—by combining those factors into a single, independent variable—likely affect institutions’ over and underperformance on the bar examination relative to the entering credentials of their matriculants. We observed a marked difference in the value of this variables between schools that over and underperformed on the bar examination relative to their students’ matriculating credentials.

Our findings are significant because the unwarranted attribution of bar success to legal pedagogy harms educators, especially untenured, support faculty. This article shows that factors beyond the control of such faculty drive bar performance. Another lingering, unresolved question might also be harming legal educators: whether ABA standard 316—which mandates a certain level of bar passage by law schools’ graduates—is ethically and morally supportable given the ability of schools to manipulate bar passage rates by modulating academic attrition and transfer rates.

I. INTRODUCTION

In 2018, Jeffrey Kinsler and Jeffrey Usman published an article ranking the bar performance of 194 law schools.¹ Kinsler’s rankings compared a school’s actual bar performance with the predicted performance of the school based on its students’ entering credentials three years earlier. Each school’s predicted performance was based on a linear- regression model that Kinsler created, and the predicted rate of bar passage for an institution in a given year was based on median, undergraduate grade-point average (“UGPA”) and Law School Admission Test (“LSAT”) scores of the school’s matriculants from three years before the bar examination.²

Kinsler recently issued a follow-up article which ranks the bar performance of 187 law schools over the combined five-year period of 2015–2019.³ To rank the schools, he examined matriculation data for all law schools from 2012–2016 and used the same predictive model from *Kinsler I*, which produced the expected bar passage rate of the school based upon its entering credentials.⁴ Kinsler then compared

1. Jeffrey S. Kinsler & Jeffrey Omar Usman, *Law Schools, Bar Passage, and Under and Overperforming Expectations*, 36 QUINNIPIAC L. REV. 183 (2018) [hereinafter *Kinsler I*].

2. *Id.* at 189–90, 199 (“Utilizing the linear regression line equation, a predicted bar passage rate or bar passage rate differential was calculated. . . . The variance was then determined by subtracting the predicted passage rate or rate differential from the actual passage rate or rate differential. The law schools were then rank-ordered based upon the variance. . . .”).

3. Jeffrey S. Kinsler, *Top Law Schools for Passing the Bar Exam*, NAT’L JURIST (forthcoming) (on file with the author) [hereinafter *Kinsler II*].

4. *Id.* (manuscript at 1–2) (“Undergraduate GPAs (UGPAs) and LSAT scores are the two primary factors considered by law school admissions offices. Statistically, students with higher UGPAs and LSAT scores are more likely to pass the bar exam than students with lower UGPAs and LSAT scores. As a consequence, a predicted bar passage rate may be calculated for each law school based upon its UGPA

the institution's observed bar passage rates three years after matriculation⁵ with the expected results that his model predicted. The school which most exceeded his model's prediction ranked highest, and the school that had the lowest, actual performance compared to the model's prediction ranked 187.⁶

Kinsler's publications are the first to apply science, specifically statistics, to the mystery of bar passage. Previous bar passage articles that appear to apply science to the study of bar passage are more akin to alchemy in terms of their unsupported cause-and-effect assertions and widespread omission of relevant data.⁷ We laud Kinsler as a pioneer of applying science the study of bar passage; his work is a milestone toward achieving the most accurate results in this field. This article aims to advance the study of bar passage by building upon Kinsler's work. Any critique this article makes of the Kinsler model is done respectfully, academically, and for the exclusive purpose of improving the scientific study of bar performance.

The Kinsler model misrepresents relative bar performance by applying statistical analysis—linear regression—that is not suitable for the dataset. By applying inappropriate statistical analysis, the Kinsler model creates misleading, mathematical bias that favors schools with average to above-average matriculating credentials, and disfavors schools with higher matriculating credentials. Furthermore, we demonstrate that law schools' attrition and net-transfer rates, variables which the Kinsler model ignores, might also affect bar performance. Such variables are mostly beyond the control of legal educators, proving that bar passage rates are not exclusively attributable to the performance of law professors and other bar preparers. Using the Analytix data platform provided by AccessLex,⁸ we created a database⁹ of all the relevant matriculation metrics on the American Bar Association ("ABA") standard 509 forms for every law school from 2012–2016, including the academic attrition and transfer-in/transfer-out percentages for each of those matriculation cohorts. The database also contains the bar-pass rates three years

and LSAT scores. Once a predicted bar passage rate is calculated, it is possible to determine which law schools are over-performing or under-performing in terms of preparing their students to pass the bar exam. In other words, it is possible to show which law schools are adding the most bar passage value to (or subtracting the most from) their students. Utilizing linear regression models, the performance of 187 ABA-approved law schools was assessed using four metrics (reported by the ABA) for each calendar year for the five-year period of 2015-2019: (1) Median LSAT and Composite Average First-Time Bar Pass Rate; (2) Median UGPA and Composite Average First-Time Bar Pass Rate; (3) Median LSAT and Composite Average First-Time Bar Pass Rate Differential; and (4) Median UGPA and Composite Average First-Time Bar Pass Rate Differential. An annual rank was then calculated for each law school based on its over-performance (or under-performance) of predicted expectations for bar passage.”).

5. Law students typically take the bar examination three years after matriculation.

6. *Kinsler II*, *supra* note 3 (manuscript at 2).

7. See generally Rory Bahadur, *Blinded by Science? A Reexamination of the Bar Ninja and Silver Bullet Bar Program Cryptids*, 49 J.L. & EDUC. 241 (2020) [hereinafter *Bar Ninja*] (explaining how the cause-and-effect implications regarding bar passage in Louis N. Schulze Jr., *Using Science to Build Better Learners: One School's Successful Efforts to Raise its Bar Passage Rates in an Era of Decline*, 68 J. LEGAL EDUC. 230 (2019) is unscientific). Conveniently, ignoring relevant data and obvious, confounding variables to suggest a correlation between pedagogy and bar passage rates is the opposite of science. *Bar Ninja*, *supra*, at 244.

8. ANALYTIX BY ACCESSLEX, <https://www.accesslex.org/analytix-by-accesslex>.

9. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6>.

after each cohort matriculated, or bar passage percentages at each institution from 2015–2019.

Next, we wrote programming code for the technical computing system, Mathematica,¹⁰ to analyze and generate graphs of this data. Our computations indicate that the bar passage data exhibited non-linearity and heteroscedasticity rather than linearity and homoscedasticity.¹¹ Consequently, linear regression is not the appropriate regression-method for comparing the entering credentials of a school's students to its predicted bar performance three years after matriculation.¹²

Our analysis also reveals that, for this data set, non-linearity and heteroscedasticity are especially significant at the upper range of matriculation credentials.¹³ As a result, the Kinsler model makes it mathematically impossible for schools with the highest entering credentials to be ranked as a top overperformer in bar performance.¹⁴ Kinsler's model is strongly biased against these schools because they are predicted to have very high bar passage rates, which leaves little room for improvement. Even if such schools outperform predicted bar performance with 100% bar passage rates, the school's overperformance is typically meager compared to overperforming schools with mid-level matriculating credentials.¹⁵ Accordingly, linear-regression models create strong biases in favor of schools in the 150–158 median LSAT range because such schools have more room to overperform on the bar exam relative to their predicted bar passage rates.¹⁶

After explaining the impropriety of linear-regression analysis, we reexamine the schools Kinsler identified as the best and worst bar performers based on their students' matriculating credentials.¹⁷ Our empirical findings counter Kinsler's assertion that the efficacy or lack thereof of a school's bar passage program, an intangible variable, primarily drives the school's over or underperformance on the bar examination.¹⁸ A combination of two tangible variables: first-year, academic-attrition rates and net-transfer rates, also impacts the bar performance of institutions.¹⁹ We combined and analyzed these two variables as

10. WOLFRAM MATHEMATICA, <https://www.wolfram.com/mathematica/>.

11. See *infra* Parts III.C–D.

12. See *infra* Part III.D.

13. *Id.*

14. *Id.*

15. *Id.*

16. *Id.*

17. See *infra* Part IV.

18. See *Kinsler II*, *supra* note 3 (manuscript at 3–4) (claiming that “the over-performance of the top five law schools is not a fluke. . . . The reason these law schools succeed is that they dedicate substantial time and resources to ensuring that their students pass the bar exam and become licensed members of the legal profession. Campbell University, for example, explicitly proclaims: “Our goal is always to have every student pass the bar exam.” In fact, most of the top performers have an experienced faculty member in charge of bar preparation, such as Professor Raul Ruiz at Florida International or Professor James McGrath at Texas A&M. Traditionally, many law school professors (and law schools) felt that the bar exam was someone else's problem. But as Professor Mario W. Maneiro wrote in 2016: “If we expect students to treat bar exam study as a ‘full-time job,’ then we must ourselves treat it as a full-time job and more, and be willing to expend whatever time is needed to deliver individualized assistance in writing, analysis, and practice to all of our students.”) (emphasis omitted).

19. See *infra* Part IV.B.

a new, independent variable which we termed a school's combined variable score ("CVS"). Our analysis of the CVSs of schools that Kinsler's ranked in the top-and-bottom fifteen of bar performance, compared with the CVSs of schools with similar matriculating credentials, empirically suggests that academic attrition and net-transfer rates affect bar performance.²⁰

Finally, an irrelevant distractor is addressed. Across the different LSAT and 75th-percentile-UGPA bands of matriculation credentials, academic-attrition rates appear to be weakly, and possibly negatively, correlated to bar passage performance. Various factors, including the complex relationships between UGPA, LSAT scores, and academic attrition; and the consequences thereof, explain how the irrelevant distractor might appear to, but does not undermine, our thesis.

In addition to advancing the study of bar performance, the purpose of this article is to prevent unjustified pressure on vulnerable, legal educators—such as untenured, academic-support faculty and other bar-preparation professionals—who do not achieve the stellar, although misleading, bar performance results of other schools.²¹ This article is offered as a continued step in the right direction and builds upon Kinsler's work. Hopefully, Kinsler and others will use this article to improve the modeling that Kinsler produced. Kinsler's research evolved the study of bar performance, away from the intangible, secret sauces²² and toward the application of real science to improve bar passage. This article is a clearly a step in an iterative process.

Perhaps the most important takeaway from this article, which is not discussed separately because it should be self-evident, is that ABA standard 316 is nonsensical.²³ It allows the ABA, when assessing a school, to rely on a standard

20. See *infra* Part IV.C.

21. See *Bar Ninja*, *supra* note 7, at 248 (explaining the uncomfortable position the unsubstantiated attribution of pedagogy innovation to bar success creates for academic-support professionals nationwide. "That problematic implied narrative is that good teaching and applying science to pedagogy are enough to drastically improve bar passage at any school. The sole reason I am writing about this implied narrative is so that the rest of the academic support world, currently also utilizing scientific and informed pedagogy but not getting the same amazing results, will be fully informed as to whether the SASP or a similar program alone causes the unprecedented increases in bar passage observed at FIU. Any accidental suggestion that scientific and good teaching alone is enough to drastically improve bar passage rates creates the impression to many deans that their Academic Support Professionals ("ASPs"), who are not achieving results like FIU, are not as capable at good science-based teaching as they should be. This impression, if not correct, is incredibly harmful, especially because ASPs are generally untenured.").

22. See Legal Skills Prof, Dean Michael Hunter Schwartz, *Florida International School of Law and the Bar Pass Secret Sauce*, LAW PROFESSOR BLOGS NETWORK: LEGAL SKILLS PROF BLOG (June 13, 2018), https://lawprofessors.typepad.com/legal_skills/2018/06/dean-michael-hunter-schwartz-florida-international-school-of-law-and-the-bar-pass-secret-sauce.html.

23. See e.g., *Bar Ninja*, *supra* note 7, at 274–75 (illustrating the arbitrary and capricious nature of standard 316 in Florida. "That these private schools provide a feeder system for FIU at the end of the first year of law school is also documented on the 509 forms. For example, in 2013, sixteen of the twenty-two students who transferred to FIU came from one of these two private institutions, and in 2014, thirteen of the twenty-four students transferring to FIU came from the other. A separate article might consider how FIU's and other schools' siphoning off the better students from Nova and St. Thomas in the numbers mentioned would presumably reduce the bar passage percentage at these schools. While FIU's transfer policy lowers the bar passage at these schools, it also presumably increases FIU's bar pass rates, thereby increasing the difference between FIU's bar pass rate and the state average. FIU's "above state average" results need to be evaluated in this light as well. In a future study, it may be also worth discussing the

which schools actively manipulate through student attrition and transfer.²⁴ Furthermore, this assessment is based on the school's performance on an exam that fails to properly assess law students' readiness for practice and is extant only because of established, monopolistic attributes.²⁵ Whether this is because the ABA is lazy or inertia perpetuates the status quo is beyond the scope of this article, but the persistence of ABA standard 316 is incredulous.

II. LINEAR REGRESSION AND RESULTS GENERATED

Kinsler published *Kinsler I* and *Kinsler II* to help address the problem of declining bar passage rates in recent years without allocating blame.²⁶ *Kinsler I*'s ranking system compared the entering credentials of students in 2012 with schools' bar passage rates in 2015.²⁷ Kinsler and Usman developed a statistical model that predicted expected bar passage in 2015 based upon the entering credentials of the 2012 matriculants.²⁸ The school that most overperformed its predicted bar-pass rate ranked first, and the school that most underperformed its predicted bar-pass rate ranked 194th.²⁹

arbitrary nature of applying the ABA 316 standard to schools in South Florida because of the high intrastate transfer numbers.”).

24. *Id.*

25. See Marsha Griggs, *Building a Better Bar Exam*, 7 TEX. A&M L. REV. 1, 39 (2019) (“Bar examiners and bar takers everywhere will need to wage battle with the NCBE to get meaningful data and insist for changes to essay grading practices. Making real change becomes less likely as the NCBE grows in force and influence with each new jurisdiction to subscribe to UBE.”).

26. *Kinsler I*, *supra* note 1, at 188–89 (“The focus of this article is not on allocating blame, but instead upon building a foundation for exploring whether there is a meaningful solution to help address the bar passage problem that can be found by looking to the legal education programs of law schools that are particularly successful in preparing students to pass the bar exam. To accomplish this aim, a critical and essential step is to begin to identify the law schools that are adding the most in terms of assisting their students to pass the bar exam. That first critical step is the step taken by this article.”).

27. *Id.* at 189–90 (“[T]his article examines the entering class of 2012 and the bar passage results of that class in 2015. In particular, this article compares 2012 input credentials--Median LSAT Scores and Median UGPAs-- with 2015 first-time bar passage rates to determine which law schools over-performed in terms of preparing students to pass the bar exam and which law schools under-performed in terms of preparing students to pass the bar exam.”).

28. *Id.* at 224–29.

29. *Id.* at 198 (“Part III of this article assesses law schools’ over-performance and under-performance utilizing linear regression analysis of LSAT and UGPA, for those students entering law school in 2012, and Composite Average First-Time Bar Pass Rate and Composite Average First-Time Bar Pass Rate Differential, for those taking the bar exam in 2015. . . . A scatterplot was generated for each metric of assessment. Linear regression analysis was then conducted on those scatterplots. As background on linear regression analysis, [a] simple linear regression attempts to find the linear relationship between two variables, x and y , and to discover a linear model, i.e., a line equation $y = b + ax$, which is the best fit to given data in order to predict values of data. This modeling line is called the regression line of y on x and the equation of that line is called a regression equation (regression model). In a simple linear regression, the x functions as the independent variable and the y as the dependent variable, using the x to predict the y . The R-squared of linear regression analysis ‘is a statistical measure of how close the data are to the fitted regression line. . . . [I]t is the percentage of the response variable variation that is explained by a linear model.’ Falling between 0 and 1, a zero would indicate that the model does not predict any of the variability in the response data while a 1 would indicate the variability predicts 100% of the response data.”).

To elaborate, Kinsler used linear-regression models for each of the following four metrics:

1. Median LSAT versus the composite average of first-time, bar-pass rate,
2. Median UGPA versus the composite average of first-time, bar-pass rate,
3. Median LSAT versus bar-pass-rate differential,³⁰ and
4. Median UGPA versus bar-pass-rate differential.³¹

This regression model predicted the bar-pass rate of each school based upon its median LSAT score or median UGPA.³² The school's actual bar-pass rate was compared to the predicted pass rate; each school's score for that measure was defined as the number of standard deviations above or below the predicted score.³³ These standardized scores were then averaged among the four measures, and the schools were ranked.³⁴

Kinsler II applied the same regression model as its predecessor to examine bar performance over a five-year period from 2015–2019. *Kinsler II* compared the credentials of a law school's students who matriculated from 2012–2016, with the bar performance of the school three years later, from 2015–2019, and “average annual rank was then calculated based on each law school's performance over the period of 2015–2019.”³⁵

Chart 1 illustrates the ranking of *Kinsler II*: the schools are listed in descending order from most overperforming to most underperforming averaged over a five-year period.³⁶

Chart 1

Law School	2012/ 2015 Rank	2013/ 2016 Rank	2014/ 2017 Rank	2015/ 2018 Rank	2016/ 2019 Rank	Five- Year- Average Rank
BELMONT UNIVERSITY	1	9	4	3	1	3.6

30. See *id.* Bar-pass-rate differential was defined as the school's bar-pass rate compared to the weighted average for the jurisdiction. *Id.*

31. *Id.*

32. *Id.*

33. *Id.*

34. *Id.*

35. *Kinsler II*, *supra* note 3 (manuscript at 2) (“Utilizing linear regression models, the performance of 187 ABA-approved law schools was assessed using four metrics (reported by the ABA) for each calendar year for the five-year period of 2015-2019: (1) Median LSAT and Composite Average First-Time Bar Pass Rate; (2) Median UGPA and Composite Average First-Time Bar Pass Rate; (3) Median LSAT and Composite Average First-Time Bar Pass Rate Differential; and (4) Median UGPA and Composite Average First-Time Bar Pass Rate Differential. An annual rank was then calculated for each law school based on its over-performance (or under-performance) of predicted expectations for bar passage. An average annual rank was then calculated based on each law school's performance over the period of 2015-2019.”).

36. *Id.* at 3–4.

FLORIDA INTERNATIONAL UNIVERSITY	4	7	12	15	9	9.4
LIBERTY UNIVERSITY	43	4	6	1	3	11.4
CAMPBELL UNIVERSITY	5	23	1	50	2	16.2
TEXAS A&M UNIVERSITY	15	13	16	30	10	16.8
DUQUESNE UNIVERSITY	46	3	8	25	12	18.8
LOUISIANA STATE UNIVERSITY	10	41	11	11	24	19.4
GEORGIA STATE UNIVERSITY	2	18	44	28	13	21
TEXAS TECH UNIVERSITY	35	25	28	6	15	21.8
UNIVERSITY OF NEW HAMPSHIRE	71	11	2	13	15	22.4
REGENT UNIVERSITY	32	36	5	29	21	24.6
UNIVERSITY OF SOUTH CAROLINA	23	10	18	32	60	28.6
SETON HALL UNIVERSITY	6	66	35	36	7	30
CLEVELAND STATE UNIVERSITY	17	21	29	4	89	32
UNIVERSITY OF OKLAHOMA	3	47	26	58	27	32.2
SAINT LOUIS UNIVERSITY	91	12	10	31	18	32.4
UNIVERSITY OF NORTH CAROLINA	28	57	39	12	28	32.8
UNIVERSITY OF MISSOURI-KANSAS CITY	16	14	14	84	46	34.8
WASHINGTON AND LEE UNIVERSITY	29	53	31	34	30	35.4
NORTHERN ILLINOIS UNIVERSITY	50	6	19	103	4	36.4
DRAKE UNIVERSITY	37	44	60	19	29	37.8
UNIVERSITY OF TULSA	56	50	22	10	54	38.4
SOUTH TEXAS COLLEGE OF LAW HOUSTON	55	37	67	23	22	40.8
FLORIDA STATE UNIVERSITY	62	54	50	7	32	41
UNIVERSITY OF MISSOURI	42	31	47	40	45	41

UNIVERSITY OF KANSAS	7	55	58	24	65	41.8
SYRACUSE UNIVERSITY	36	39	46	52	38	42.2
UNIVERSITY OF MEMPHIS	72	22	24	77	26	44.2
SOUTHERN UNIVERSITY	106	8	62	21	24	44.2
LOYOLA UNIVERSITY NEW ORLEANS	33	24	43	16	109	45
UNIVERSITY OF NEW MEXICO	38	108	20	17	57	48
BAYLOR UNIVERSITY	110	63	21	20	31	49
UNIVERSITY OF ILLINOIS	92	45	37	64	18	51.2
DREXEL UNIVERSITY	34	20	85	46	81	53.2
UNIVERSITY OF MIAMI	120	38	9	35	66	53.6
WASHBURN UNIVERSITY	41	17	56	121	36	54.2
WAKE FOREST UNIVERSITY	76	15	13	108	64	55.2
NORTH CAROLINA CENTRAL UNIVERSITY	63	52	126	5	41	57.4
UNIVERSITY OF NEBRASKA	59	32	55	57	88	58.2
UNIVERSITY OF CINCINNATI	39	29	54	119	51	58.4
OHIO NORTHERN UNIVERSITY	70	48	33	135	6	58.4
STETSON UNIVERSITY	20	34	89	96	53	58.4
LINCOLN MEMORIAL UNIVERSITY	165	1	38	9	80	58.6
OHIO STATE UNIVERSITY	40	35	61	59	100	59
CITY UNIVERSITY OF NEW YORK	31	85	17	80	92	61
MERCER UNIVERSITY	88	128	32	49	8	61
ST. MARY'S UNIVERSITY	158	2	3	83	61	61.4
UNIVERSITY OF DENVER	45	42	76	79	69	62.2
UNIVERSITY OF LOUISVILLE	22	80	90	53	78	64.6
WAYNE STATE UNIVERSITY	24	104	63	98	49	67.6

SAMFORD UNIVERSITY	54	142	88	18	37	67.8
UNIVERSITY OF MONTANA	166	43	40	26	68	68.6
LOYOLA UNIVERSITY CHICAGO	98	92	86	56	14	69.2
JOHN MARSHALL LAW SCHOOL	30	62	25	71	159	69.4
WIDENER UNIVERSITY COMMONWEALTH	9	5	57	180	96	69.4
NOVA SOUTHEASTERN UNIVERSITY	64	16	23	177	74	70.8
CAPITAL UNIVERSITY	58	123	92	38	48	71.8
GONZAGA UNIVERSITY	13	69	135	89	56	72.4
UNIVERSITY OF IDAHO	118	51	49	39	107	72.8
UNIVERSITY OF BALTIMORE	81	75	91	55	67	73.8
QUINNIPIAC UNIVERSITY	14	133	53	51	126	75.4
ST. JOHN'S UNIVERSITY	74	99	45	78	86	76.4
UNIVERSITY OF ARKANSAS AT LITTLE ROCK	27	68	27	111	150	76.6
BOSTON COLLEGE	82	98	70	74	59	76.6
WILLAMETTE UNIVERSITY	125	185	41	22	10	76.6
UNIVERSITY OF FLORIDA	19	78	113	127	50	77.4
UNIVERSITY OF GEORGIA	53	76	93	126	39	77.4
UNIVERSITY OF MAINE	131	27	73	47	113	78.2
UNIVERSITY OF PITTSBURGH	77	144	69	43	62	79
CATHOLIC UNIVERSITY OF AMERICA	193	138	48	14	22	83
FAULKNER UNIVERSITY	101	19	174	106	18	83.6
VILLANOVA UNIVERSITY	26	72	160	120	43	84.2
UNIVERSITY OF TOLEDO	143	154	71	8	46	84.4
UNIVERSITY OF UTAH	140	64	95	73	52	84.8

UNIVERSITY OF ARKANSAS FAYETTEVILLE	107	79	30	130	85	86.2
UNIVERSITY OF KENTUCKY	69	114	65	27	156	86.2
UNIVERSITY OF MICHIGAN	57	59	121	99	98	86.8
UNIVERSITY OF HOUSTON	163	40	66	94	75	87.6
UNIVERSITY OF OREGON	160	124	75	48	34	88.2
UNIVERSITY OF IOWA	114	70	122	100	40	89.2
TEMPLE UNIVERSITY	87	30	105	118	106	89.2
WILLIAM AND MARY LAW SCHOOL	123	67	108	54	95	89.4
UNIVERSITY OF MASSACHUSETTS DARTMOUTH	177	95	7	2	170	90.2
UNIVERSITY OF CONNECTICUT	115	115	99	72	57	91.6
UNIVERSITY OF DETROIT MERCY	94	110	42	45	168	91.8
UNIVERSITY OF SOUTHERN CALIFORNIA	51	46	100	149	115	92.2
ILLINOIS INSTITUTE OF TECHNOLOGY CHICAGO-KENT COLLEGE OF LAW	73	65	138	125	63	92.8
FORDHAM UNIVERSITY	111	81	81	88	104	93
ST. THOMAS UNIVERSITY (FLORIDA)	129	175	84	37	41	93.2
CASE WESTERN RESERVE UNIVERSITY	65	97	51	133	129	95
SOUTHERN METHODIST UNIVERSITY	80	73	116	87	120	95.2
VANDERBILT UNIVERSITY	153	90	83	75	78	95.8
UNIVERSITY OF CALIFORNIA BERKELEY	104	105	104	61	114	97.6
UNIVERSITY OF ST. THOMAS (MINNESOTA)	52	168	59	154	55	97.6
BROOKLYN LAW SCHOOL	79	91	112	140	72	98.8

SANTA CLARA UNIVERSITY	89	93	34	139	140	99
FLORIDA COASTAL SCHOOL OF LAW	66	179	183	33	35	99.2
UNIVERSITY OF TEXAS AT AUSTIN	97	61	137	109	94	99.6
UNIVERSITY OF AKRON	8	136	161	162	33	100
DUKE UNIVERSITY	139	102	82	95	82	100
MICHIGAN STATE UNIVERSITY	134	134	72	65	97	100.4
UNIVERSITY OF NORTH DAKOTA	164	149	102	76	17	101.6
UNIVERSITY OF CALIFORNIA IRVINE	61	71	117	153	108	102
CORNELL UNIVERSITY	48	88	123	116	137	102.4
UNIVERSITY OF COLORADO	85	127	74	110	117	102.6
UNIVERSITY OF MARYLAND	167	137	127	41	44	103.2
LOYOLA MARYMOUNT UNIVERSITY LOS ANGELES	78	100	115	112	115	104
BOSTON UNIVERSITY	109	117	128	62	105	104.2
ELON UNIVERSITY	18	129	163	122	92	104.8
UNIVERSITY OF WYOMING	135	28	147	107	111	105.6
GEORGE MASON UNIVERSITY	182	84	87	85	91	105.8
ALBANY LAW SCHOOL	156	56	130	66	122	106
UNIVERSITY OF MISSISSIPPI	25	49	150	156	152	106.4
WIDENER UNIVERSITY DELAWARE	11	172	111	63	178	107
NEW YORK UNIVERSITY	60	94	131	102	149	107.2
UNIVERSITY OF WASHINGTON	90	60	156	69	161	107.2
ARIZONA STATE UNIVERSITY	44	86	158	168	84	108
SEATTLE UNIVERSITY	117	82	80	113	157	109.8
UNIVERSITY OF NOTRE DAME	141	139	78	93	99	110
AVE MARIA SCHOOL OF LAW	138	74	132	44	165	110.6

WEST VIRGINIA UNIVERSITY	99	163	52	68	171	110.6
PACE UNIVERSITY	150	83	110	91	120	110.8
ROGER WILLIAMS UNIVERSITY	49	101	68	169	169	111.2
FLORIDA A&M UNIVERSITY	21	122	157	138	122	112
UNIVERSITY OF NEVADA LAS VEGAS	108	165	79	81	128	112.2
INDIANA UNIVERSITY INDIANAPOLIS	67	131	109	90	165	112.4
UNIVERSITY OF ALABAMA	127	119	77	134	112	113.8
CREIGHTON UNIVERSITY	96	147	118	70	138	113.8
UNIVERSITY OF HAWAII	75	153	140	42	163	114.6
UNIVERSITY OF CALIFORNIA LOS ANGELES	95	130	136	105	109	115
OKLAHOMA CITY UNIVERSITY	169	135	64	86	125	115.8
UNIVERSITY OF TENNESSEE	83	126	103	167	102	116.2
COLUMBIA UNIVERSITY	119	107	129	92	136	116.6
MCGEORGE SCHOOL OF LAW	93	120	98	152	124	117.4
CALIFORNIA WESTERN SCHOOL OF LAW	121	26	114	147	180	117.6
UNIVERSITY OF SAN DIEGO	145	89	96	128	131	117.8
UNIVERSITY OF DAYTON	137	182	170	97	5	118.2
UNIVERSITY OF SOUTH DAKOTA	148	116	188	67	72	118.2
STANFORD UNIVERSITY	105	112	119	117	142	119
DEPAUL UNIVERSITY	84	109	153	173	87	121.2
CARDOZO SCHOOL OF LAW	146	151	94	123	100	122.8
GEORGETOWN UNIVERSITY	151	87	120	129	127	122.8
NORTHEASTERN UNIVERSITY	126	156	133	82	118	123
HOWARD UNIVERSITY	159	181	15	131	130	123.2
LEWIS AND CLARK COLLEGE	154	161	107	124	73	123.8

UNIVERSITY OF VIRGINIA	102	145	124	115	134	124
UNIVERSITY OF CALIFORNIA DAVIS	147	152	148	104	75	125.2
NORTHERN KENTUCKY UNIVERSITY	170	33	164	114	148	125.8
UNIVERSITY OF RICHMOND	103	58	171	145	152	125.8
MISSISSIPPI COLLEGE	12	158	154	157	160	128.2
TEXAS SOUTHERN UNIVERSITY	128	77	101	178	175	131.8
VERMONT LAW SCHOOL	142	106	168	60	185	132.2
SOUTHERN ILLINOIS UNIVERSITY CARBONDALE	113	140	144	142	139	135.6
UNIVERSITY OF CHICAGO	132	111	125	171	141	136
NEW ENGLAND LAW BOSTON	112	103	175	158	132	136
INDIANA UNIVERSITY BLOOMINGTON	149	121	162	164	89	137
YALE UNIVERSITY	116	118	145	150	161	138
HARVARD UNIVERSITY	124	146	152	137	132	138.2
WESTERN NEW ENGLAND UNIVERSITY	130	96	142	179	158	141
BRIGHAM YOUNG UNIVERSITY	136	141	151	136	143	141.4
APPALACHIAN SCHOOL OF LAW	122	190	36	192	172	142.4
UNIVERSITY OF PENNSYLVANIA	152	113	141	161	147	142.8
CHAPMAN UNIVERSITY	68	159	169	143	176	143
BARRY UNIVERSITY	162	148	97	172	150	145.8
SUFFOLK UNIVERSITY	86	167	159	155	167	146.8
CHARLESTON SCHOOL OF LAW	144	125	187	101	179	147.2
WESTERN STATE COLLEGE OF LAW	175	174	106	141	146	148.4
GEORGE WASHINGTON UNIVERSITY	168	150	134	146	145	148.6

UNIVERSITY OF ARIZONA	47	170	165	184	182	149.6
PEPPERDINE UNIVERSITY	180	157	184	163	82	153.2
TULANE UNIVERSITY	157	164	139	144	164	153.6
WASHINGTON UNIVERSITY	161	162	149	151	155	155.6
TOURO COLLEGE	183	132	143	182	143	156.6
UNIVERSITY OF MINNESOTA	184	171	166	166	103	158
NORTHWESTERN UNIVERSITY	173	178	155	132	154	158.4
ATLANTA'S JOHN MARSHALL LAW SCHOOL	185	180	172	189	70	159.2
NEW YORK LAW SCHOOL	181	160	180	160	119	160
UNIVERSITY OF CALIFORNIA HASTINGS	179	189	185	181	75	161.8
EMORY UNIVERSITY	133	176	179	170	173	166.2
WESTERN MICHIGAN UNIVERSITY THOMAS M. COOLEY	171	155	176	148	183	166.6
STATE UNIVERSITY OF NEW YORK AT BUFFALO	174	169	146	174	174	167.4
AMERICAN UNIVERSITY	190	183	182	159	135	169.8
HOFSTRA UNIVERSITY	175	166	173	185	184	176.6
SOUTHWESTERN LAW SCHOOL	189	187	177	165	177	179
GOLDEN GATE UNIVERSITY	194	188	167	183	181	182.6
UNIVERSITY OF THE DISTRICT OF COLUMBIA	188	177	190	176	186	183.4
UNIVERSITY OF SAN FRANCISCO	192	191	181	190	187	188.2

The next chart, Chart 2, is the ranking of the top-fifteen overperforming schools according to the results of *Kinsler II*'s linear-regression model. The number-one-ranked school most overperformed on the bar examination relative to its entering credentials.

Chart 2

Rank	Top-Fifteen Law Schools for Bar Passage ³⁷
1	Belmont University
2	Florida International University
3	Liberty University
4	Campbell University
5	Texas A&M University
6	Duquesne University
7	Louisiana State University
8	Georgia State University
9	Texas Tech University
10	University of New Hampshire
11	Regent University
12	University of South Carolina
13	Seton Hall University
14	Cleveland State University
15	University of Oklahoma

In contrast, Chart 3 is the ranking of the bottom-fifteen schools according to the results of the *Kinsler II* model. The school ranked 187th most underperformed on the bar examination relative to its entering credentials.

Chart 3

Rank	Bottom-Fifteen Law Schools for Bar Passage ³⁸
173	Touro College
174	University of Minnesota
175	Northwestern University
176	Atlanta's John Marshall Law School
177	New York Law School
178	University of California Hastings
179	Emory University
180	Western Michigan University Thomas M. Cooley
181	State University of New York at Buffalo
182	American University
183	Hofstra University
184	Southwestern Law School

³⁷ *Id.* at 3.

³⁸ *Id.* at 4.

185	Golden Gate University
186	University of the District of Columbia
187	University of San Francisco

The *Kinsler II* model's positive aspects are that it uses two of the top predictors of bar passage rates: LSAT scores and UGPA, and it uses four different measures; two of the four measures compare the schools with their jurisdiction's average, which partially reduces jurisdiction bias.³⁹ The most serious flaw with the model is, however, that it uses linear-regression analysis, which is not optimal for analyzing the relationship of variables that are non-linear and heteroscedastic.⁴⁰

III. PROBLEMS WITH LINEAR REGRESSION

A. Linear Regression Basics

The statistical calculation called simple linear-regression attempts to describe how a continuous, dependent variable, Y , is related to a continuous, independent variable, X .⁴¹ The relationship is described using a linear equation of the form:

$$Y = mX + b.$$

Kinsler's model used linear regression—a form of inferential statistics—to evaluate matriculants' LSAT scores and UGPAs, which are not continuous variables. Linear regression should be applied to continuous variables to generate the most valid statistical inferences.⁴² Broadly defined, a continuous variable is a quantitative variable that is not limited to integers, halves, quarters, etc. Continuous variables include decimal values and the smallest quantifiable increments that observation methods allow; they can also be measurements such as heights, weights, distances, and times.⁴³

Although LSAT scores and UGPA are non-continuous variables, the use of UGPA might have little negative impact upon linear-regression analysis. LSAT scores are not continuous variables because they are restricted to whole numbers. Likewise, UGPAs are not continuous data because they have a finite number of possible values, such as 3.0, 3.5, etc. However, a student's UGPA is the average of many courses, typically forty,⁴⁴ and UGPA—which is synonymous with a student's

39. See *Kinsler II*, *supra* note 3 (manuscript at 2) (explaining the Kinsler model).

40. See *infra* Parts III.C–D.

41. See Lisa Sullivan, *Correlation and Linear Regression*, BOSTON UNIVERSITY SCHOOL OF PUBLIC HEALTH: ONLINE LEARNING MODULES, [https://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_correlation-regression/bs704_correlation-regression_print.html#:~:text=Simple%20linear%20regression%20is%20a,dependent%20\(or%20outcome\)%20variable.&text=In%20regression%20analysis%2C%20the%20dependent%20variable%20is%20denoted%20Y%20and,independent%20variable%20is%20denoted%20X](https://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_correlation-regression/bs704_correlation-regression_print.html#:~:text=Simple%20linear%20regression%20is%20a,dependent%20(or%20outcome)%20variable.&text=In%20regression%20analysis%2C%20the%20dependent%20variable%20is%20denoted%20Y%20and,independent%20variable%20is%20denoted%20X).

42. See *id.*

43. See *Continuous Variable*, SCIENCE DIRECT, <https://www.sciencedirect.com/topics/computer-science/continuous-variable>.

44. Abigail Endsley, *How Many Credits Do I Need for a Bachelor's Degree?*, PEARSON (July 22, 2017), <https://pearsonaccelerated.com/blog/how-many-credits-do-i-need-for-a-bachelors-degree>.

undergraduate, cumulative GPA—has a larger range of values relative to the value ranges of LSAT scores. A cumulative GPA can include almost any tenth and hundredth of a number. This large range of values, combined with schools typically averaging the UGPAs of many students to establish the UGPA credentials of a matriculating class, might mitigate errors associated with UGPA being a non-continuous variable. Consequently, UGPA might be similar enough to continuous data that using UGPA to proceed with linear regression may be harmless error.

B. The Four Required Conditions of Linear Regression

Apart from the suitability of continuous variables for inferential statistics,⁴⁵ linear regression requires that data satisfy the following four conditions:

1. “Linearity: a linear relationship between the independent variable X and the dependent variable Y ,”
2. “Homoscedasticity: the variance of the residuals is the same for any value of X ,”
3. “Independence: the residuals are independent of each other, and”
4. “Normality: for any fixed value of X , Y is normally distributed.”⁴⁶

Calculating a linear-regression line is possible even if these four conditions are not satisfied. However, the validity of inferences made (conclusions, estimates, predictions, hypotheses, etc.) is suspect when linear regression is applied to data that does not meet all four conditions.⁴⁷ Consequently, Kinsler applying linear regression to data that is neither linear nor homoscedastic⁴⁸ lessens the validity of his inferential conclusions.

C. Non-Linearity of the Relationship between Entering Credentials and Bar Performance

Linear regression assumes that a linear relationship exists between the x and y variables.⁴⁹

Graph 1 below—representing simulated, randomly generated LSAT scores and bar passage rates which satisfy the four requirements of linear regression—helps contextualize linearity. We used the linear equation, $y = 5/3x - 200$. The random-

45. See *Continuous Variable*, *supra* note 43.

46. *Correlation and Regression with R*, BOSTON UNIVERSITY SCHOOL OF PUBLIC HEALTH: ONLINE LEARNING MODULES, https://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/R/R5_Correlation-Regression/R5_Correlation-Regression4.html#:~:text=There%20are%20four%20assumptions%20associated,are%20independent%20of%20each%20other.

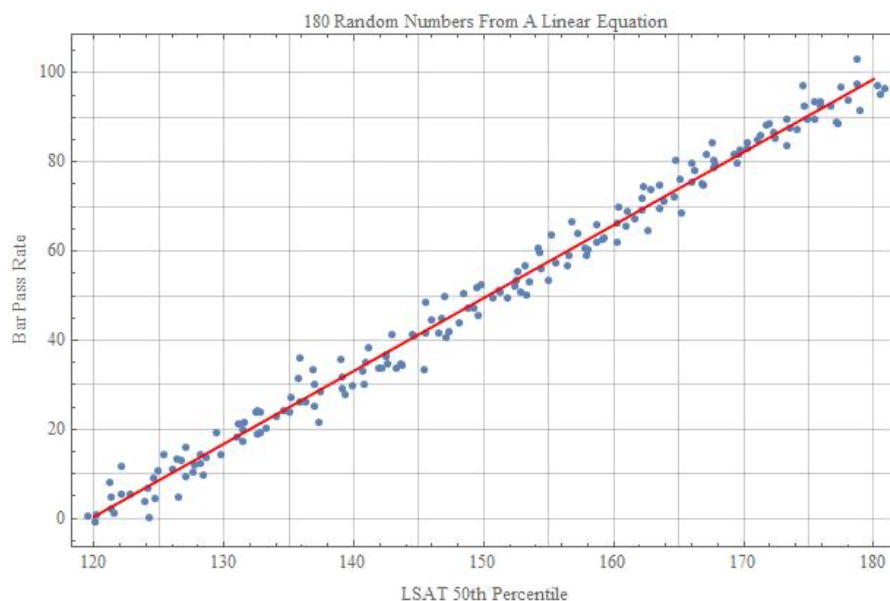
47. See *Advantages and Disadvantages of Linear Regression*, OPENGUNUS IQ, <https://iq.opengenus.org/advantages-and-disadvantages-of-linear-regression/>. Because linear regression assumes a linear relationship between the input and output variables, it fails to properly fit complex datasets. In most real-application scenarios, the relationship between the variables of the dataset is not linear; thus, a straight line does not properly fit the data. *Id.*

48. See *infra* Parts III.C–D.

49. *Assumptions of Linear Regression*, STATISTICS SOLUTIONS, <https://www.statisticssolutions.com/assumptions-of-linear-regression/>.

number generator was limited to selecting from a range of x -values (LSAT 50th percentile) between approximately 120 and 180, and a range of y -values (Bar-Pass Rate) between approximately zero and 100. This range of data represents simulated-LSAT scores and bar passage rates. In each of the following graphs the dots represent Bar-Pass Rates while the straight line represents the Best Fit Linear Model.

Graph 1



Apart from some random variations above and below the line, linearity is satisfied for this data set because the data appears to be trending in a straight line. Linear regression calculates a straight line which passes through the data points while minimizing the residuals, which are sometimes called errors.⁵⁰ A residual is the vertical distance from an actual data point to the regression line—the straight line drawn through all data points.⁵¹

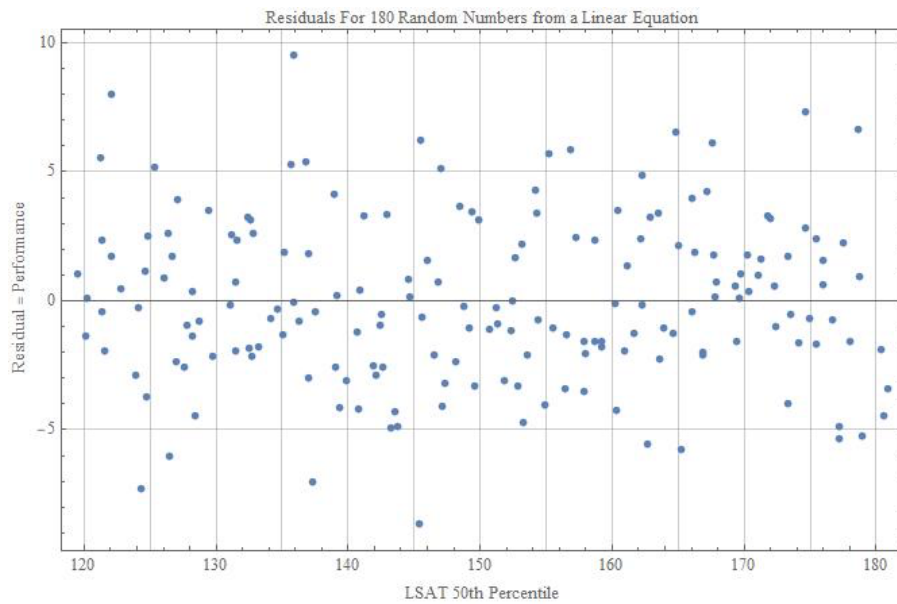
In regression analysis, residuals help inform whether the statistical model is a good fit for the evaluated data. A residual is the difference between the actual y -value and the predicted y -value represented by the regression model for a particular x -value. Graphing residuals can hint about whether residuals are random.

Graphing datasets helps understand the importance of residuals. In the graph below, the horizontal line at zero on the y -axis represent the regression line of the previous graph. Each of the data points we used to calculate the regression line in the previous graph is expressed as a residual in the graph below; this simplifies visualizing the distance of each data point from the generated line.

50. *Residual Values (Residuals) in Regression Analysis*, STATISTICS HOW TO, <https://www.statisticshowto.com/residual/#:~:text=A%20residual%20is%20the%20vertical,at%20that%20point%20is%20zero.>

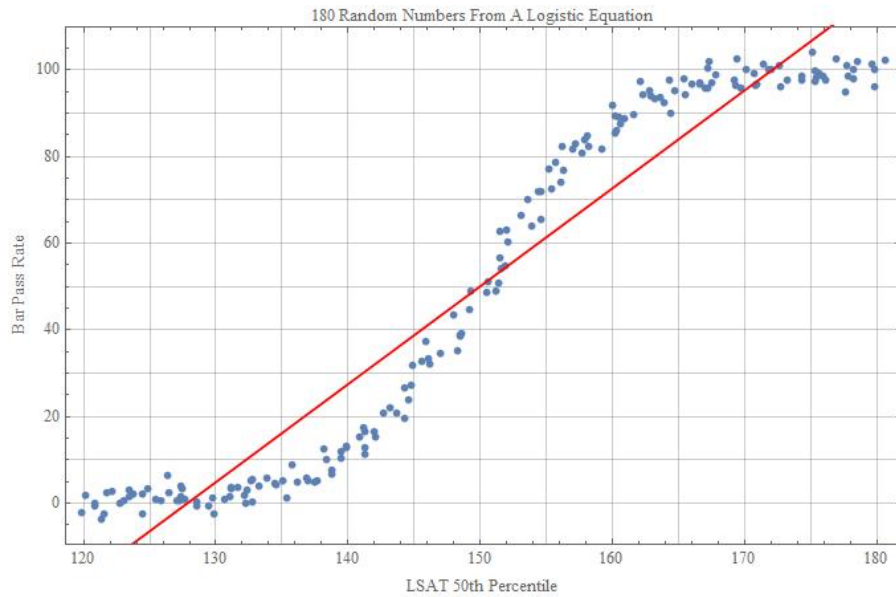
51. *Id.*

Graph 2



Graph 2 illustrates that, across the entire range, an approximately equal number of data points are above and below the x -axis. This distribution is indicative of linear data. In contrast to data suitable for linear regression, the next graph applies linear regression to a dataset of random numbers computed from a non-linear or logistic equation.

Graph 3



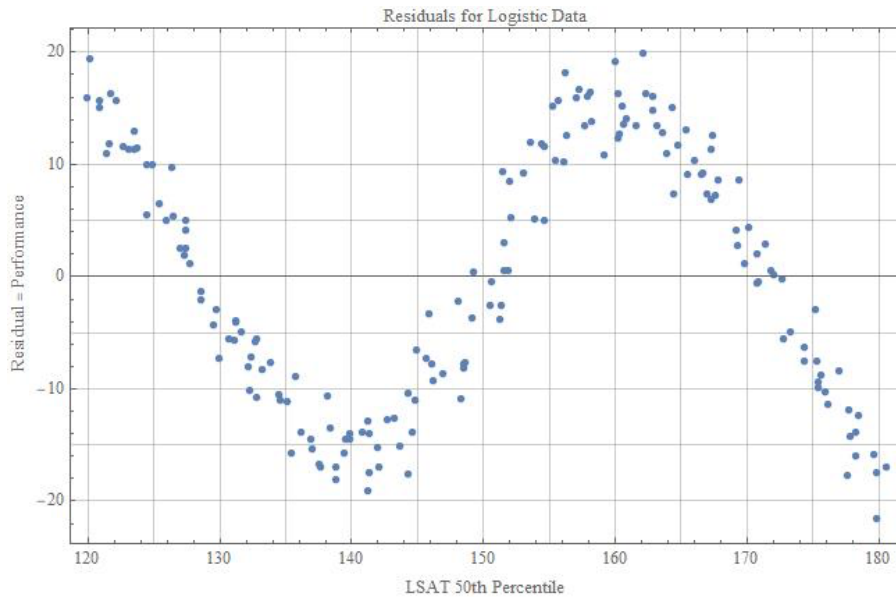
The relationship between the datapoints in Graph 3 is not linear because they plot in a serpentine rather than straight pattern. Although a nearly equal amount of data points appear to be above and below the line, the distribution is not consistent throughout the entire range—datapoints are either exclusively above or below the line for different ranges of values. The significance of this for the Kinsler ranking is that, if the relationship between matriculation credentials and bar performance is non-linear, then creating a linear-regression line will erroneously indicate over and underperformance.

Essentially, when linear regression is performed for non-linear data, the conclusions and observations drawn about the data can be erroneous. The straight line produced by linear regression is not suitable for representing the relationship between the variables in the dataset.

For example, because the above graph applies linear regression to a non-linear dataset, schools with a median LSAT of around 140 are furthest from and below the line which would, according to the Kinsler model, rank as most underperforming. Comparatively, schools in the 160-median LSAT bracket would be most overperforming because they are furthest above the line.

Graphing residuals makes the bias created by using linear regression to describe the relationship between non-linear variables more apparent. Kinsler's model calculates bar performance as the distance between the regression line and the residual-data plot for each school. The graph below plots the residuals of the previous graph relative to its regression line. Recall that the previous graph applies linear regression to a simulated, non-linear dataset.

Graph 4



Graphing the residuals of this simulated dataset to which linear regression is applied illustrates that schools with LSAT scores around 140 and 180 would be the largest underperformers according to the Kinsler model. The residuals representing these schools are furthest from and below the x -axis. Comparatively, schools in the 120 and 160 LSAT range would rank as most overperforming because the residuals representing these schools are furthest above the x -axis.

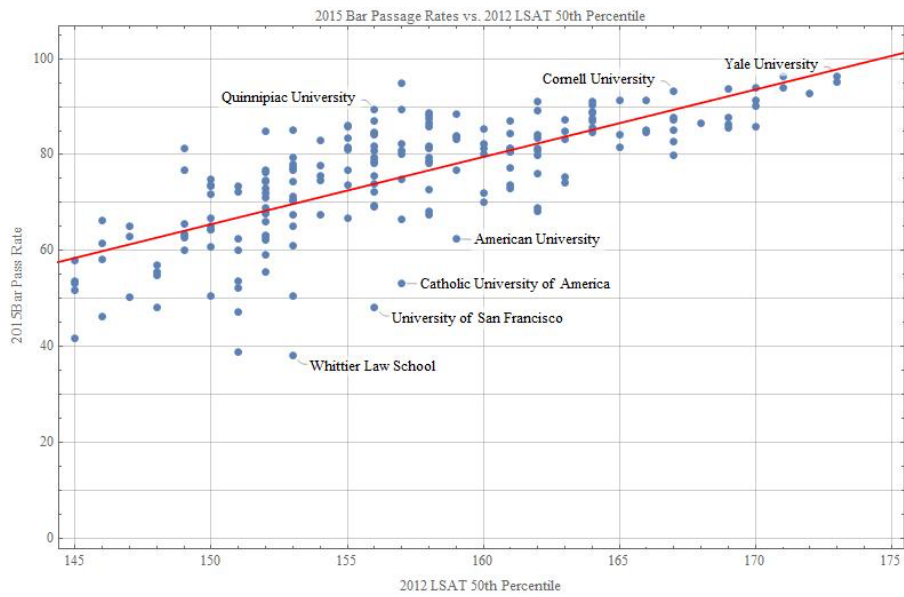
Understanding the application of linear regression to linear and non-linear dataset frames the following section, which examines the relationship between actual, median-matriculating-LSAT scores and bar performance three years later.

1. *Usain Bolt and the Non-linearity of the Relationship between Median matriculating LSAT and Bar Performance*

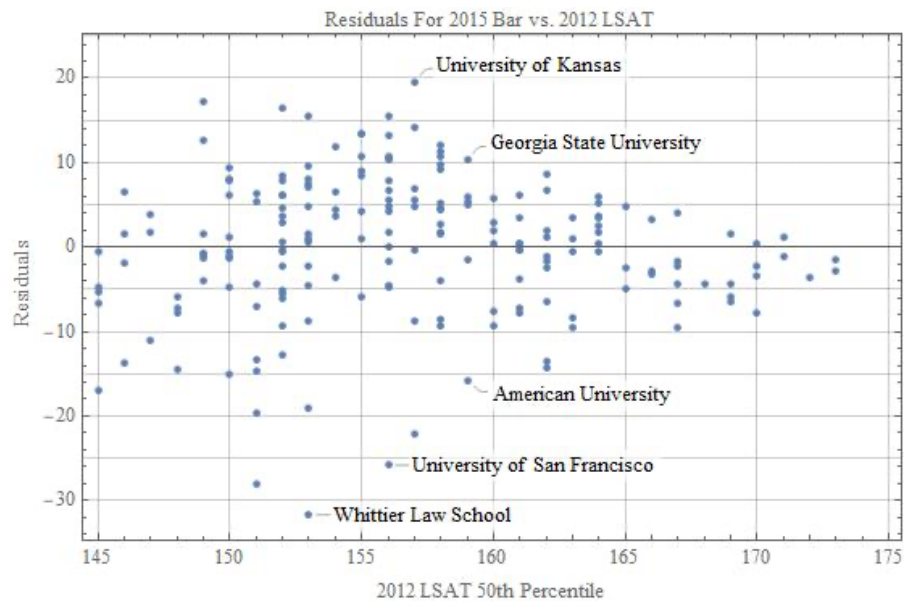
The following graphs represent the scatter and residual plots, respectively, for the relationships between 2012 median LSAT and 2015 bar performance of all law schools evaluated.⁵²

52. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (2012 Enrollment Sheet).

Graph 5



Graph 6



These datasets, like most real-world data, generate scatterplots that do not perfectly match any textbook regression-model, whether linear, logistic, or other models. As a result, these graphs do not appear precisely like the graphs in the previous section, which we generated using random numbers. Kinsler used median LSAT as one of the variables for comparing bar performance with entering credentials.

The data in the above graph initially might appear to be approximately linear. However, more focused inspection reveals, especially when examining the residual plot of the data, that more data points are below the regression line in the upper-LSAT range above 165. This suggests a small degree of downward curvature (concave down) of the data above 165 LSAT scores.

When evaluating the residual plot above according to Kinsler's model, overperformance on the bar examination means that the residual representing the school is above the horizontal line.⁵³ Conversely, underperformance means that the residual representing the school is below the horizontal line.⁵⁴ The greater the distance between the data point and horizontal line, the greater the school's students over or underperformed on the bar exam.⁵⁵ The graph above demonstrates that the use of a linear-regression model for comparing matriculation credentials to bar-pass rates creates a bias against schools with high, median-matriculating-LSAT scores.

The graph shows that linear regression condemns most of the law schools that have LSAT scores greater than or equal to 165 to being classified as underperformers on the bar examination. Three of the law schools that have high-LSAT scores—Emory, Northwestern, and Minnesota—are three (20%) of the fifteen schools that Kinsler identified as most underperforming. Zero of the high-LSAT schools are included in Kinsler's list of most-overperforming schools.⁵⁶ This is unsurprising considering the nature of the analyzed data.

Kinsler's model makes it difficult, and sometimes impossible, for schools that have the highest LSAT scores to be classified as overperformers. Such schools have little or no capacity to exceed predicted bar performance. Because the maximum possible bar passage rate is 100%, schools that score in the 90th percentile have the most difficulty increasing bar performance.

High-LSAT schools' difficulty increasing bar performance is analogous to Usain Bolt increasing his sprinting speed over 100 meters. Usain Bolt sprints 100 meters near or at the upper limit of human ability; consequently, he would find it nearly impossible to significantly increase his sprinting performance over 100 meters. Schools with median-matriculating-LSAT scores of 165 or greater perform near the upper limit of 100% on bar passage performance. Like Usain Bolt sprinting over 100 meters, these schools cannot significantly increase their performance.

53. See *Kinsler I*, *supra* note 1, at 199 ("Utilizing the linear regression line equation, a predicted bar passage rate or bar passage rate differential was calculated based upon either LSAT or UGPA, respectively. The variance was then determined by subtracting the predicted passage rate or rate differential from the actual passage rate or rate differential. The law schools were then rank-ordered based upon the variance, and the variance for each law school was recorded.").

54. *Id.* at 200.

55. *Id.*

56. See *Kinsler II*, *supra* note 3 (manuscript at 3).

In the chart below, which demonstrate and help contextualize the bias linear regression creates against high-LSAT schools, we developed regression equations to predict bar passage for 2015–2019 based upon median-LSAT score and 75th-percentile UGPA three years earlier. In Chart 4’s regression equations, the variable x represents the matriculating credentials for 2012–2015, and y represents the bar passage three years later for the years 2015–2019.

Chart 4

Relationship Between:	Regression Equation for the Relationship
2012 median LSAT and 2015 bar passage rate	$y = 1.40223x - 144.806$
2012 median-75th-percentile UGPA and 2015 bar passage rate	$y = 57.5552x - 132.29$
2013 median LSAT and 2016 bar passage rate	$y = 1.66253x - 186.223$
2013 median 75th-percentile UGPA and 2016 bar passage rate	$y = 63.529x - 155.639$
2014 median LSAT and 2017 bar passage rate	$y = 1.58068x - 169.789$
2014 median-75th-percentile UGPA and 2017 bar passage rate	$y = 60.0118x - 139.535$
2015 median LSAT and 2018 bar passage rate	$y = 1.72422x - 194.447$
2015 median-75th-percentile UGPA and 2018 bar passage rate	$y = 67.0478x - 167.781$
2016 median LSAT and 2019 bar passage rate	$y = 1.50272x - 155.621$
2016 median-75th-percentile UGPA and 2019 bar passage rate	$y = 60.2629x - 139.681$

Yale exemplifies the bias linear regression creates against high-LSAT schools. The linear-regression equation describing the relationship between 2012 LSAT medians and 2015 bar passage is $y = 1.40223x - 144.806$, where y is bar-pass rates and x is median-matriculating LSAT three years earlier. Plugging into this equation Yale’s 2012 median LSAT of 173, Yale had a predicted, bar passage rate of 97.78%. Yale’s actual bar-pass rate in 2015 was 96.32%.⁵⁷ Even with a bar pass of 96.32%, Yale is classified as an underperforming school in bar passage in 2015 because its bar passage rate was lower than the linear-regression model predicted.

According to Kinsler’s model, Yale could not have been classified as top-fifteen, overperforming school in bar performance in 2015, even if Yale had a 100% bar-pass rate. Kinsler’s model ranked Gonzaga the sixteenth-most overperforming school in bar performance in 2015.⁵⁸ In 2012, Gonzaga had a median-matriculating

57. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (2012 Enrollment).

58. Kinsler I, *supra* note 1, at 201.

LSAT of 155.⁵⁹ The regression equation above predicts that Gonzaga should have had a bar-pass score of 72.54% in 2015.⁶⁰ Gonzaga had an actual, bar-pass score of 83.34%.⁶¹ Thus, according to the Kinsler model, the sixteenth-ranked, overperforming school in bar passage in 2015 overperformed the model's prediction by 10.8%. For Yale to have ranked as a top-fifteen overperformer in 2015, Yale must have had a bar-pass rate 10.8% greater than the linear-regression model's predicted score. Yale's graduates must have passed the bar at a rate of $(97.78 + 10.8)$ 108.58% to be classified as a top-fifteen, overperforming school. *This is impossible.*

Whether a similar curvature in the data exists for schools that have a lower-end LSAT score is unclear. However, more than a few schools in the 145–150 LSAT range have bar passage scores above the horizontal line in the residual plot.⁶² The 2015 bar passage rates relative to schools' matriculating-75th-percentile UGPA indicates that non-linearity might make less likely for a low-UGPA school to be considered overperforming.

2. *Non-linearity of the Relationship between Median-Matriculating, 75th-percentile UGPA and Bar Performance*

For consistency in examining Kinsler's results, we compared bar performance to nearly the same variables that Kinsler used to ascertain schools' over and underperformance on the bar exam. The two variables with which Kinsler compared bar performance are median LSAT and median UGPA.⁶³ However, instead of using median UGPA, we elected to plot the relationship between 75th-percentile UGPA and bar performance because a recent, statistical study found that a school's 75th-percentile UGPA is the strongest predictor of bar performance three years after students matriculated.⁶⁴ The following graphs represent the scatter and residual plots, respectively, for the relationships between 2012 matriculating 75th-percentile UGPA and 2015 bar performance for all schools evaluated.

59. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (2012 Enrollment).

60. See *supra* Chart 4 (applying the equation $y = 1.40223x - 144.806$, where y is predicted bar-pass rate, and x is median-matriculation LSAT).

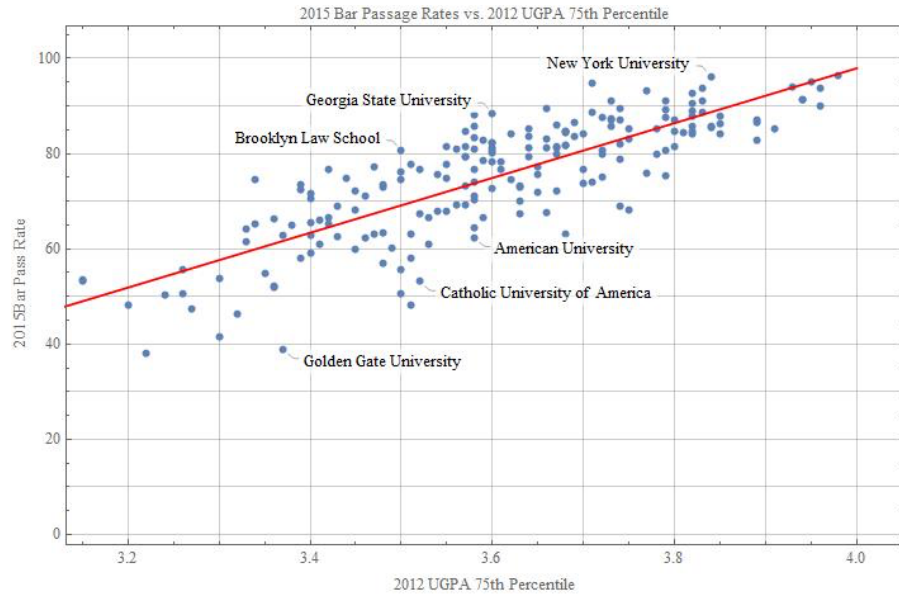
61. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (2012 Enrollment).

62. See *supra* Graph 6.

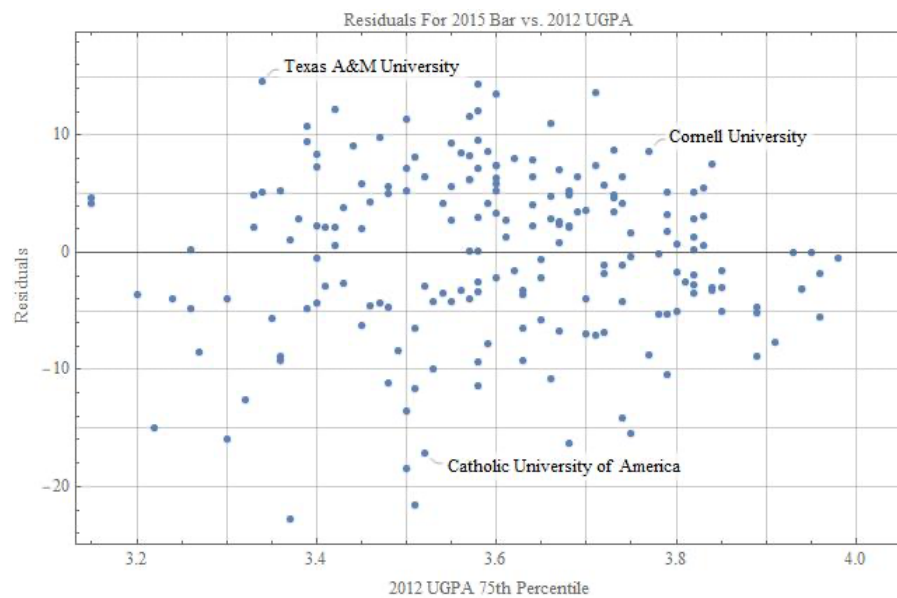
63. See *supra* note 4 (explaining the Kinsler methodology).

64. See *infra* notes 87, 89 and accompanying text.

Graph 7



Graph 8



These graphs demonstrate, like the plots for median LSAT in the previous section, that most schools with high-UGPA matriculants are below the horizontal line on the residual plot. Additionally, most of the schools that have a 75th-percentile, matriculant UGPA below 3.3 are below the residual line located at zero on the y -axis. This suggests, based upon a linear-regression model, that such schools have difficulty being classified as overperformers.

Three reasons might explain why certain LSAT or UGPA matriculant scores are more frequently below the line and less likely to overperform. First, randomness might explain this phenomenon. Second, schools in that range might poorly prepare their students for the bar examination. Finally, the relationship between matriculating credentials and bar passage might be non-linear. Our graphs demonstrate that the data is non-linear for schools that have high, matriculating-median LSATs and 75th-percentile UGPAs, and possibly for schools with low, entering 75th-percentile UGPAs.⁶⁵

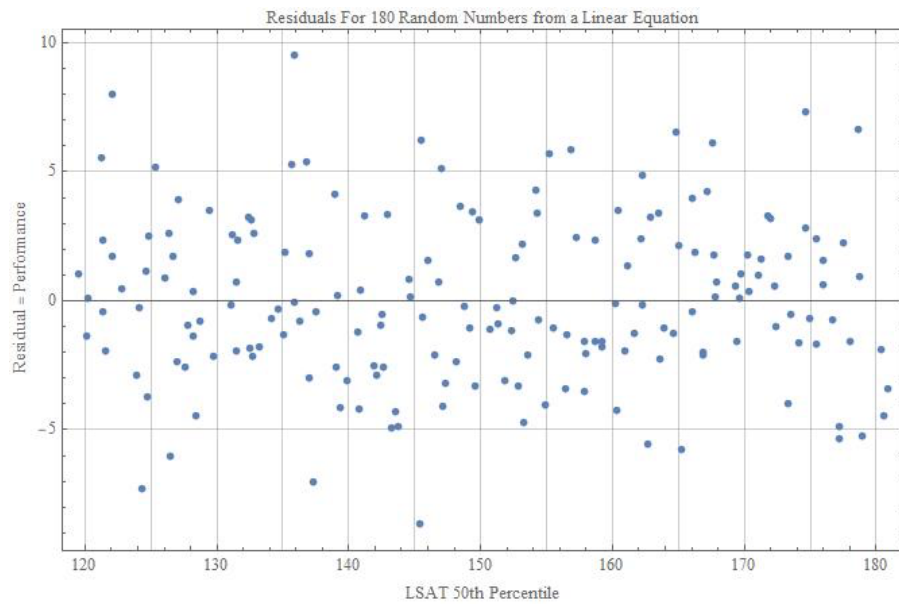
To summarize, the curvature or non-linearity of the data for the schools with highest matriculation credentials sufficiently shows that Kinsler's ranking formula is biased in favor of schools in the middle-LSAT range and middle-UGPA range, and biased against schools in the high, 75th-percentile UGPA range. Kinsler's ranking formula might also be biased against schools in the lower range of 75th-percentile UGPAs.

D. Heteroscedasticity

Reexamining our random-number, linear-data plot (reposted below), the residual points across the entire LSAT range—from 120 to 180—are distributed approximately equally above and below the x -axis. This even distribution of the residuals across the data spectrum is called homoscedasticity, which is a necessary condition of data used in linear-regression analysis to achieve the most reliable results.

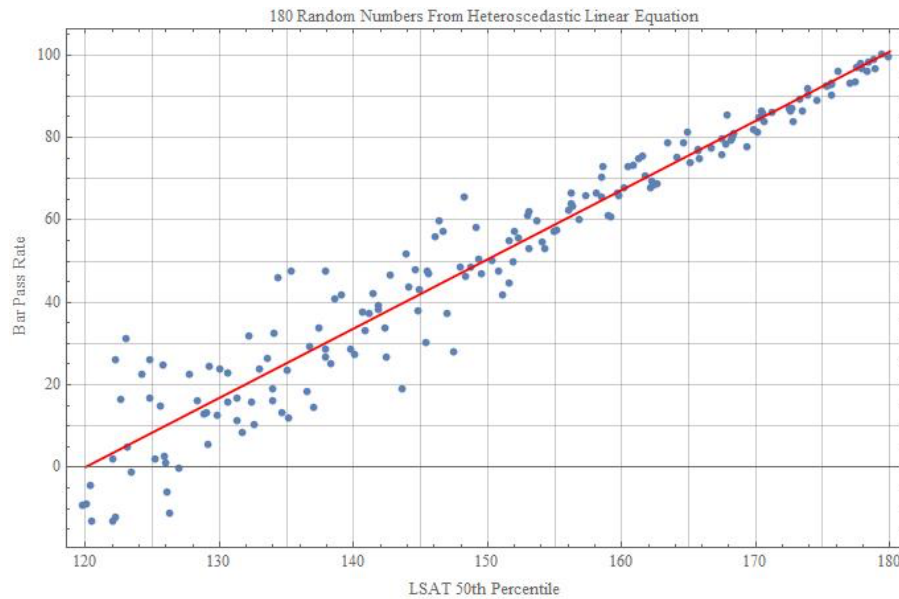
65. See *supra* Graphs 5, 7.

Graph 9



By contrast, the following, simulated graph illustrates the linear regression of a dataset that has a non-constant variance of Y (bar passage). When the variance of one variable relative to the other is not constant across the range of the data, such data is termed heteroscedastic.

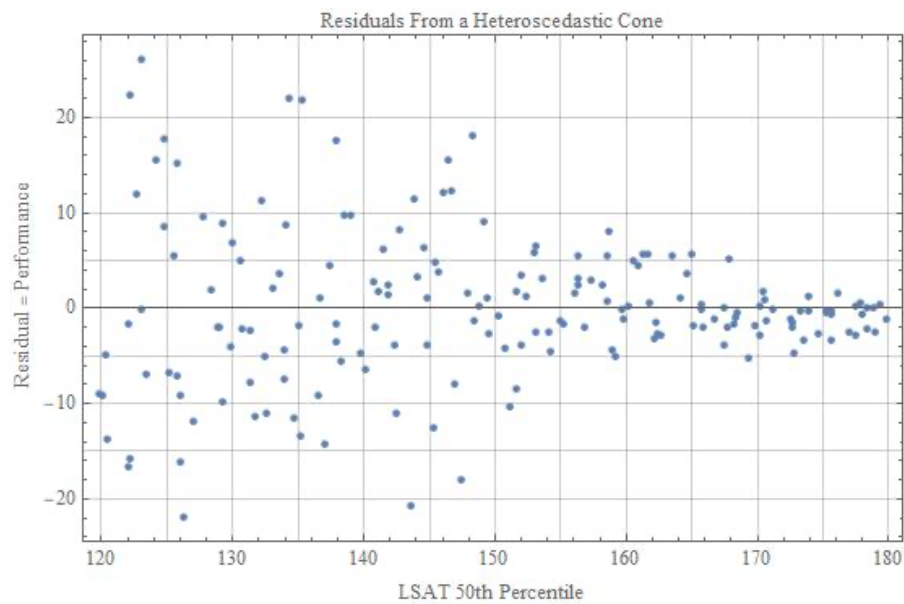
Graph 10



The dataset in the simulated plot above is heteroscedastic because the data points tend to be closer to the regression line for higher values of simulated-LSAT scores, and the data points for lower values of the simulated-LSAT scores are more spread apart. This data-relationship is known as cone-shaped.

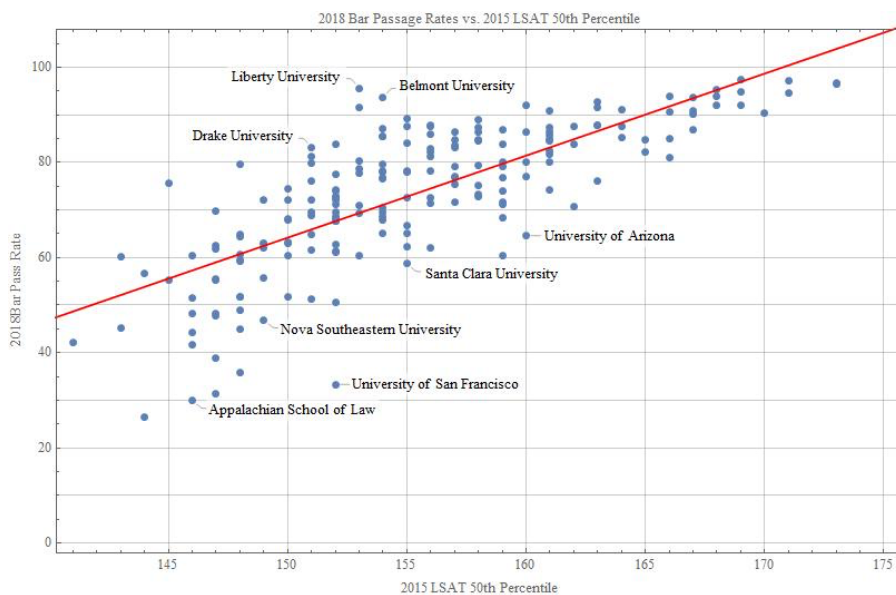
Plotting the residuals makes more apparent the heteroscedasticity of the dataset. In the graph below, the residuals of the simulated-LSAT scores for higher values are mostly closer to one another and the horizontal line, and lower values of the simulated-LSAT scores are generally more scattered and further from the x -axis. Stated differently, the data is not homoscedastic because the range of the residuals is not constant across the entire data range.

Graph 11



The dataset of median-LSAT scores for 2015 matriculants and bar passage performance for all law schools three years later in 2018 is heteroscedastic. This dataset's heteroscedasticity is apparent in graphs below: a linear-regression scatterplot and a plot of the residuals, respectively.

Graph 12



These graphs illustrate that, consistent with the discussion on linearity, variation is small in the higher-LSAT region, and much higher in the middle-LSAT region. The residual value for every school that has a 165 median LSAT or above is approximately plus-or-minus ten. By contrast, schools in the 150–160 range have residuals of approximately plus-or-minus thirty.

Importantly, for the residual plot above, remember that Kinsler’s model defines over and underperformance as a residual score above and below the line, respectively. The most overperforming schools have residuals furthest above the line, and the most underperforming schools have residuals furthest below the line.

The heteroscedasticity of this data creates for Kinsler’s model the most serious issues of bias, and such bias infects the inferences and ranking system of the model. The dataset for 2018 bar passage versus 2015 LSAT best illustrates the bias of Kinsler’s model. The linear-regression equation for this dataset is:

$$y = 1.72x - 194$$

Where y represents 2018 bar passage rate as a percentage, and x represents the school’s median-matriculating-LSAT score in 2015.

Any school that has a 2015 median-matriculating-LSAT score of 171 or greater is doomed to receive an underperforming rating. If a school has a 2015 median-matriculating-LSAT score of 171, then the regression equation predicts that the school’s bar passage rate would be 100.12%.⁶⁶ Thus, any school with a median-matriculating-LSAT score of 171 or greater cannot possibly receive an

66. See *supra* Chart 4 (substituting 171 for x , the regression equation is $y = 1.72(171) - 194$, which equals 100.12).

overperforming rating because, according to the linear-regression model, such schools are expected to have a bar-performance score of greater than 100%. In this model, these schools are therefore relegated to permanent-underperformer status because achieving a bar-pass rate of greater than 100% is impossible.

Additionally, applying linear regression to this heteroscedastic, non-linear dataset makes mathematically impossible for any school that has a 2015 median LSAT of 164 or greater to be included in the top-fifteen overperformers. Comparing a school that had a 2015 median-matriculating LSAT greater than 164 with the fifteenth-ranked school in 2018, which had a sub-164 LSAT in 2015, illustrates this issue.

In 2018, the Kinsler model's fifteenth-most-overperforming school on the bar exam in relation to the school's median-matriculating LSAT was Florida International University ("FIU").⁶⁷ In 2015, FIU had a median-matriculating-LSAT score of 156⁶⁸ and bar-pass rate of 87.75%.⁶⁹ This represented an overperformance of 13.4% because the linear-regression equation predicted a bar passage rate of 74.32%.⁷⁰

A school that had an LSAT score of 164 or greater in 2015 could not have ranked as a top-fifteen overperformer. According to the linear-regression model, if a school had a median-matriculating-LSAT score of 164 in 2015, then the predicted bar passage rate would be 88.08%.⁷¹ Even if that school had a pass rate of 100% on the 2018 bar exam, that school could not have ranked as a top-fifteen overperformer. The school's overperformance would be only 11.92%,⁷² which is lower than the overperformance calculated for the fifteenth-place school in 2018.⁷³

Because an institution's bar passage rate cannot exceed 100%, ranking as one of Kinsler's top-fifteen overperformers in 2018 bar passage is mathematically impossible for any school with a median-matriculating-LSAT score of 164 or higher in 2015. For a school with a 164 LSAT to have been included into Kinsler's 2018 top-fifteen list, the school's students must have had a bar-pass rate of 13.5%⁷⁴ or greater than the model's predicted rate. Again, the predicted bar-pass rate in 2018 for a 164-LSAT school is 88.08%.⁷⁵ According to a linear-regression model, to have ranked as a top-fifteen overperformer in 2018, the school having a median-matriculating LSAT of 164 in 2015 must have achieved a 2018 bar-pass rate for its students of at least 101.58%. *This is impossible!*

67. See *supra* Chart 1.

68. See RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (2015 Enrollment).

69. *Id.*

70. See *supra* Chart 4 (substituting 156 for x , the regression equation is $y = 1.72*(156) - 194$, which equals 74.32).

71. See *supra* Chart 4 (substituting 164 for x , the regression equation is $y = 1.72*(164) - 194$, which equals 88.08).

72. Overperformance is the school's actual performance (100%) minus predicted performance (88.08%), which equals 11.92%.

73. See *supra* note 70 and accompanying text.

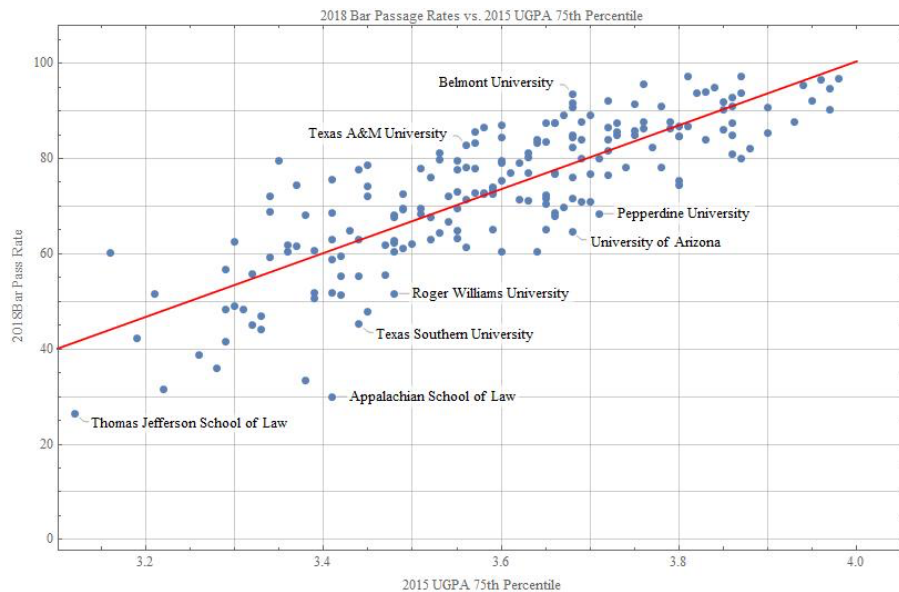
74. These are the percentages because FIU, the fifteenth-ranked school, overperformed the model's prediction by that amount.

75. See *supra* note 71 and accompanying text.

Similar to irrationally expecting Usain Bolt to run the 100-meter sprint in less than zero seconds, a school should not be expected to achieve a bar-pass rate of greater than 100% and penalty labeled as an underperformer when failing to meet this impossible expectation. This issue occurs because of the application of linear regression to a heteroscedastic, non-linear dataset. Applying linear regression to such data also explains why many schools that had 2015 LSATs of 164 or greater; including Emory, Northwestern, and Minnesota; are included in Kinsler's list of the fifteen most underperforming schools despite having 2018 bar passage rates of 82.11%, 91.97%, and 85.33% respectively.⁷⁶

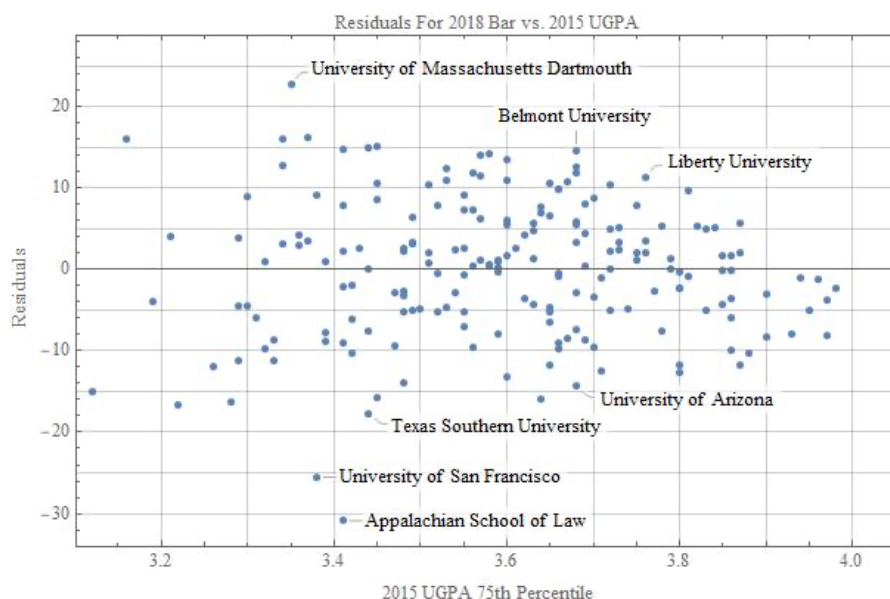
Like 2015 LSAT scores, the relationship between 75th-percentile UGPA for 2015 matriculants and bar passage rates in 2018 is heteroscedastic. The graphs of this data below are a scatter plot and a plot of the residuals, respectively.

Graph 13



76. See RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (noting these schools' LSAT scores and 2018 bar-pass rates). See also *supra* Chart 3.

Graph 14



Like the regression comparing LSAT scores with bar passage, the above graphs demonstrate that heteroscedasticity exists in the upper-GPA range of this plotted dataset. Large, positive variations—which are indicative of overperformance—are rare for schools that have high-UGPA 75th percentiles. This is unsurprising because, when a linear-regression model is applied to this dataset, such schools can overperform only by having bar passage rates near the 100% maximum. Also, schools with high 75th-percentile UGPA might infrequently have large negative variations—which are indicative of underperformance—because students with high GPAs are likely the most reliable and consistent bar performers.⁷⁷

When linear regression is used to evaluate this heteroscedastic dataset of comparing bar passage with 75th-percentile UGPA, the variance of residuals is highest for middle-UGPA schools. This is also true for schools in the mid-LSAT range.⁷⁸ Because Kinsler measures bar performance as residuals—the distance between the straight, regression line and the school's bar-pass rate—schools in the middle-LSAT and middle-UGPA ranges have the highest probability of overperforming and ranking in the top fifteen.⁷⁹ The favorable bias that Kinsler's model creates for schools in the middle-LSAT and middle-UGPA regions exemplifies that applying linear regression to heteroscedastic data is not ideal.

77. Cf. *infra* note 87 and accompanying text. The 75th-percentile UGPA of student is one of the strongest predictors of bar passage. Thus, following that logic, students who have high UGPAs reliably and consistently perform well on the bar exams.

78. See *supra* Graph 12.

79. See Kinsler I, *supra* note 1, at 199.

*Unsurprisingly, all of Kinsler's top-fifteen, most overperforming schools in bar performance are uncoincidentally in the 150–160 median-LSAT range.*⁸⁰

Overall, the data's heteroscedasticity impeaches the validity of the ability of Kinsler's linear-regression model to accurately identify over and underperforming schools. Because Kinsler's linear-regression model cannot accurately predict schools' bar performance relative to entering credentials, heteroscedasticity therefore also impeaches the validity of Kinsler's conclusion which emanates from his rankings: the efficacy of a school's bar-preparation program primarily influences over and underperformance on the bar exam.⁸¹

Like the data comparing 2012 or 2015 matriculating credentials with, respectively, 2015 or 2018 bar passage, the datasets that Kinsler ranked for each matriculating year between 2012–2016 are non-linear and heteroscedastic. We used regression equations to create graphs that illustrate the relationships between 2012–2016 matriculation credentials and bar passage in 2015–2019.⁸²

IV. AN ALTERNATIVE EXPLANATION FOR THE BAR PERFORMANCE OF KINSLER'S FIFTEEN MOST OVER AND UNDERPERFORMING SCHOOLS

A. Assumptions Based on Established Statistical Correlations in the Field of Bar Passage

In 2019, at the Association of Academic Support Educators conference, BARBRI gave a presentation about which statistical factors are the strongest predictors of a school's bar passage rate. This presentation is among the most complete and comprehensive studies of bar performance, and BARBRI happily shared their information. The information that BARBRI shared covers the effect that every metric on the 509-form (since those forms were first generated in 2011) has on bar passage.⁸³

Objectively, public knowledge has recognized five variables that are the strongest pre-admission predictors of bar passage rates at the school level.⁸⁴ These five, pre-admission variables, which account for seventy-nine percent of the variance in between schools' bar-pass rates, are:

1. 75th-percentile UGPA,
2. 25th-percentile-LSAT score,
3. Section size,
4. Costs of living, and
5. Minority enrollment levels.⁸⁵

80. Paul Caron, *Bahadur: Attrition and Bar Performance*, LAW PROFESSOR BLOG NETWORK: TAXPROF BLOG (Sept. 14, 2020), https://taxprof.typepad.com/taxprof_blog/2020/09/bahadur-attrition-and-bar-performance.html.

81. See *supra* note 18 and accompanying text.

82. See *infra* Appendix A.

83. Interview with Dr. David Clark, Senior Vice President, Learning, BARBRI (2019).

84. *Id.*

85. *Id.*

Dr. David Clark, a BARBRI statistician, used a hypothetical, puzzle analogy to explain these pre-admission variable's effect on a school's bar passage: If the things that affect a law school's bar passage are pieces of a 100-piece puzzle, then the five pre-admission variables account for seventy-nine percent of those puzzle pieces at the admission stage.⁸⁶ Of these five, pre-admission variables, 75th-percentile UGPA is the strongest indicator of bar passage.⁸⁷

Dr. Clark also explained that, compared with the statistical analysis of a school's bar-pass rates, the statistics are different for the predictors of individual students passing the bar exam.⁸⁸ LSAT score and first-year-of-law-school ("1L") GPA are the two strongest predictors of bar passage for individual students.⁸⁹

Dr. Clark explains how statistical analysis shows that LSAT scores and 1L GPAs are reliable predictors of bar passage accordingly.⁹⁰ P-values—an indicator of statistical relationships—show significant correlation between bar passage and students' LSAT scores and 1L GPAs. The P-values of LSATs and 1L GPAs are both less than 0.001, which means that a less than a 1-in-1000 (0.1%) possibility exists that these factors are not accurate predictors of bar passage. Dr. Clark continues by noting that the Nagelkerke R^2 illuminates this relationship.

The R^2 values of LSATs and 1L GPAs can be considered the percentage that these factors contribute to predicting bar passage-variance. LSAT's R^2 value is eleven percent, and the R^2 value of 1L GPAs is 34.2%. These are "large" R^2 values. To help understand these R^2 values, imagine that a 100-piece jigsaw puzzle represents a composite of bar passage, and each puzzle piece helps predict the picture of the completed puzzle. Knowing LSATs and 1L GPAs is like having eleven and thirty-four puzzle pieces, respectively. Because having these puzzle pieces helps anticipate the picture of the completed puzzle, this puzzle analogy shows that 1L GPA has a large, predictive effect on bar passage. According to Dr. Clark, student-specific variables are much better predictors of bar passage than pre-admission, school-wide predictors.⁹¹

Given that 1L GPA is a significant predictor of bar passage, schools could manipulate academic attrition to manipulate bar passage. For example, a law school that admitted students based upon their LSATs and UGPAs might one year later

86. *Id.*

87. *Id.*

88. *Id.*

89. *Id.* Other scholars have also established that the most significant predictor of an individual student's probability of success on the bar examination is that student's 1L GPA. *See, e.g.,* Katherine A. Austin, Catherine Martin Christopher & Darby Dickerson, *Will I Pass the Bar Exam?: Predicting Student Success Using LSAT Scores And Law School Performance*, 45 HOFSTRA L. REV. 753, 768 (2017) ("In sum, 1L and final law school GPA present statistically as the same indicator that strongly predicts bar exam performance, but both cannot be included in the analysis. Our analysis revealed that 1L and final law school GPA overlap so strongly that they respond mathematically as one variable. Adding both in the analysis does not add to our knowledge of the relationship between law course performance and bar exam performance. From a law school administration perspective, 1L GPA can be used to predict bar exam performance just as strongly as using final law school GPA. Clearly, examining 1L performance provides opportunity for positive educational intervention strategies to aid the student in future bar performance.").

90. *See* Interview with Dr. David Clark, *supra* note 83. *See also* E-mail from Mike Sims, President, BARBRI, to author (Aug. 30, 2020) (on file with author) (confirming the accuracy of these assertions).

91. *See* Interview with Dr. David Clark, *supra* note 83.

academically dismiss a relatively significant portion of those students because they had low 1L GPAs. The school then transfers-in students who achieved high 1L GPAs. Effectively, the school would be manipulatively attempting to increase its bar-pass rate by replacing its students with those who have credentials (higher 1L GPAs) indicating greater probability of passing the bar exam. This combination of academic attrition and transfer would therefore result in a cohort of rising-second-year students (“2L”) who have better, bar passage predictors than the corresponding, original-1L class had.⁹²

Because schools can use academic attrition and student transfers to artificially increase bar-pass rates, we evaluated bar performance with the following assumptions. First, a law school that has high, 1L-academic-attrition rates or percentages has better bar passage than the matriculation credentials recorded for the entering class three years earlier predict. The basis of this assumption is that students who attrited due to low 1L-GPA should be least likely to pass the bar because, as previously established, 1L GPA is a significant predictor of bar performance.⁹³

We also made assumptions regarding student transfer. We assumed that transfer-in students most often transfer “up”—achieving relatively high 1L-GPAs enables these students to transfer to a school that they were previously unqualified to attend based upon entering credentials.⁹⁴ Consequently, students who transfer into a school are more likely to pass the bar and positively impact the bar passage rate of the transfer-in school. Conversely, the transfer-out school’s bar passage-rate decreases because of the loss of students who achieved high 1L-GPAs and are likely to pass the bar exam.⁹⁵

Based upon our student-transfer assumptions, we identified the best metric to evaluate the impact that student-transfer has on the bar passage of a school. This

92. To qualify this claim, we are not asserting that academic attrition is inappropriate or should not exist. If students’ performance is poor to the degree that such students have a very low probability of passing the bar and becoming competent attorneys, then schools do those students no favors by retaining and possibly graduating them. Such institutional conduct could even be considered financially exploitative. We discuss academic attrition’s impact on the composition of student cohorts because ignoring the impact academic attrition has on schools’ relative, bar passage success would be disingenuous.

93. See Austin et al., *supra* note 89, at 768 (portion of relevant text is quoted in footnote).

94. We recognize that students might have other reasons for transferring schools, such as to live closer to home or for other personal reasons. However, we believe that such transfer-explanations are exceptions to our assumed rule.

95. Professor Jerry Organ has authored numerous blog posts on the details of the transfer and attrition among law schools. See, e.g., Jerry Organ, *2019 Transfer Data Show Continued Decline In Number and Percentage of Transfers*, L. PROFESSOR BLOG NETWORK: TAXPROF BLOG (Dec. 16, 2019), https://taxprof.typepad.com/taxprof_blog/2019/12/2019-transfer-data-shows-ongoing-decline-in-number-and-percentage-of-transfers.html; Jerry Organ, *2018 ABA Data Show Continued Decline In Number and Percentage of Transfers*, L. PROFESSOR BLOG NETWORK: TAXPROF BLOG (Dec. 17, 2018), https://taxprof.typepad.com/taxprof_blog/2018/12/2018-transfer-data-shows-continued-decline-in-number-and-percentage-of-transfers.html; Jerry Organ, *Updated Analysis of Law School Attrition Data - 2018*, L. PROFESSOR BLOG NETWORK: TAXPROF BLOG (Jan. 16, 2018) [hereinafter *Updated 2018*], https://taxprof.typepad.com/taxprof_blog/2018/01/updated-analysis-of-attrition-data-2018.html; Jerry Organ, *The 2017 Law School Transfer Market*, L. PROFESSOR BLOG NETWORK: TAXPROF BLOG (Dec. 18, 2017), https://taxprof.typepad.com/taxprof_blog/2017/12/updates-on-the-transfer-market-for-2017.html. The details of the transfer market as explored in these blog posts are beyond the scope of this article.

metric is the school's *net-transfer percentage*: the percentage of transfer-in students minus the percentage of transfer-out students.

B. Methodology

We derived net-transfer rates by subtracting the number of students transferring out of an institution from the number of transfer-in students. Because net-transfer rates and academic-attrition rates can be expressed as a percentage of the matriculating-class size, we combined those two variables to generate a combined-variable score—CVS—which is expressed as a percentage.

A positive CVS indicates that a school's academic attrition and student transfer rate after the first year altered the original, matriculating-class composition post-matriculation. Consequently, the rising-2L class consists of students who have better, bar passage indicators compared with the bar-pass indicators of the matriculating 1Ls one year prior.⁹⁶ This group of rising 2Ls is likely to overperform on the bar exam relative to the expectations formed from the entering credentials of the original, matriculated cohort.⁹⁷ The greater the CVS, the more a school should overperform on the bar exam compared with the performance that entering credentials of three years prior predicted.

A negative CVS indicates that academic attrition and student transfer rate after the first year resulted in a rising-2L class that consists of students who have lower, bar passage indicators than the matriculating class of 1Ls had one year prior.⁹⁸ This group of rising 2Ls is likely to underperform compared with expectations based on the credentials of the original, matriculated cohort.⁹⁹ The lower the CVS, the more a school should underperform relative to the performance that the entering credential of three years prior predicted.

For the period of 2012–2016, we compared the CVSs of Kinsler's top-fifteen schools that most over-or-underperformed on the bar exam with one another and peer-schools (schools that had similar matriculating credentials).¹⁰⁰ The peer groups consisted of all law schools that had either median-LSAT scores within plus-or-minus two, or 75th-percentile UGPAs within plus-or-minus 0.1 of the entering credentials of a school that Kinsler ranked in the top fifteen or bottom fifteen of bar performers.¹⁰¹ Our analysis shows that, with few exceptions, the schools that Kinsler ranked as a top-fifteen overperformer or underperformer have, respectively, higher or lower CVSs than the CVSs of peer-schools.¹⁰² We are confident in the accuracy of our results, but our analysis had limitations.

Schools' 509 forms have a variety of inconsistencies which limited our analysis. For example, some schools report on 509 forms academic attrition and students transfer as 2L academic-attrition; as a result, the reported 2L-attrition and

96. See *supra* Part IV.A.

97. See *id.*

98. See *id.*

99. See *id.*

100. The Mathematica program enabled us to create graphical representations of these comparisons. See *infra* Part IV.C.3.

101. See *id.*

102. See *id.*

student transfer for these schools is much higher than the reported 1L-attrition.¹⁰³ For these schools, we used the 2L-attrition numbers because they better conceptualize the change in the matriculant pool from matriculation through graduation.¹⁰⁴ For the few schools that Kinsler identified as routine reporters of higher numbers of students who transferred out or were academically attrited as 2Ls, we analyzed the data as though such students were 1L attritions.

Additionally, ABA guidance on the attrition metrics included on the 509 forms varied during 2012–2016. In 2012, attrition was reported as academic attrition and other attrition. As a result, no record of transfer attrition for students who matriculated in 2012 exists.¹⁰⁵ Furthermore, the ABA did not require schools to report academic attrition for 2016 matriculants. Schools were instead mandated to report only, “Non-Transfer Attrition.”¹⁰⁶ As a result, net-transfer-variable comparisons exist only for matriculants during 2013–2015 but not the entire 2012–2016 period which Kinsler studied. However, the data is informative.

C. Summary of Results

1. Top-Fifteen Schools 2013–2015 Matriculants

Chart 5¹⁰⁷

Kinsler’s Top-Fifteen Schools ¹⁰⁸	Top-Fifteen Schools’ CVSs (as a percentage)	LSAT-Peers’ CVSs (as a percentage)	Percentage of Top-Fifteen Schools that have Greater CVSs than the CVSs	75th-percentile UGPA-Peers’ CVSs (as a percentage)	Percentage of Top-Fifteen Schools that have Greater CVSs than the CVSs of 75th-

103. Interview with Jerry Organ, Professor of L., Univ. of St. Thomas Sch. of L. (Nov. 25, 2020). *See, e.g.,* UNIV. OF CAL. HASTINGS, *2015 Standard 509 Informaiton Report*, ABA REQUIRED DISCLOSURES 1, at 3 (2015), <https://www.uchastings.edu/home/aba-required-disclosures/> (select “2015 Standard 509 Information Report” from list of reports under the heading “ABA Standard 509 Information Reports”) (reporting that the number of 2015 transfer-in students for 2Ls and 1Ls were forty-three and zero, respectively).

104. *See* UNIV. OF CAL. HASTINGS, *supra* note 103, at 3.

105. *See, e.g.,* UNIV. OF OKLA., *2013 Standard 509 Informaiton Report*, ABA REQUIRED DISCLOSURES 1, at 2 (2013), <https://law.ou.edu/about/aba-required-disclosures> (select “ABA Standard 509 Information Report (2013)” from list of reports under the heading “ABA Standard 509 Reports”) (reporting attrition for the previous academic year (2012) as only “Academic” or “Other Attrition”).

106. *See, e.g.,* UNIV. OF OKLA., *2017 Standard 509 Informaiton Report*, ABA REQUIRED DISCLOSURES 1, at 3 (2017), <https://law.ou.edu/about/aba-required-disclosures> (select “ABA Standard 509 Information Report (2017)” from list of reports under the heading “ABA Standard 509 Reports”) (reporting “Non-Transfer Attrition” for the previous (2016) academic year).

107. *See* RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Top-Fifteen Schools 2013–2015 Matriculants).

108. We did not include Texas A&M in our analysis of the schools ranked by Kinsler because of the high percentage of part-time students, which would impact the assumption that, generally, the students were taking the bar exam three years after matriculation.

			of LSAT- Peers		percentile UGPA- Peers
FIU	19.10	4.08	98.67	6.04	95.4
LIBERTY	16.17	3.65	95.43	4.23	95.03
REGENT	13.68	4.02	92.47	4.09	91.47
SETON HALL	12.11	4.4	89.40	4.74	89.30
BELMONT	8.38	3.62	78.20	4.08	77.63
CAMPBELL	9.66	3.85	76.77	3.83	75.97
GEORGIA STATE	7.22	4.46	68	3.74	72.13
TEXAS TECH	7.74	3.56	69.53	4.36	68.87
SOUTH CAROLINA	5.41	3.62	62.47	3.66	60.30
CLEVELAND STATE	5.78	3.47	68.53	4.20	68.67
OKLAHOMA	6.95	4.44	61.97	6.42	57.8
DUQUESNE	2	3.85	40.6	4.31	36.73
LSU	2.57	3.71	40.27	4.34	44.8
NEW HAMPSHIRE	2.72	4.2	40.33	4.28	41.50

Chart 5 illustrates immense disparities between the CVSs of Kinsler's top-fifteen schools that most overperformed on the bar exam and the CVSs of peer-schools. FIU, Liberty, Regent, and Seton Hall have higher CVSs than approximately ninety percent of LSAT-peers and 75th UGPA-peers. Belmont, Campbell, and Georgia State had greater CVSs than seventy percent of peer-schools. Texas Tech, South Carolina, Cleveland State, and Oklahoma had CVSs higher than sixty percent of their respective peers. Only three of these overperforming schools, Duquesne, LSU, and New Hampshire had CVSs in the forty-percent range; nonetheless, they had scores higher than 40.6%, 40.27%, and 40.33% of their LSAT-peers, respectively. These significant CVS disparities—substantial changes in class composition between matriculation and bar passage—should not be discounted as an explanation for why a school performs better on the bar exam than its entering credentials predicted.

2. Bottom-fifteen Schools 2013-2015 Matriculants

Chart 6¹⁰⁹

Kinsler's Bottom-Fifteen Schools ¹¹⁰	Top-Fifteen Schools' CVSs (as a percentage)	LSAT-Peers' CVSs (as a percentage)	Percentage of Bottom-Fifteen Schools that have Greater CVSs than the CVSs of LSAT-Peers	75th-percentile UGPA-Peers' CVSs (as a percentage)	Percentage of Bottom-Fifteen Schools that have Greater CVSs than the CVSs of 75th-percentile UGPA-Peers
THOMAS COOLEY	12.3	7.69	83.43	5.37	74.43
SOUTHWESTERN	4.36	3.89	66.73	4.58	56.5
HOFSTRA	4.26	3.92	58	3.82	60
NYLS	3.51	3.97	57.7	3.84	54.97
GOLDEN GATE	5.84	5.32	57.43	5.92	52.53
SAN FRANCISCO	3.96	3.96	56.13	4.58	49.13
SUNY	3.38	3.72	49.23	4.52	49.1
D.C.	-26	4.54	27.4	5.24	24.83
ATLANTA'S JOHN MARSHALL	-78	4.69	29.47	23.47	6.91
TOURO	-3.18	5.53	16.2	5.34	17.63
HASTINGS	-4.14	4.34	6.78	4.41	6.53
AMERICAN	-11.24	4.25	0.67	3.99	0.9

Chart 6 illustrates that, in stark contrast to the schools that Kinsler identified as overperforming, Thomas Cooley is the only underperforming school that has a higher CVS than seventy percent of peer-schools. The heteroscedastic nature of the data might explain why, of all the schools that have the lowest entering credentials, Thomas Cooley is uniquely affected. Thomas Cooley's average entering-LSAT score for the 2013–2015 period was 143.4, which is conspicuously lower than all

109. See RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Bottom-Fifteen Schools 2013–2015 Matriculants).

¹¹⁰ Emory, Northwestern, and the University of Minnesota were excluded from the comparison because of Kinsler's model misspecification (non-linearity and heteroscedasticity). See explanation *supra* Part Error! Reference source not found. Error! Reference source not found.–Error! Reference source not found..

other schools in Kinsler's most-underperforming list. Such schools' average-median-LSAT scores ranged from 147.4–156.6, and only one other school in the bottom fifteen, Atlanta's John Marshall, had a 75th-percentile-UGPA score below 3.3.

Summarizing general trends, besides Thomas Cooley, less than half of the most-underperforming schools—five of twelve¹¹¹—have CVSs higher than fifty percent of peer-schools. Furthermore, five of the most-underperforming schools have higher CVSs compared with the CVSs of less than thirty percent and twenty-five percent of LSAT-peers and 75th UGPA peers, respectively. Most notably, American and Hastings have CVSs greater than only seven percent of peer-schools.

The CVSs of American and Hastings show that this metric should be seriously considered as an explanation for the two schools underperforming on the bar exam. American has a CVS higher than, respectively, only 0.67% and 0.9% of LSAT-peers and 75th-percentile UGPA-peers. Hastings similarly has a CVS higher than only 6.78% and 6.53% of LSAT-peers and 75th-percentile UGPA-peers, respectively. The transfer-out rate of both schools is abnormally high; consequently, these two schools are losing a high percentage of matriculants who are most likely to perform well on the bar exam. Unsurprisingly, the two schools' bar performance is much lower than the credentials of the pre-transfer class anticipated.

3. Detailed Results and Graphic Comparisons for Each School

a. Results for Kinsler's Top-Fifteen Schools

Belmont University

Belmont University's (Belmont) relative bar performance is summarized accordingly. Kinsler ranked Belmont the most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹¹² During the period of 2012–2016, Belmont matriculated students with an average-median-LSAT score of 154.75 and an average 75th-percentile-UGPA score of 3.66.¹¹³ Belmont's CVS for 2013–2015 matriculants was 8.38%.¹¹⁴ The average CVS was 3.62% for of all other schools that had matriculating credentials within two points of the median LSAT of Belmont.¹¹⁵ The average CVS was 4.08% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Belmont.¹¹⁶ From 2013–2015, Belmont's average CVS was higher than 78.20 % of LSAT-peers and 77.63% of 75th-percentile UGPA-peers.¹¹⁷ The following graphs illustrate these CVS comparisons.

111. Only twelve of the fifteen most-underperforming schools were evaluated. See *supra* text accompanying note 110.

112. *Kinsler II*, *supra* note 3 (manuscript at 3).

113. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Belmont University).

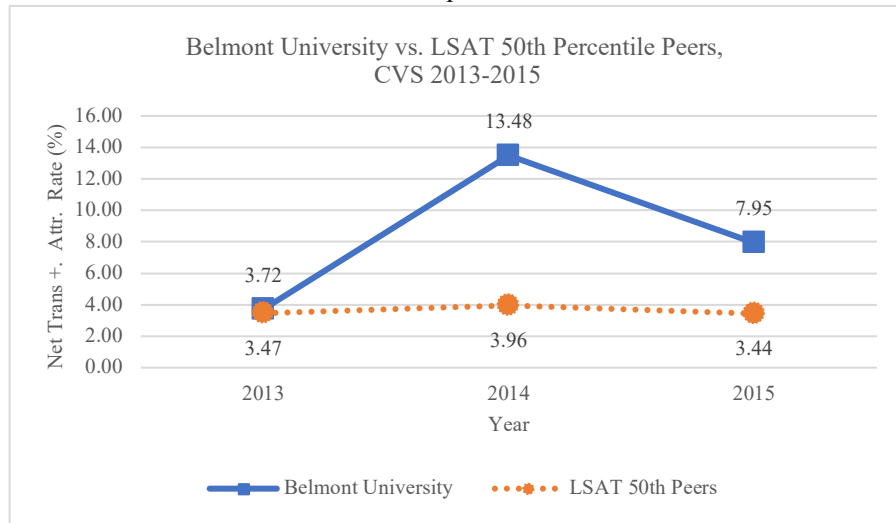
114. *Id.*

115. *Id.*

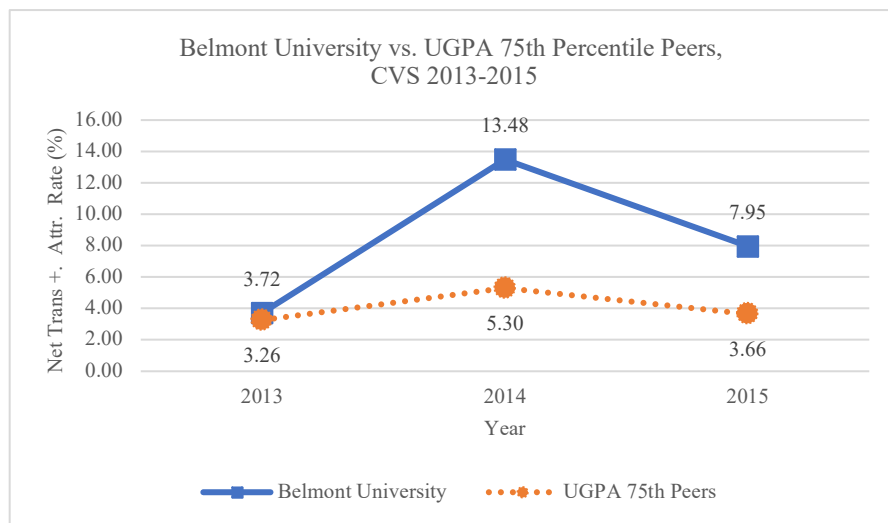
116. *Id.*

117. *Id.*

Graph 15



Graph 16



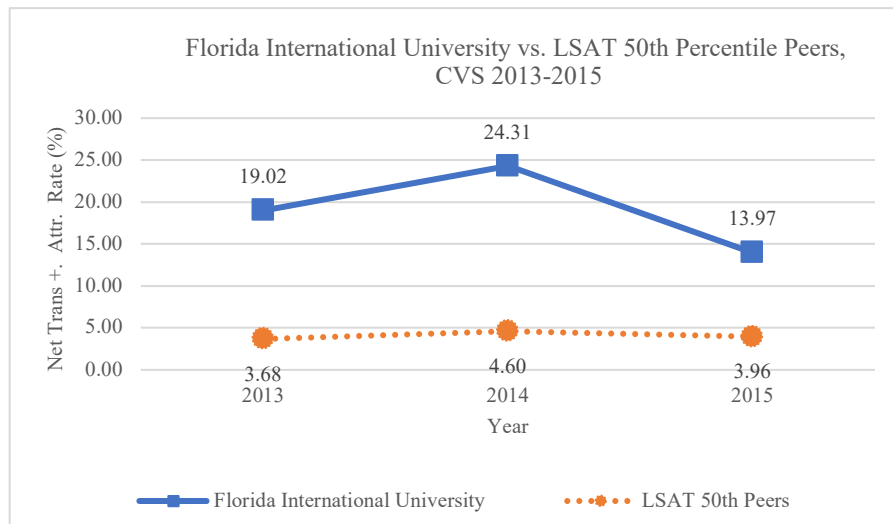
Florida International University

Florida International University's (FIU) relative bar performance is summarized accordingly. Kinsler ranked FIU the second-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹¹⁸ During the period of 2012–2016, FIU

118. *Kinsler II*, *supra* note 3 (manuscript at 3).

matriculated students with an average-median-LSAT score of 156 and an average 75th-percentile-UGPA score of 3.75.¹¹⁹ FIU's CVS for 2013–2015 matriculants was 19.10%.¹²⁰ The average CVS was 4.08% for all other schools that had matriculating credentials within two points of the median LSAT of FIU.¹²¹ The average CVS was 6.04% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of FIU.¹²² From 2013–2015, FIU's average CVS was higher than 98.67% of LSAT-peers and 95.4% of 75th-percentile UGPA-peers.¹²³ For 2013 and 2014 matriculants, FIU had CVSs higher than 100% of its median-LSAT peers.¹²⁴ The following graphs illustrate these CVS comparisons.

Graph 17



119. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Florida International University).

120. *Id.*

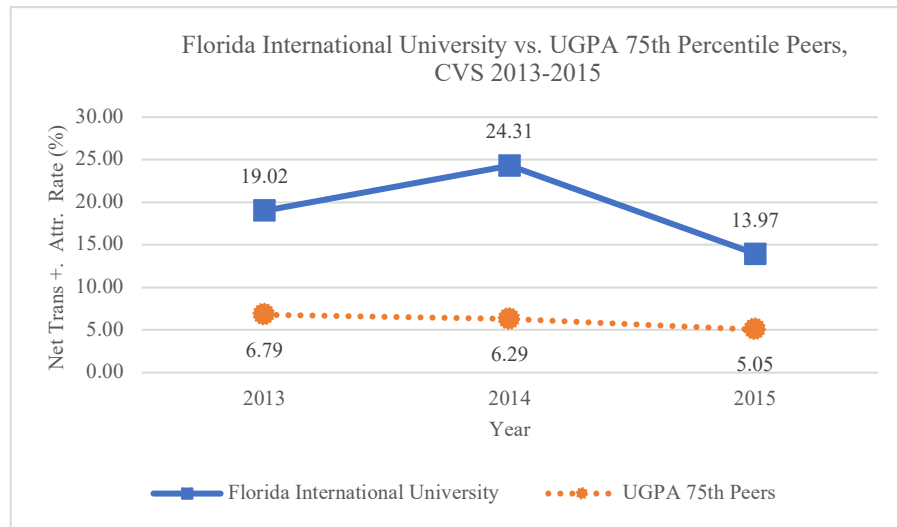
121. *Id.*

122. *Id.*

123. *Id.*

124. *Id.*

Graph 18



Liberty University

Liberty University's (Liberty) relative bar performance is summarized accordingly. Kinsler ranked Liberty the third-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹²⁵ During the period of 2012–2016, Liberty matriculated students with an average-median-LSAT score of 151.4 and an average 75th-percentile-UGPA score of 3.65.¹²⁶ Liberty's CVS for 2013–2015 matriculants was 16.17%.¹²⁷ The average CVS was 3.65% for all other schools that had matriculating credentials within two points of the median LSAT of Liberty.¹²⁸ The average CVS was 4.23% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Liberty.¹²⁹ From 2013–2015, Liberty's average CVS was higher than 95.43% of LSAT-peers and 95.03% of 75th-percentile UGPA-peers.¹³⁰ The following graphs illustrate these CVS comparisons.

125. *Kinsler II*, *supra* note 3 (manuscript at 3).

126. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Liberty University).

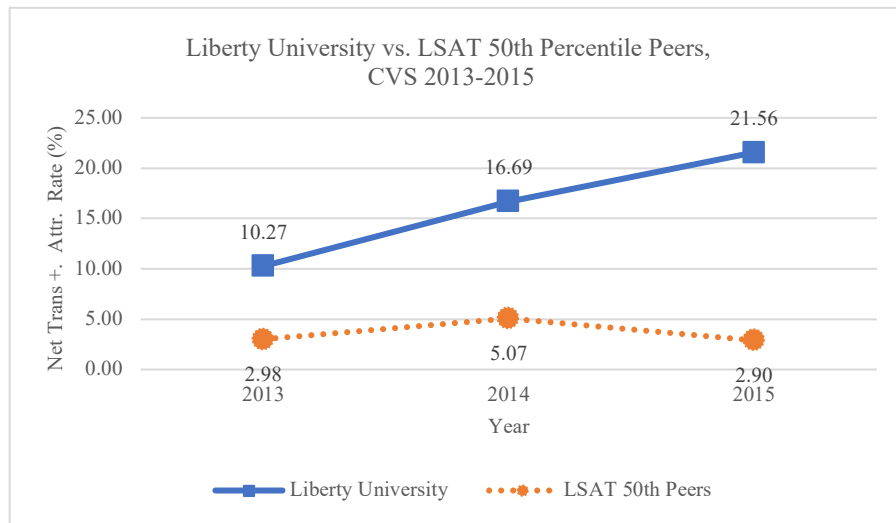
127. *Id.*

128. *Id.*

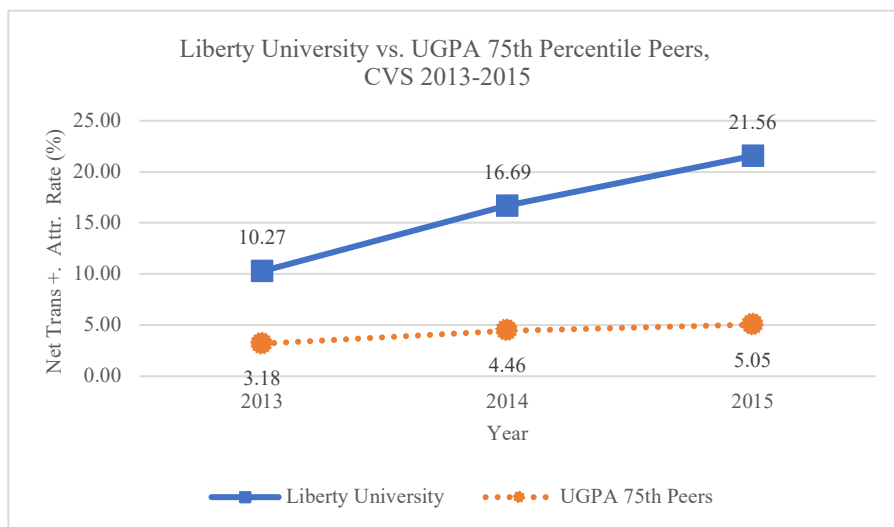
129. *Id.*

130. *Id.*

Graph 19



Graph 20



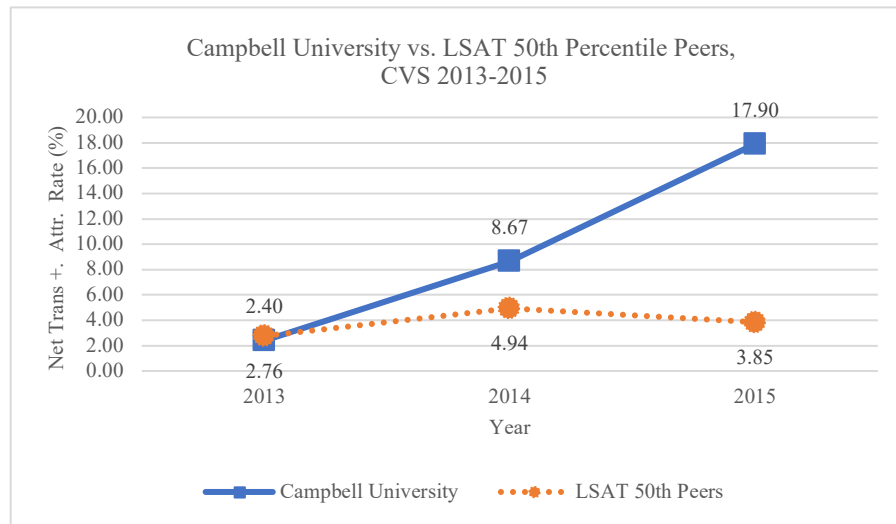
Campbell University

Campbell University's (Campbell) relative bar performance is summarized accordingly. Kinsler ranked Campbell the fourth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹³¹ During the period of 2012–2016, Campbell matriculated students

131. *Kinsler II*, *supra* note 3 (manuscript at 3).

with an average-median-LSAT score of 152.6 and an average 75th-percentile-UGPA score of 3.53.¹³² Campbell's CVS for 2013–2015 matriculants was 9.66%.¹³³ The average CVS was 3.85% for all other schools that had matriculating credentials within two points of the median LSAT of Campbell.¹³⁴ The average CVS was 3.83% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Campbell.¹³⁵ From 2013–2015, Campbell's average CVS was higher than 76.77% of LSAT-peers and 75.97% of 75th-percentile UGPA-peers.¹³⁶ The following graphs illustrate these CVS comparisons.

Graph 21



132. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Campbell University).

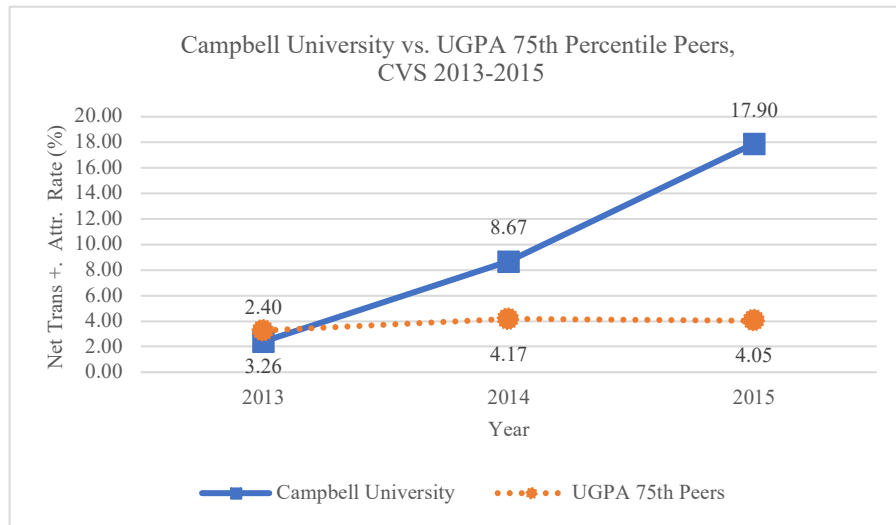
133. *Id.*

134. *Id.*

135. *Id.*

136. *Id.*

Graph 22



*Texas A&M*¹³⁷

Duquesne University

Duquesne University's (Duquesne) relative bar performance is summarized accordingly. Kinsler ranked Duquesne the sixth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹³⁸ During the period of 2012–2016, Duquesne matriculated students with an average-median-LSAT score of 152 and an average 75th-percentile-UGPA score of 3.63.¹³⁹ Duquesne's CVS for 2013–2015 matriculants was two percent.¹⁴⁰ The average CVS was 3.85% for of all other schools that had matriculating credentials within two points of the median LSAT of Duquesne.¹⁴¹ The average CVS was 3.31% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Duquesne.¹⁴² From 2013–2015, Duquesne's average CVS was higher than 40.6% of LSAT-peers and 37.73% of 75th-percentile UGPA-peers.¹⁴³ The following graphs illustrate these CVS comparisons.

137. Texas A&M, the fifth-most-over performing school according to Kinsler's rankings, is omitted from this analysis. *See supra* note 108.

138. *Kinsler II*, *supra* note 3 (manuscript at 3).

139. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Duquesne University).

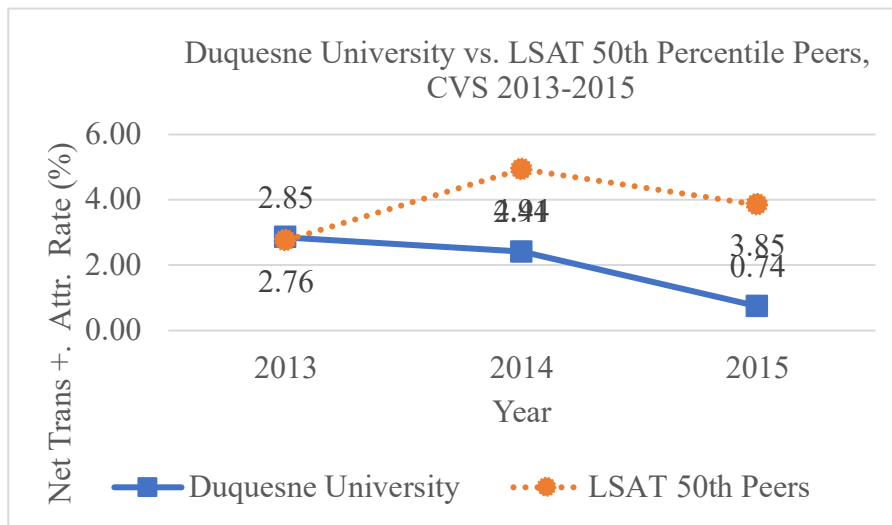
140. *Id.*

141. *Id.*

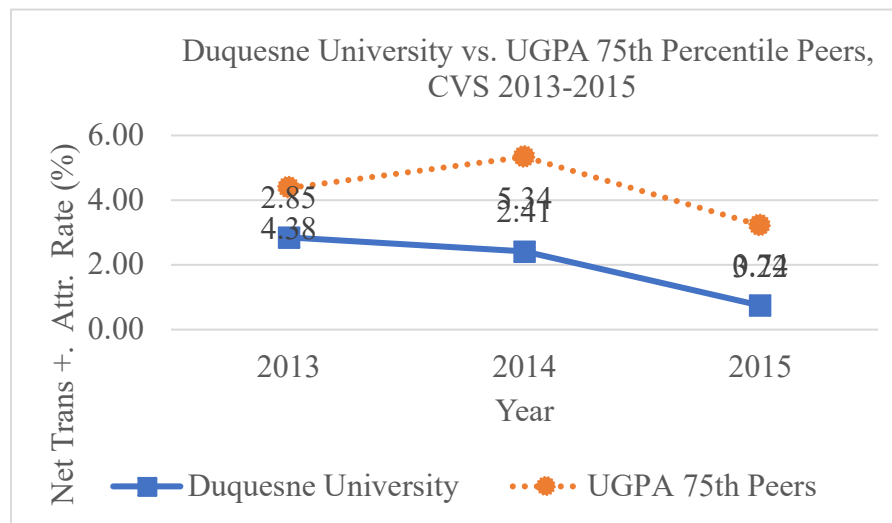
142. *Id.*

143. *Id.*

Graph 23



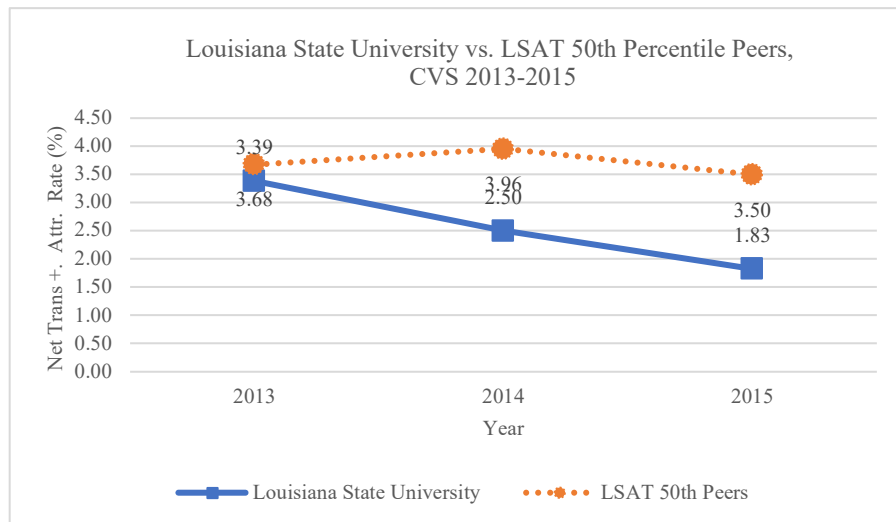
Graph 24



Louisiana State University

Louisiana State University's (LSU) relative bar performance is summarized accordingly. Kinsler ranked LSU the seventh-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁴⁴ During the period of 2012–2016, LSU matriculated students with an average-median-LSAT score of 155.4 and an average 75th-percentile-UGPA score of 3.63.¹⁴⁵ LSU's CVS for 2013–2015 matriculants was 2.57%.¹⁴⁶ The average CVS was 3.71% for all other schools that had matriculating credentials within two points of the median LSAT of LSU.¹⁴⁷ The average CVS was 4.34% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of LSU.¹⁴⁸ From 2013–2015, LSU's average CVS was higher than 40.27% of LSAT-peers and 40.8% of 75th-percentile UGPA-peers.¹⁴⁹ The following graphs illustrate these CVS comparisons.

Graph 25



144. *Kinsler II*, *supra* note 3 (manuscript at 3).

145. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Louisiana State University).

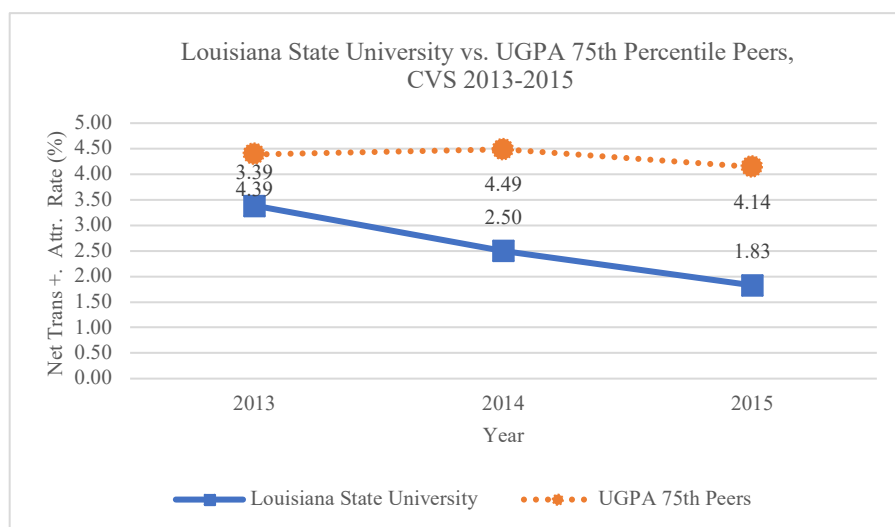
146. *Id.*

147. *Id.*

148. *Id.*

149. *Id.*

Graph 26



Georgia State University

Georgia State University's (Georgia State) relative bar performance is summarized accordingly. Kinsler ranked Georgia State the eighth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁵⁰ During the period of 2012–2016, Georgia State matriculated students with an average-median-LSAT score of 158.4 and an average 75th-percentile-UGPA score of 3.59.¹⁵¹ Georgia State's CVS for 2013–2015 matriculants was 7.22%.¹⁵² The average CVS was 4.46% for of all other schools that had matriculating credentials within two points of the median LSAT of Georgia State.¹⁵³ The average CVS was 3.74% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Georgia State.¹⁵⁴ From 2013–2015, Georgia State's average CVS was higher than sixty-eight percent of LSAT-peers and 72.13% of 75th-percentile UGPA-peers.¹⁵⁵ The following graphs illustrate these differences.

150. *Kinsler II*, *supra* note 3 (manuscript at 3).

151. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Georgia State University).

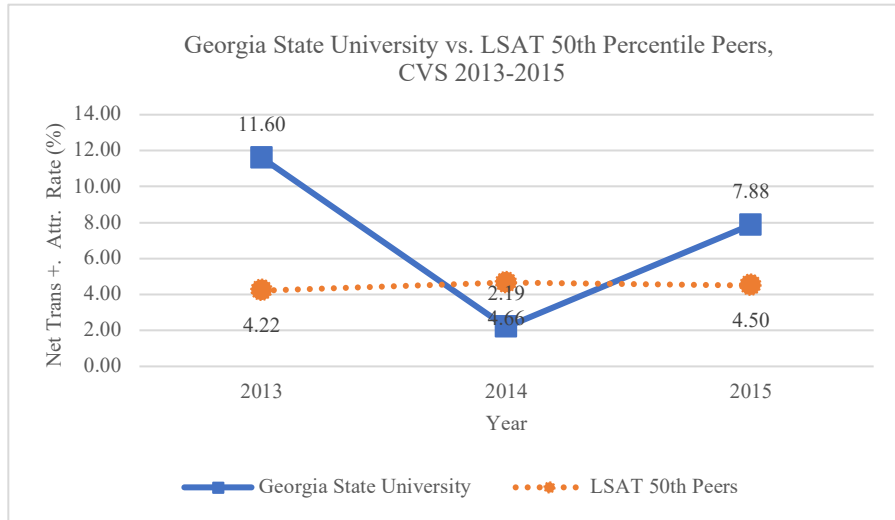
152. *Id.*

153. *Id.*

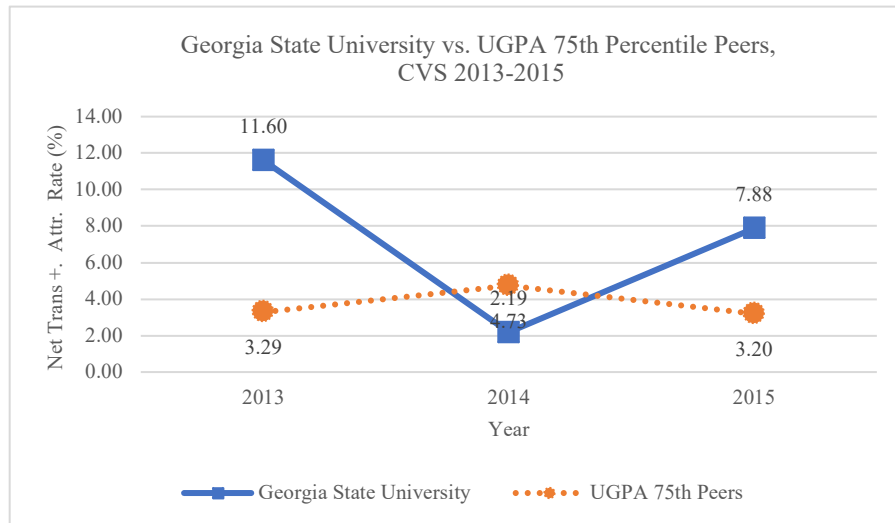
154. *Id.*

155. *Id.*

Graph 27



Graph 28



Texas Tech University

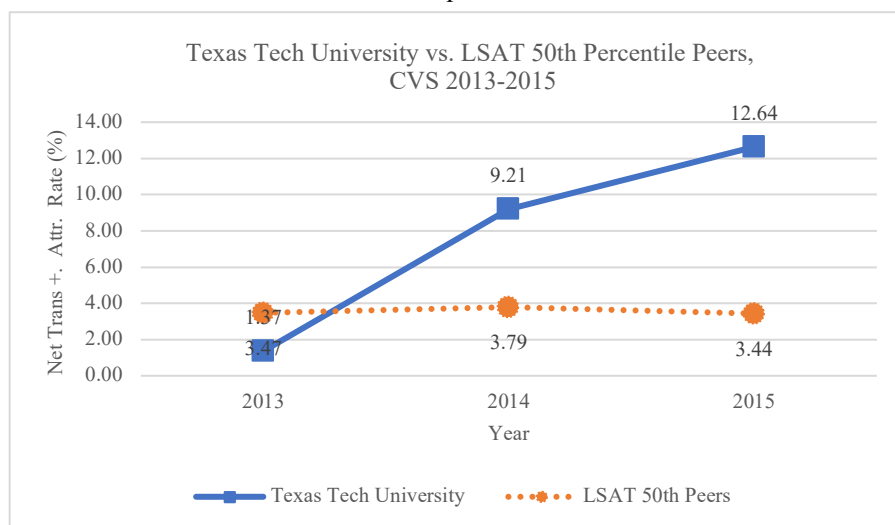
Texas Tech University's (Texas Tech) relative bar performance is summarized accordingly. Kinsler ranked Texas Tech the ninth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁵⁶ During the period of 2012–2016, Texas Tech matriculated students with an average-median-LSAT score of 154.4 and an

156. *Kinsler II*, *supra* note 3 (manuscript at 3).

average 75th-percentile-UGPA score of 3.63.¹⁵⁷ Texas Tech's CVS for 2013–2015 matriculants was 7.74%.¹⁵⁸ The average CVS was 3.56% for of all other schools that had matriculating credentials within two points of the median LSAT of Texas Tech.¹⁵⁹ The average CVS was 4.36% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Texas Tech.¹⁶⁰ From 2013–2015, Texas Tech's average CVS was higher than 69.53% of LSAT-peers and 68.87% of 75th-percentile UGPA-peers.¹⁶¹ For 2014 and

2015, Texas Tech's CVS was higher than 84.2% and 95% of LSAT-peers, and higher than 95% and 96.20% of its 75th- percentile UGPA-peers, respectively.¹⁶² The following graphs illustrate these differences.

Graph 29



157. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Texas Tech University).

158. *Id.*

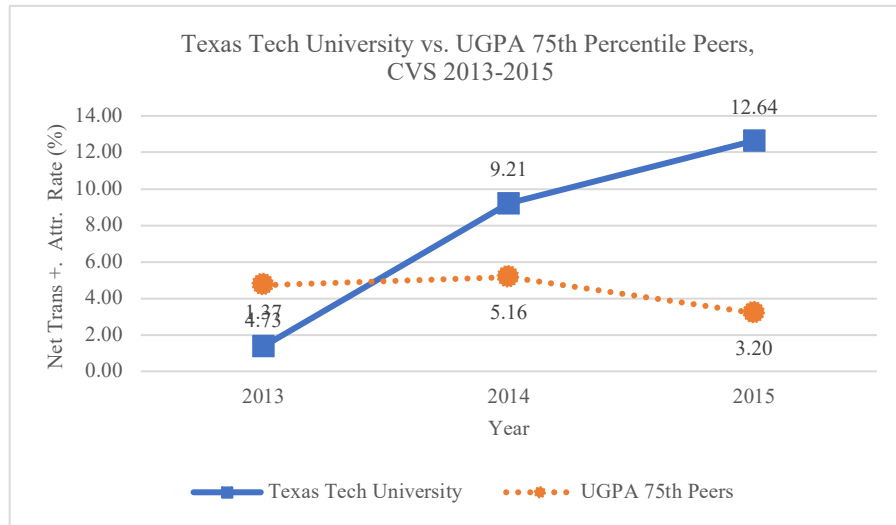
159. *Id.*

160. *Id.*

161. *Id.*

162. *Id.*

Graph 30



University of New Hampshire

University of New Hampshire's (New Hampshire) relative bar performance is summarized accordingly. Kinsler ranked New Hampshire the tenth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁶³ During the period of 2012–2016, New Hampshire matriculated students with an average-median-LSAT score of 156.4 and an average 75th-percentile-UGPA score of 3.65.¹⁶⁴ New Hampshire's CVS for 2013–2015 matriculants was 2.72%.¹⁶⁵ The average CVS was 4.2% for of all other schools that had matriculating credentials within two points of the median LSAT of New Hampshire.¹⁶⁶ The average CVS was 4.28% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of New Hampshire.¹⁶⁷ From 2013–2015, New Hampshire's average CVS was higher than 40.03% of LSAT-peers and 41.5% of 75th-percentile UGPA-peers.¹⁶⁸ The following graphs illustrate these CVS comparisons.

163. *Kinsler II*, *supra* note 3 (manuscript at 3).

164. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of New Hampshire).

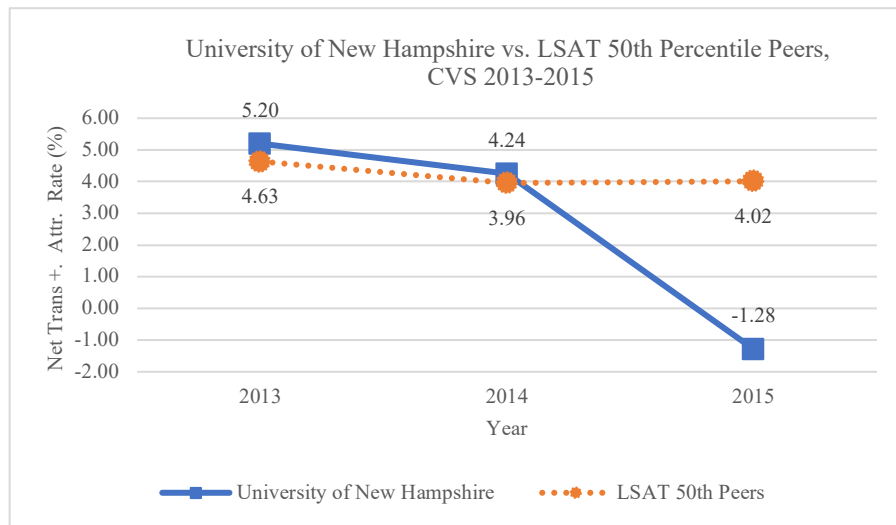
165. *Id.*

166. *Id.*

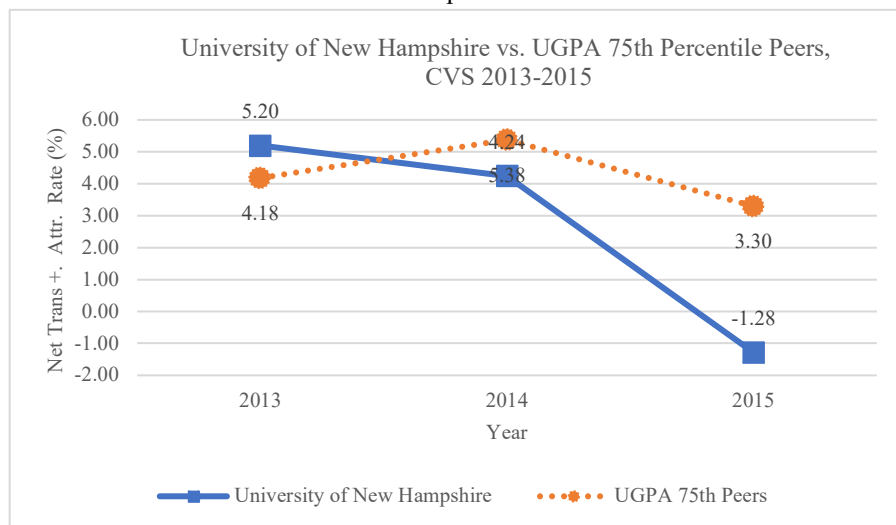
167. *Id.*

168. *Id.*

Graph 31



Graph 32



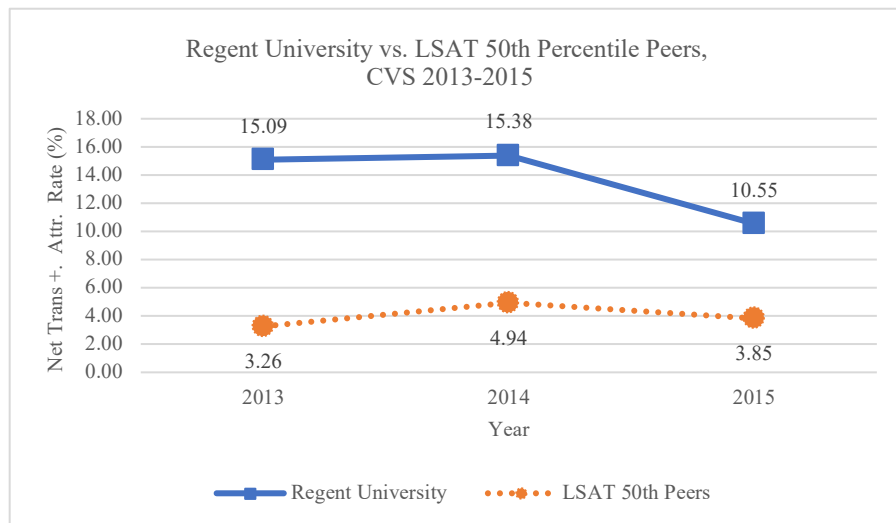
Regent University

Regent University's (Regent) relative bar performance is summarized accordingly. Kinsler ranked Regent the eleventh-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁶⁹ During the period of 2012–2016, Regent matriculated students with an average-median-LSAT score of 152.4 and an average 75th-percentile-UGPA

169. *Kinsler II*, *supra* note 3 (manuscript at 3).

score of 3.61.¹⁷⁰ Regent's CVS for 2013–2015 matriculants was 13.68%.¹⁷¹ The average CVS was 4.02% for all other schools that had matriculating credentials within two points of the median LSAT of Regent.¹⁷² The average CVS was 4.09% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Regent.¹⁷³ From 2013–2015, Regent's average CVS was higher than 92.47% of LSAT-peers and 91.47% of 75th-percentile UGPA-peers.¹⁷⁴ The following graphs illustrate these CVS comparisons.

Graph 33



170. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Regent University).

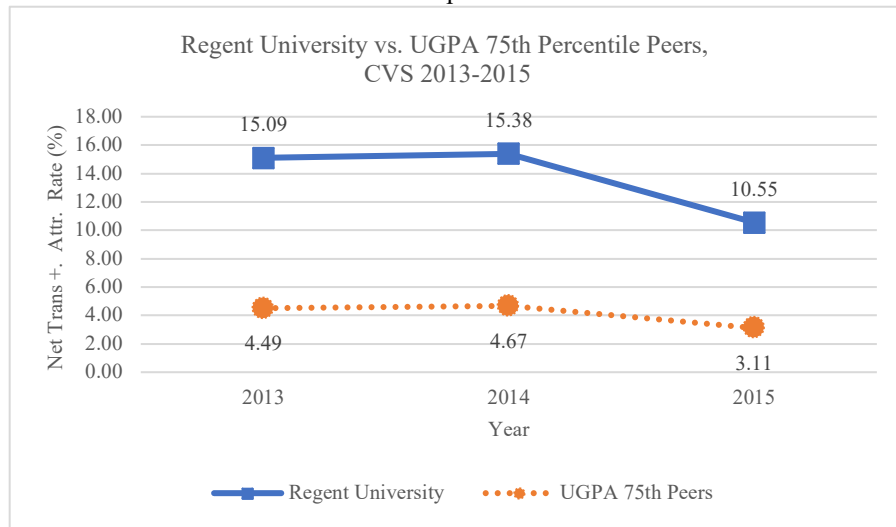
171. *Id.*

172. *Id.*

173. *Id.*

174. *Id.*

Graph 34



University of South Carolina

University of South Carolina's (South Carolina) relative bar performance is summarized accordingly. Kinsler ranked South Carolina the twelfth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁷⁵ During the period of 2012–2016, South Carolina matriculated students with an average-median-LSAT score of 155 and an average 75th-percentile-UGPA score of 3.57.¹⁷⁶ South Carolina's CVS for 2013–2015 matriculants was 5.41%.¹⁷⁷ The average CVS was 3.62% for all other schools that had matriculating credentials within two points of the median LSAT of South Carolina.¹⁷⁸ The average CVS was 3.66% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of South Carolina.¹⁷⁹ From 2013–2015, South Carolina's average CVS was higher than 62.47% of LSAT-peers and 60.3% of 75th-percentile UGPA-peers.¹⁸⁰ The following graphs illustrate these CVS comparisons.

175. *Kinsler II*, *supra* note 3 (manuscript at 3).

176. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of South Carolina).

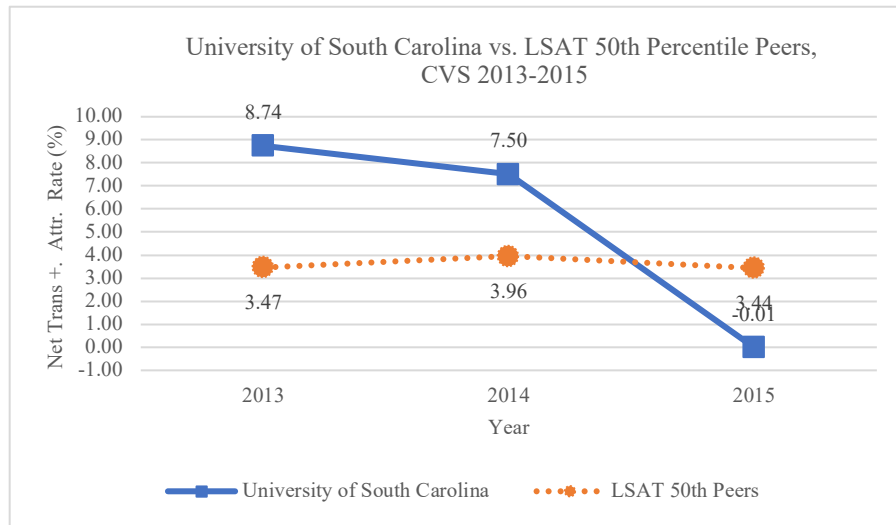
177. *Id.*

178. *Id.*

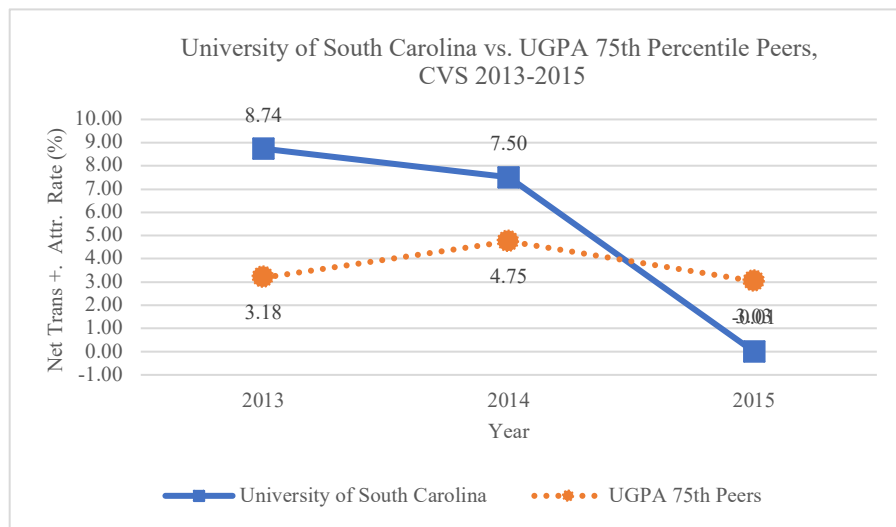
179. *Id.*

180. *Id.*

Graph 35



Graph 36



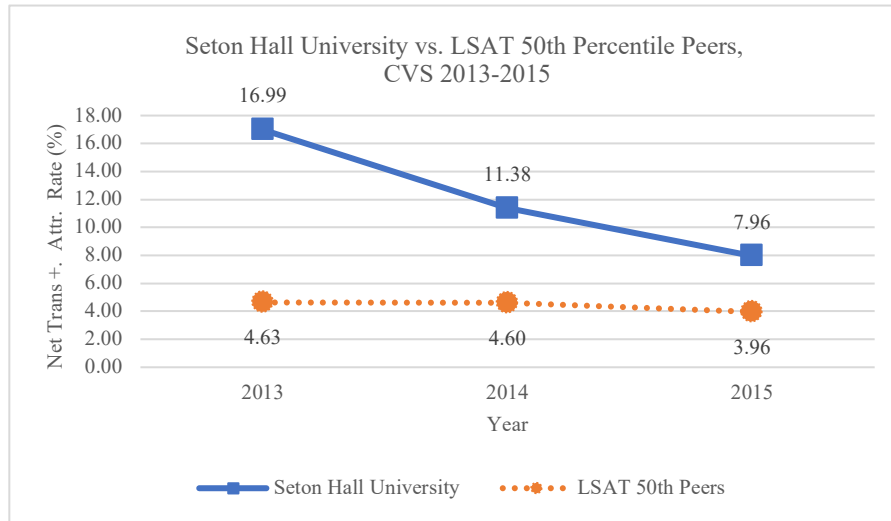
Seton Hall

Seton Hall's relative bar performance is summarized accordingly. Kinsler ranked Seton Hall the thirteenth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁸¹ During the period of 2012–2016, Seton Hall matriculated students with an average-median-LSAT score of 156.6 and an average 75th-percentile-UGPA score

181. *Kinsler II*, *supra* note 3 (manuscript at 3).

of 3.7.¹⁸² Seton Hall's CVS for 2013–2015 matriculants was 12.11%.¹⁸³ The average CVS was 4.4% for all other schools that had matriculating credentials within two points of the median LSAT of Seton Hall.¹⁸⁴ The average CVS was 4.74% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Seton Hall.¹⁸⁵ From 2013–2015, Seton Hall's average CVS was higher than 89.4% of LSAT-peers and 89.3% of 75th-percentile UGPA-peers.¹⁸⁶ The following graphs illustrate these CVS comparisons.

Graph 37



182. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Seton Hall).

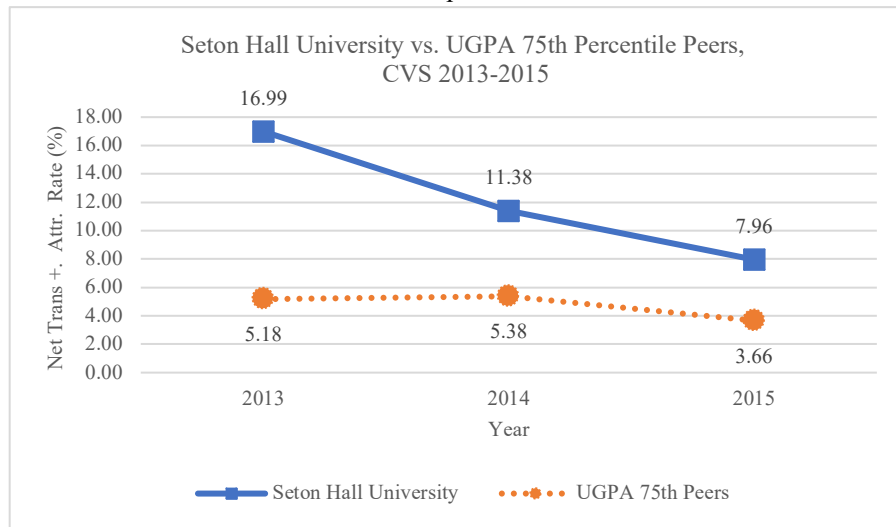
183. *Id.*

184. *Id.*

185. *Id.*

186. *Id.*

Graph 38



Cleveland State

Cleveland State's relative bar performance is summarized accordingly. Kinsler ranked Cleveland State the fourteenth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁸⁷ During the period of 2012–2016, Cleveland State matriculated students with an average-median-LSAT score of 153 and an average 75th-percentile-UGPA score of 3.59.¹⁸⁸ Cleveland State's CVS for 2013–2015 matriculants was 5.78%.¹⁸⁹ The average CVS was 3.47% for of all other schools that had matriculating credentials within two points of the median LSAT of Cleveland State.¹⁹⁰ The average CVS was 4.20% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Cleveland State.¹⁹¹ From 2013–2015, Cleveland State's average CVS was higher than 68.53% of LSAT-peers and 68.67% of 75th-percentile UGPA-peers.¹⁹² The following graphs illustrate these CVS comparisons.

187. *Kinsler II*, *supra* note 3, (manuscript at 3).

188. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Cleveland State University).

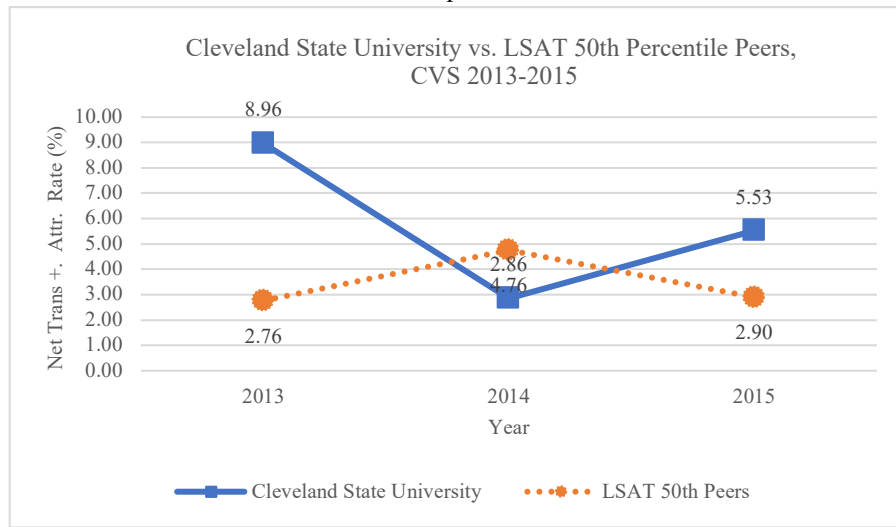
189. *Id.*

190. *Id.*

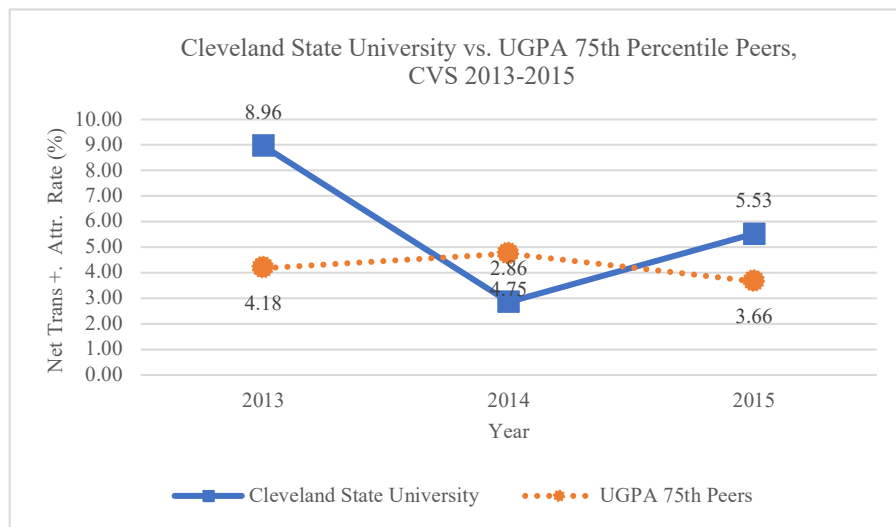
191. *Id.*

192. *Id.*

Graph 39



Graph 40



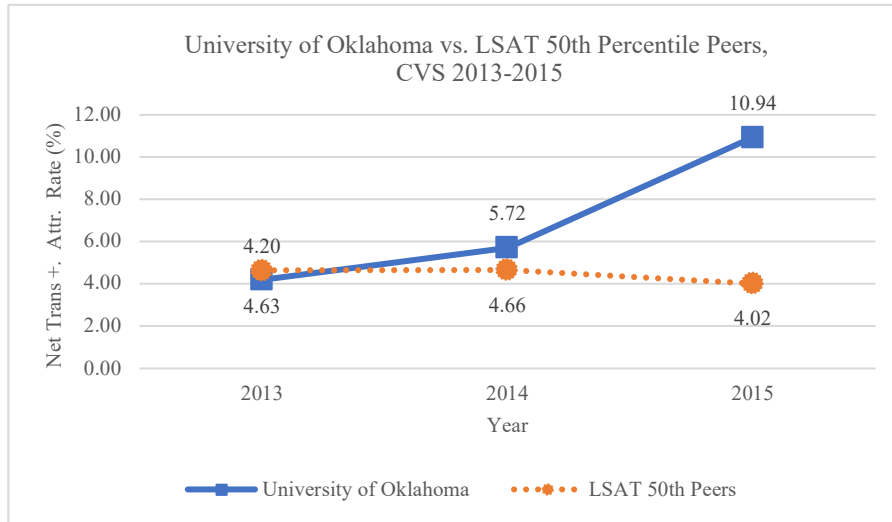
University of Oklahoma

University of Oklahoma's (Oklahoma) relative bar performance is summarized accordingly. Kinsler ranked Oklahoma the fifteenth-most-overperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁹³ During the period of 2012–2016, Oklahoma matriculated students with an average-median-LSAT score of 157.2

193. *Kinsler II*, *supra* note 3, (manuscript at 3).

and an average 75th-percentile-UGPA score of 3.72.¹⁹⁴ Oklahoma's CVS for 2013–2015 matriculants was 6.95%.¹⁹⁵ The average CVS was 4.44% for all other schools that had matriculating credentials within two points of the median LSAT of Oklahoma.¹⁹⁶ The average CVS was 6.45% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Oklahoma.¹⁹⁷ From 2013–2015, Oklahoma's average CVS was higher than 61.97% of LSAT-peers and 57.8% of 75th-percentile UGPA-peers.¹⁹⁸ The following graphs illustrate these CVS comparisons.

Graph 41



194. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of Oklahoma).

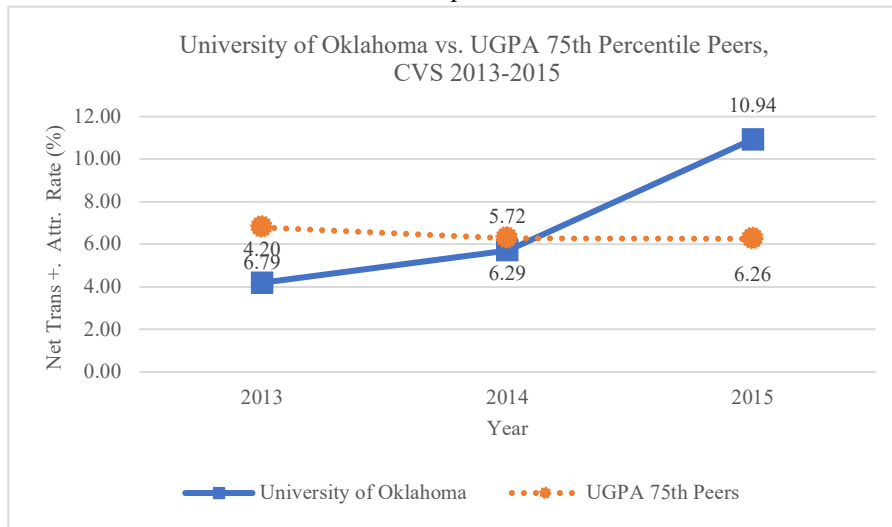
195. *Id.*

196. *Id.*

197. *Id.*

198. *Id.*

Graph 42



b. Results for Kinsler's Bottom-Fifteen Schools

University of San Francisco

University of San Francisco's (San Francisco) relative bar performance is summarized accordingly. Kinsler ranked San Francisco the most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.¹⁹⁹ During the period of 2012–2016, San Francisco matriculated students with an average-median-LSAT score of 153 and an average 75th-percentile-UGPA score of 3.43.²⁰⁰ San Francisco's CVS for 2013–2015 matriculants was 3.96%.²⁰¹ The average CVS was 3.96% for of all other schools that had matriculating credentials within two points of the median LSAT of San Francisco.²⁰² The average CVS was 4.58% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of San Francisco.²⁰³ From 2013–2015, San Francisco's average CVS was higher than 56.13% of LSAT-peers and 49.13% of 75th-percentile UGPA-peers.²⁰⁴ The following graphs illustrate these CVS comparisons.

199. *Kinsler II*, *supra* note 3, (manuscript at 4).

200. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of San Francisco).

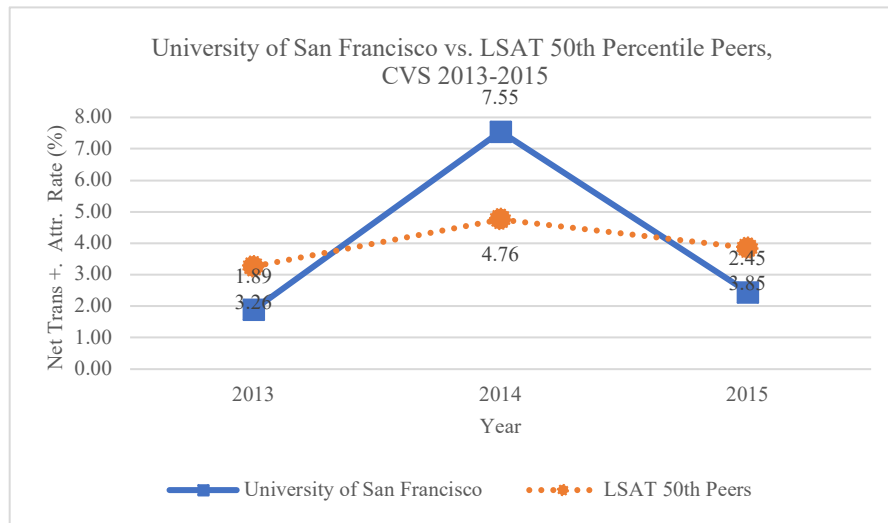
201. *Id.*

202. *Id.*

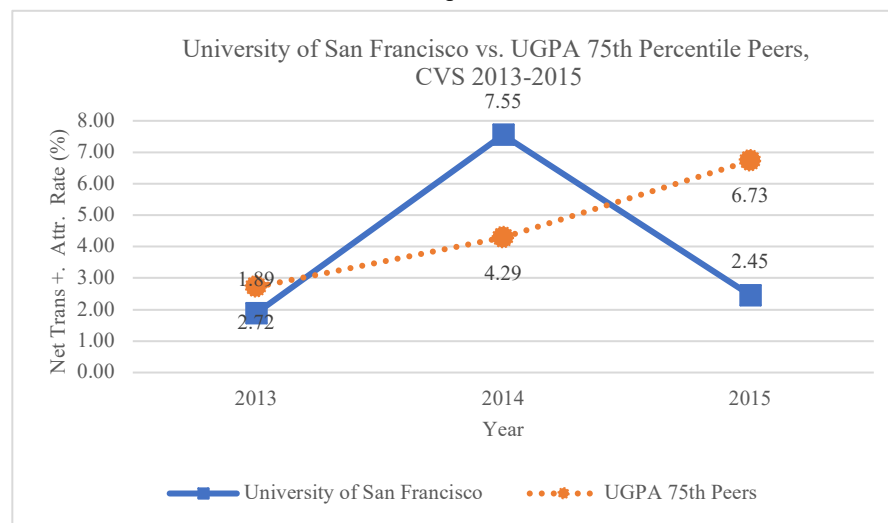
203. *Id.*

204. *Id.*

Graph 43



Graph 44



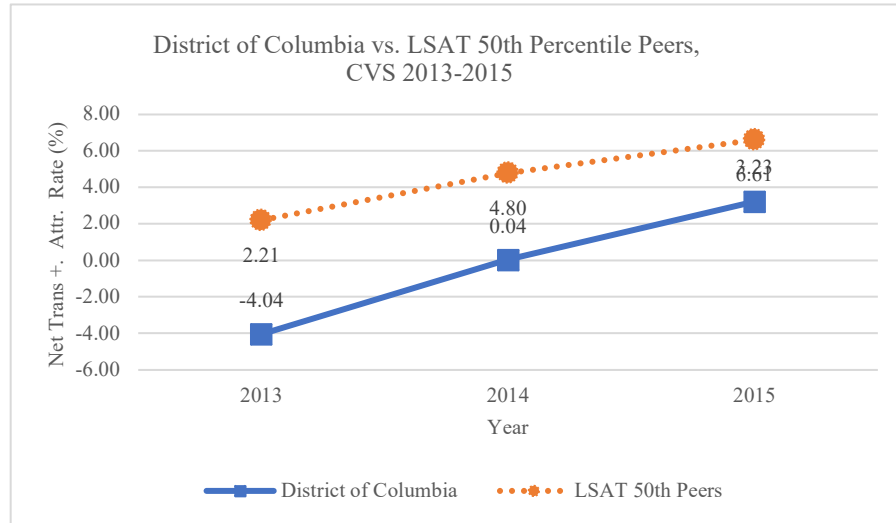
University of the District of Columbia

University of District of Columbia's (D.C.) relative bar performance is summarized accordingly. Kinsler ranked D.C. the second-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁰⁵ During the period of 2012–2016, D.C. matriculated students with an average-median-LSAT score of 148.6 and an average

205. *Kinsler II*, *supra* note 3, (manuscript at 4).

75th-percentile-UGPA score of 3.31.²⁰⁶ D.C.'s CVS for 2013–2015 matriculants was -0.26%.²⁰⁷ The average CVS was 4.54% for all other schools that had matriculating credentials within two points of the median LSAT of D.C.²⁰⁸ The average CVS was 5.24% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of D.C.²⁰⁹ From 2013–2015, D.C.'s average CVS was higher than 27.4% of LSAT-peers and 24.83% of 75th-percentile UGPA-peers.²¹⁰ The following graphs illustrate these CVS comparisons.

Graph 45



206. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of the District of Columbia).

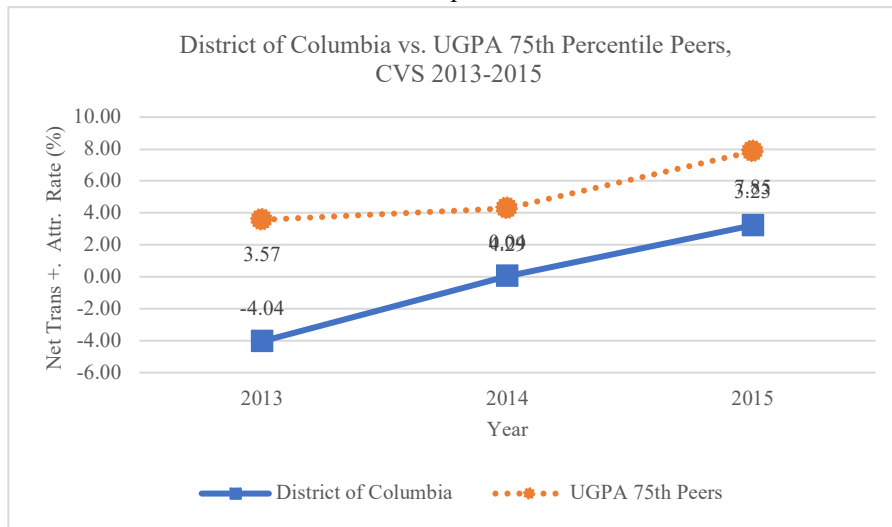
207. *Id.*

208. *Id.*

209. *Id.*

210. *Id.*

Graph 46



Golden Gate University

Golden Gate University's (Golden Gate) relative bar performance is summarized accordingly. Kinsler ranked Golden Gate the third-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²¹¹ During the period of 2012–2016, Golden Gate matriculated students with an average-median-LSAT score of 149.4 and an average 75th-percentile-UGPA score of 3.33.²¹² Golden Gate's CVS for 2013–2015 matriculants was 5.84%.²¹³ The average CVS was 5.32% for all other schools that had matriculating credentials within two points of the median LSAT of Golden Gate.²¹⁴ The average CVS was 5.92% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Golden Gate.²¹⁵ From 2013–2015, Golden Gate's average CVS was higher than 57.43% of LSAT-peers and 52.53% of 75th-percentile UGPA-peers.²¹⁶ The following graphs illustrate these CVS comparisons.

211. *Kinsler II*, *supra* note 3, (manuscript at 4).

212. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Golden Gate University).

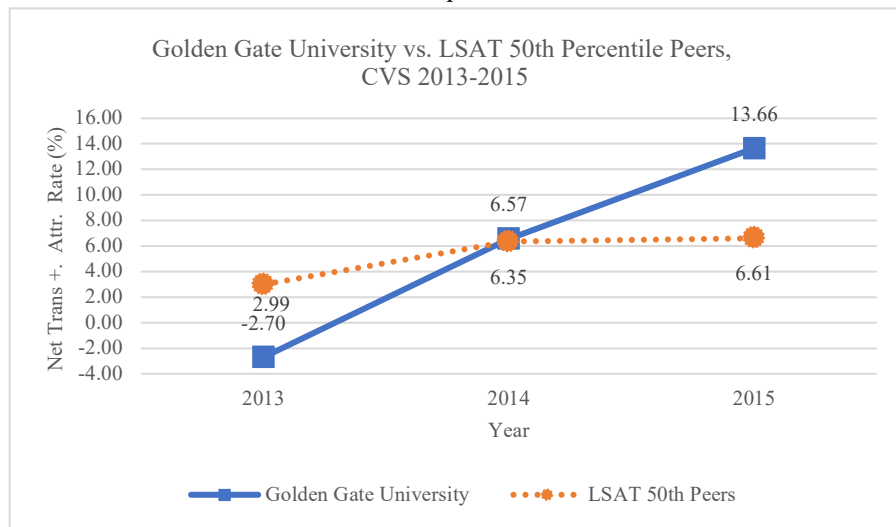
213. *Id.*

214. *Id.*

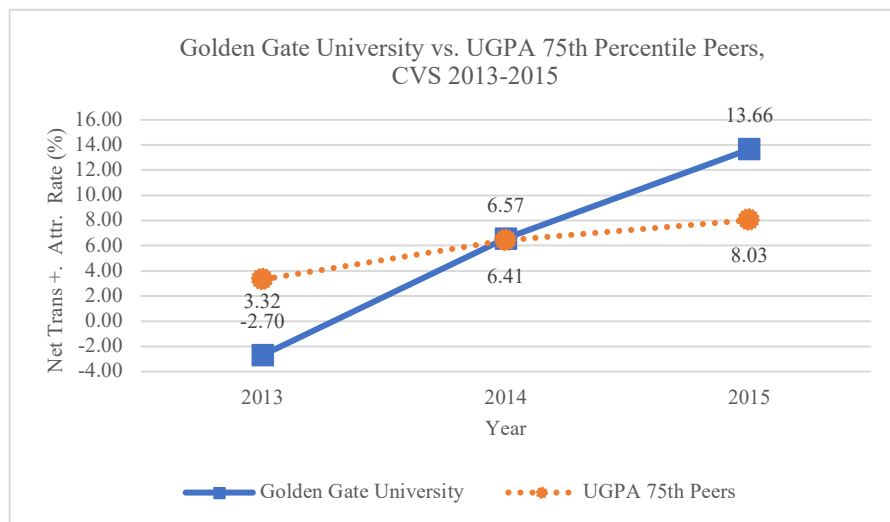
215. *Id.*

216. *Id.*

Graph 47



Graph 48



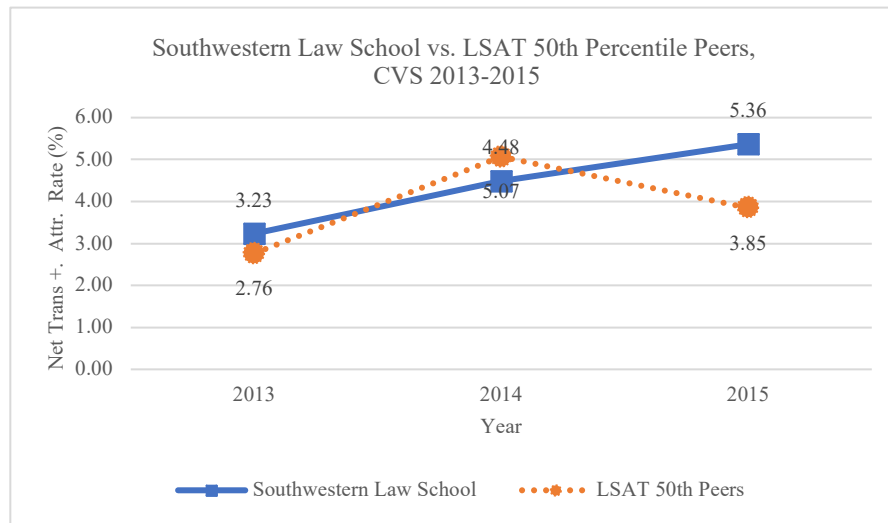
Southwestern Law School

Southwestern Law School's (Southwestern) relative bar performance is summarized accordingly. Kinsler ranked Southwestern the fourth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²¹⁷ During the period of 2012–

217. *Kinsler II*, *supra* note 3, (manuscript at 3).

2016, Southwestern matriculated students with an average-median-LSAT score of 152 and an average 75th-percentile-UGPA score of 3.42.²¹⁸ Southwestern's CVS for 2013–2015 matriculants was 4.36%.²¹⁹ The average CVS was 3.89% for of all other schools that had matriculating credentials within two points of the median LSAT of Southwestern.²²⁰ The average CVS was 4.58% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Southwestern.²²¹ From 2013–2015, Southwestern's average CVS was higher than 66.73% of LSAT-peers and 56.5% of 75th-percentile UGPA-peers.²²² The following graphs illustrate these CVS comparisons.

Graph 49



218. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Southwestern Law School).

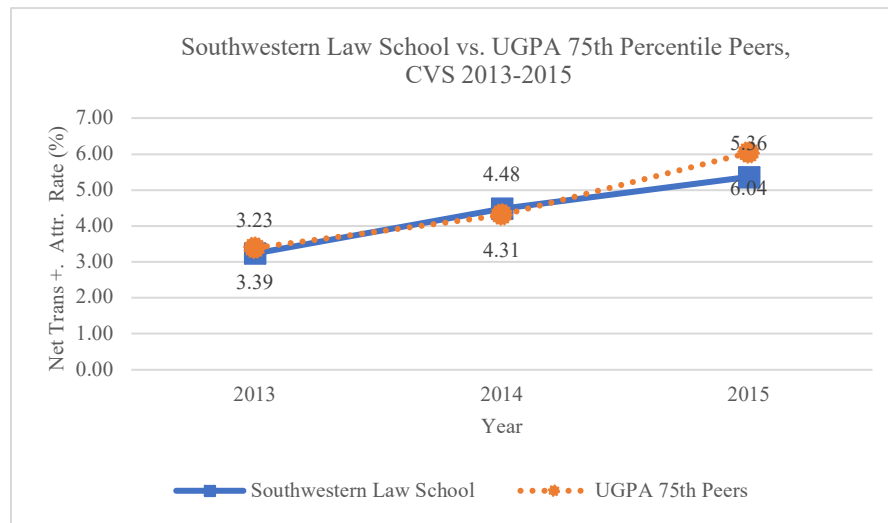
219. *Id.*

220. *Id.*

221. *Id.*

222. *Id.*

Graph 50



Hofstra University

Hofstra University's (Hofstra) relative bar performance is summarized accordingly. Kinsler ranked Hofstra the fifth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²²³ During the period of 2012–2016, Hofstra matriculated students with an average-median-LSAT score of 153.4 and an average 75th-percentile-UGPA score of 4.26.²²⁴ Hofstra's CVS for 2013–2015 matriculants was 4.36%.²²⁵ The average CVS was 3.92% for all other schools that had matriculating credentials within two points of the median LSAT of Hofstra.²²⁶ The average CVS was 3.82% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Hofstra.²²⁷ From 2013–2015, Hofstra's average CVS was higher than fifty-eight percent of LSAT-peers and sixty percent of 75th-percentile UGPA-peers.²²⁸ The following graphs illustrate these CVS comparisons.

223. *Kinsler II*, *supra* note 3, (manuscript at 4).

224. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Hofstra University).

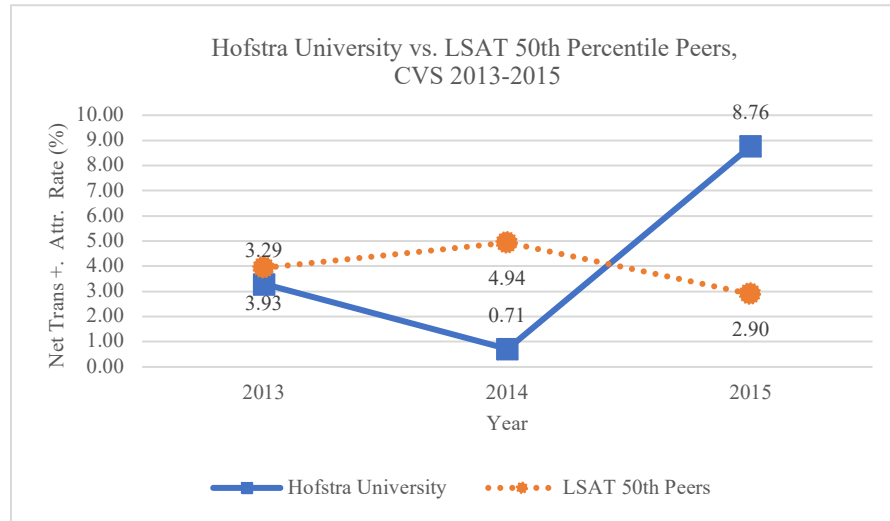
225. *Id.*

226. *Id.*

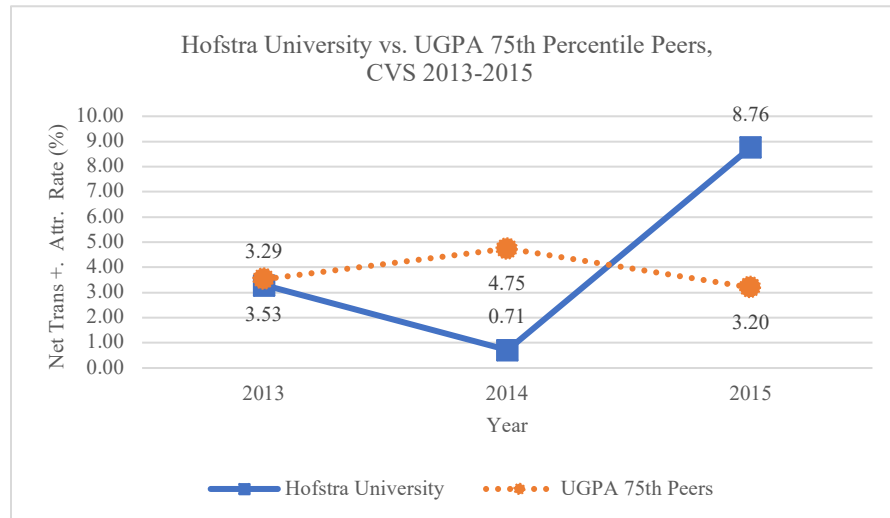
227. *Id.*

228. *Id.*

Graph 51



Graph 52



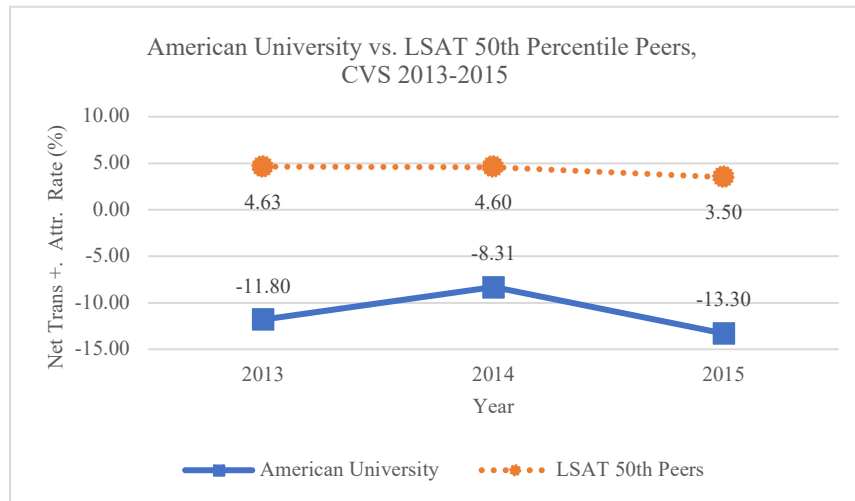
American University

American University's (American) relative bar performance is summarized accordingly. Kinsler ranked American the sixth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²²⁹ During the period of 2012–2016, American matriculated students

229. Kinsler II, *supra* note 3, (manuscript at 4).

with an average-median-LSAT score of 156.6 and an average 75th-percentile-UGPA score of 3.55.²³⁰ American's CVS for 2013–2015 matriculants was -11.24%.²³¹ The average CVS was 4.25% for all other schools that had matriculating credentials within two points of the median LSAT of American.²³² The average CVS was 3.99% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of American.²³³ From 2013–2015, American's average CVS was higher than 0.67% of LSAT-peers and 0.9% of 75th-percentile UGPA-peers.²³⁴ The following graphs illustrate these CVS comparisons.

Graph 53



230. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (American University).

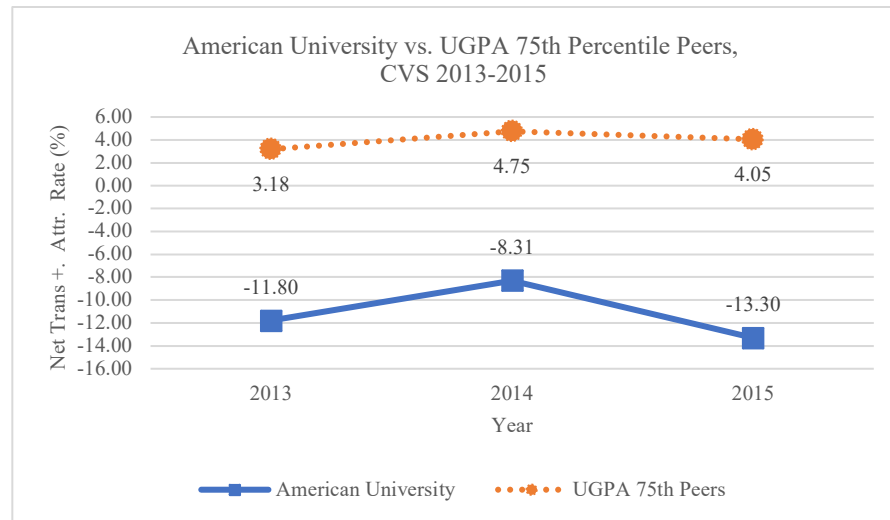
231. *Id.*

232. *Id.*

233. *Id.*

234. *Id.*

Graph 54



State University of New York at Buffalo

State University of New York at Buffalo's (SUNY) relative bar performance is summarized accordingly. Kinsler ranked SUNY the seventh-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²³⁵ During the period of 2012–2016, SUNY matriculated students with an average-median-LSAT score of 154.4 and an average 75th-percentile-UGPA score of 3.67.²³⁶ SUNY's CVS for 2013–2015 matriculants was 3.38%.²³⁷ The average CVS was 3.72% for of all other schools that had matriculating credentials within two points of the median LSAT of SUNY.²³⁸ The average CVS was 4.52% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of SUNY.²³⁹ From 2013–2015, SUNY's average CVS was higher than 49.23% of LSAT-peers and 49.1% of 75th-percentile UGPA-peers.²⁴⁰ The following graphs illustrate these CVS comparisons.

235. *Kinsler II*, *supra* note 3, (manuscript at 4).

236. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (State University of New York at Buffalo).

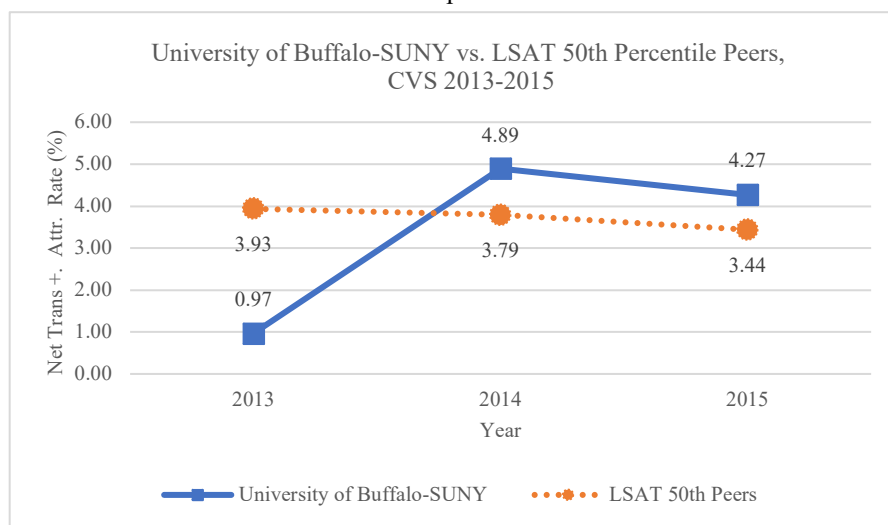
237. *Id.*

238. *Id.*

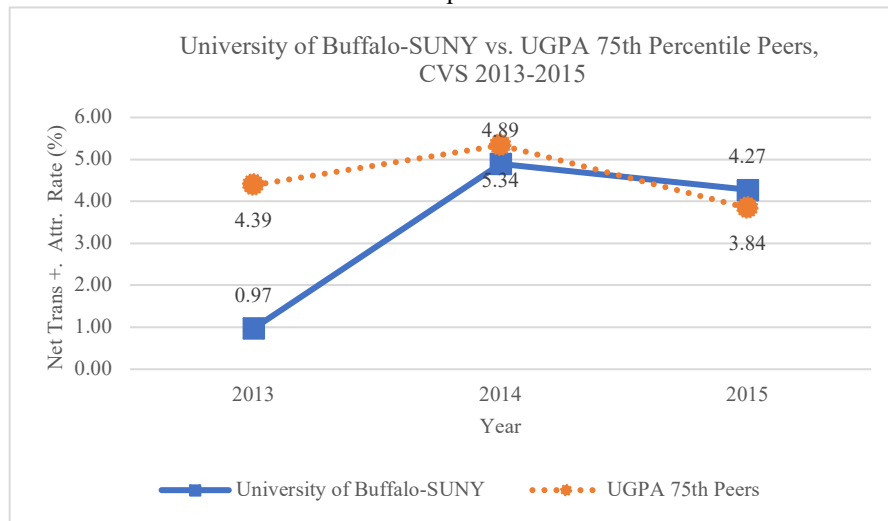
239. *Id.*

240. *Id.*

Graph 55



Graph 56



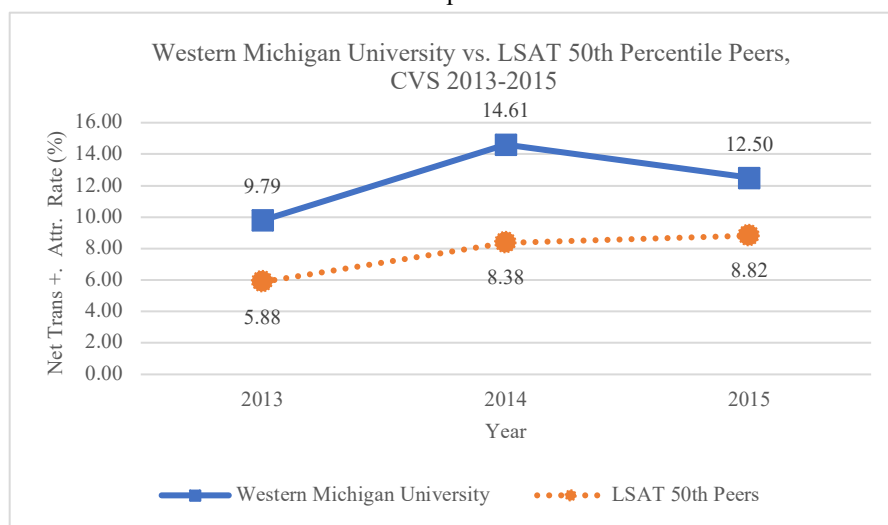
Western Michigan University Thomas M. Cooley

Western Michigan University Thomas Cooley's (Thomas Cooley) relative bar performance is summarized accordingly. Kinsler ranked Thomas Cooley the eighth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁴¹ During the period of 2012–2016, Thomas Cooley matriculated students with an average-

241. *Kinsler II*, *supra* note 3, (manuscript at 4).

median-LSAT score of 143.4 and an average 75th-percentile-UGPA score of 3.27.²⁴² Thomas Cooley's CVS for 2013–2015 matriculants was 12.3%.²⁴³ The average CVS was 7.69% for all other schools that had matriculating credentials within two points of the median LSAT of Thomas Cooley.²⁴⁴ The average CVS was 5.37% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Thomas Cooley.²⁴⁵ From 2013–2015, Thomas Cooley's average CVS was higher than 83.43% of LSAT-peers and 74.43% of 75th-percentile UGPA-peers.²⁴⁶ The following graphs illustrate these CVS comparisons.

Graph 57



242. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Western Michigan University Thomas Cooley).

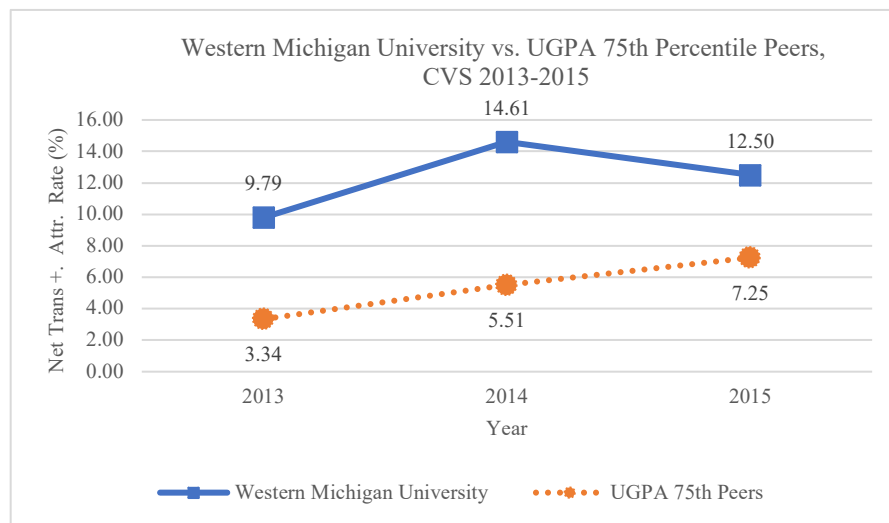
243. *Id.*

244. *Id.*

245. *Id.*

246. *Id.*

Graph 58

*Emory University*²⁴⁷*University of California Hastings*

University of California Hastings's (Hastings) relative bar performance is summarized accordingly. Kinsler ranked Hastings the tenth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁴⁸ During the period of 2012–2016, Hastings matriculated students with an average-median-LSAT score of 159.4 and an average 75th-percentile-UGPA score of 3.67.²⁴⁹ Hastings's CVS for 2013–2015 matriculants was -4.14%.²⁵⁰ The average CVS was 4.34% for of all other schools that had matriculating credentials within two points of the median LSAT of Hastings.²⁵¹ The average CVS was 4.41% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Hastings.²⁵² From 2013–2015, Hastings's average CVS was higher than 6.77% of LSAT-peers and 6.53% of 75th-percentile UGPA-peers.²⁵³ The following graphs illustrate these CVS comparisons.

247. Emory University, the ninth-most-underperforming school according to Kinsler's rankings, is omitted from this analysis. *See supra* note 110.

248. *Kinsler II*, *supra* note 3 (manuscript at 4).

249. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (University of California Hastings).

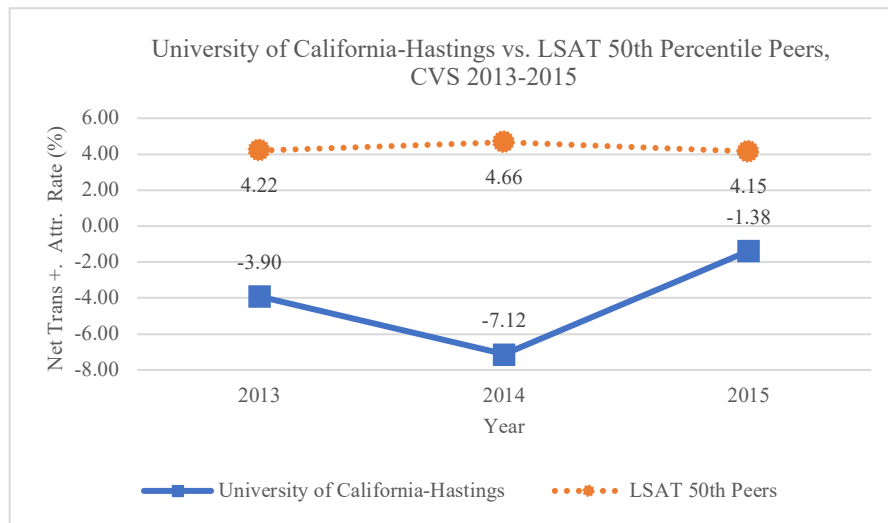
250. *Id.*

251. *Id.*

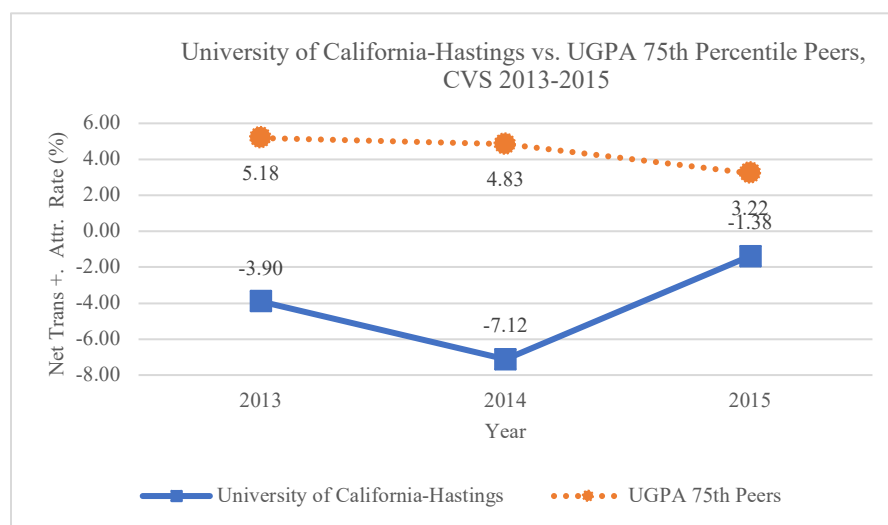
252. *Id.*

253. *Id.*

Graph 59



Graph 60



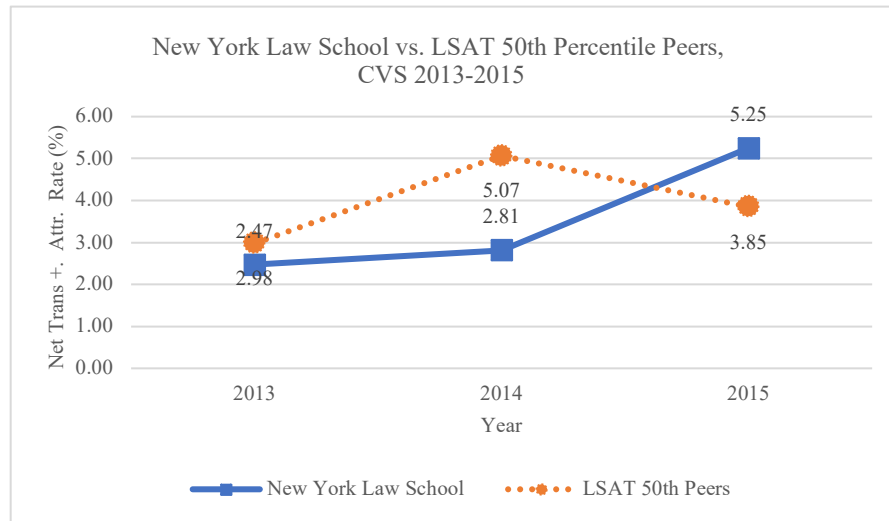
New York Law School

New York Law School's (NYLS) relative bar performance is summarized accordingly. Kinsler ranked NYLS the eleventh-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁵⁴ During the period of 2012–2016, NYLS matriculated students with an average-median-LSAT score of 151.6 and an average 75th-

254. *Kinsler II*, *supra* note 3 (manuscript at 4).

percentile-UGPA score of 3.47.²⁵⁵ NYLS's CVS for 2013–2015 matriculants was 3.51%.²⁵⁶ The average CVS was 3.97% for all other schools that had matriculating credentials within two points of the median LSAT of NYLS.²⁵⁷ The average CVS was 3.84% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of NYLS.²⁵⁸ From 2013–2015, NYLS's average CVS was higher than 57.7% of LSAT-peers and 54.97% of 75th-percentile UGPA-peers.²⁵⁹ The following graphs illustrate these CVS comparisons.

Graph 61



255. RELATIVE BAR PERFORMANCE DATA REPOSITORY,
<https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (New York Law School).

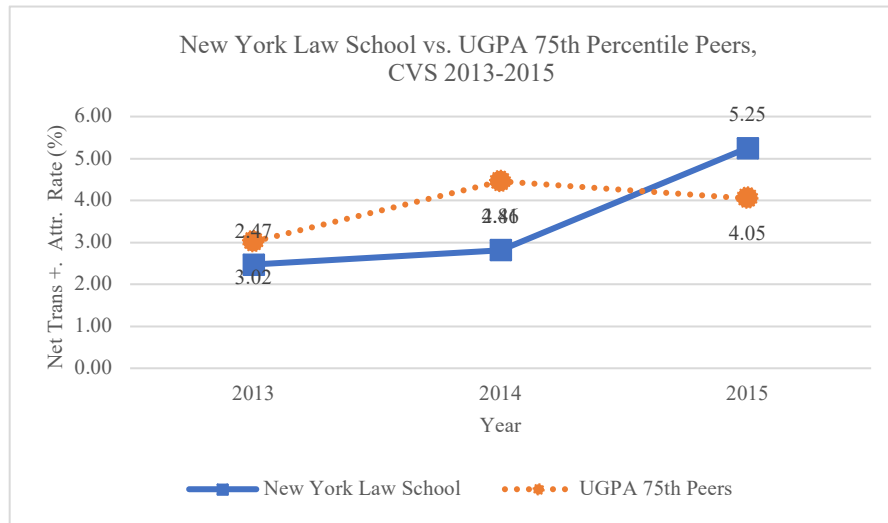
256. *Id.*

257. *Id.*

258. *Id.*

259. *Id.*

Graph 62



Atlanta's John Marshall

Atlanta's John Marshall's (AJM) relative bar performance is summarized accordingly. Kinsler ranked AJM the twelfth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁶⁰ During the period of 2012–2016, AJM matriculated students with an average-median-LSAT score of 148.4 and an average 75th-percentile-UGPA score of 3.27.²⁶¹ AJM's CVS for 2013–2015 matriculants was -0.78%.²⁶² The average CVS was 4.69% for all other schools that had matriculating credentials within two points of the median LSAT of AJM.²⁶³ The average CVS was 6.91% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of AJM.²⁶⁴ From 2013–2015, AJM's average CVS was higher than 29.47% of LSAT-peers and 23.47% of 75th-percentile UGPA-peers.²⁶⁵ The following graphs illustrate these CVS comparisons.

260. *Kinsler II*, *supra* note 3 (manuscript at 4).

261. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Atlanta's John Marshall).

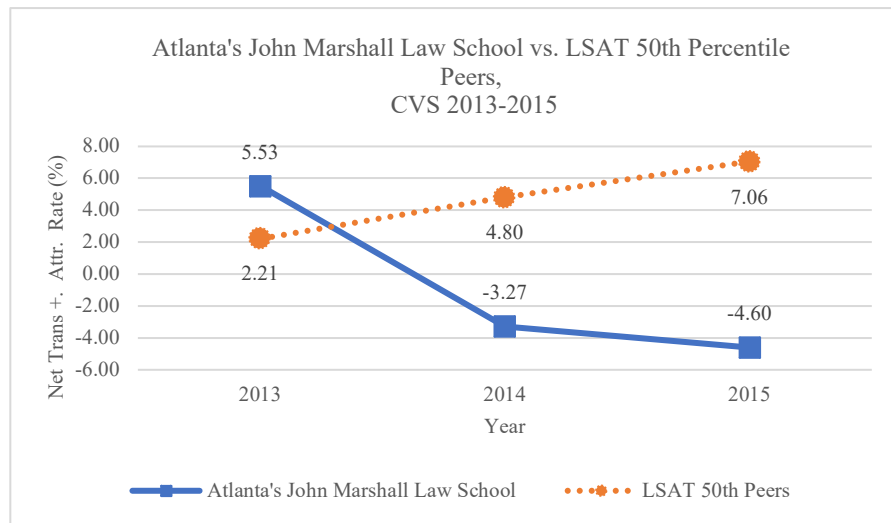
262. *Id.*

263. *Id.*

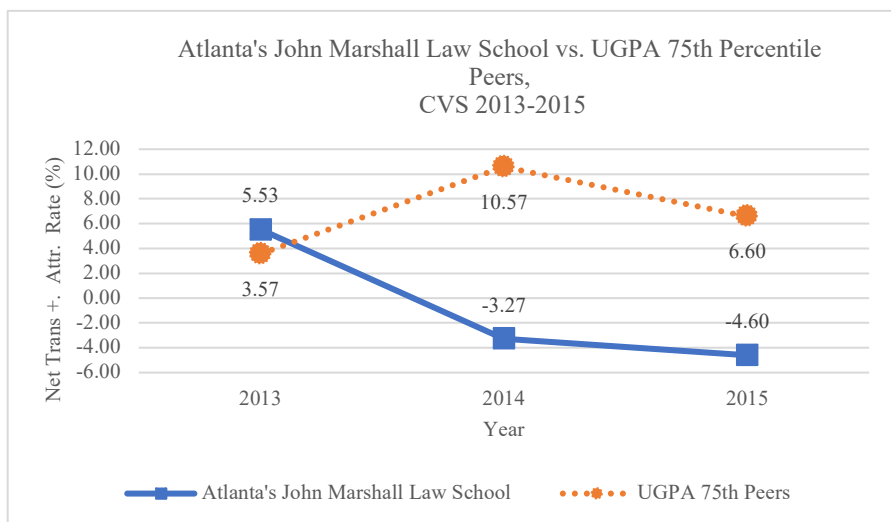
264. *Id.*

265. *Id.*

Graph 63



Graph 64



*Northwestern University*²⁶⁶

*University of Minnesota*²⁶⁷

Touro College

Touro College's (Touro) relative bar performance is summarized accordingly. Kinsler ranked Touro the fifteenth-most-underperforming school on the bar exam for the years 2015–2019 compared to its students' matriculating credentials in 2012–2016.²⁶⁸ During the period of 2012–2016, Touro matriculated students with an average-median-LSAT score of 147.4 and an average 75th-percentile-UGPA score of 3.34.²⁶⁹ Touro's CVS for 2013–2015 matriculants was -3.18%.²⁷⁰ The average CVS was 5.53% for of all other schools that had matriculating credentials within two points of the median LSAT of Touro.²⁷¹ The average CVS was 5.34% for all other schools that had matriculating credentials within 0.1 point of the 75th-UGPA score of Touro.²⁷² From 2013–2015, Touro's average CVS was higher than 16.2% of LSAT-peers and 17.63% of 75th-percentile UGPA-peers.²⁷³ The following graphs illustrate these CVS comparisons.

266. Northwestern University, the thirteenth-most-underperforming school according to Kinsler's rankings, is omitted from this analysis. *See supra* note 110.

267. University of Minnesota, the Fourteenth-most-underperforming school according to Kinsler's rankings, is omitted from this analysis. *See supra* note 110.

268. *Kinsler II*, *supra* note 3 (manuscript at 4).

269. RELATIVE BAR PERFORMANCE DATA REPOSITORY, <https://digitalrepository.unm.edu/nmlr/vol52/iss1/6> (Touro College).

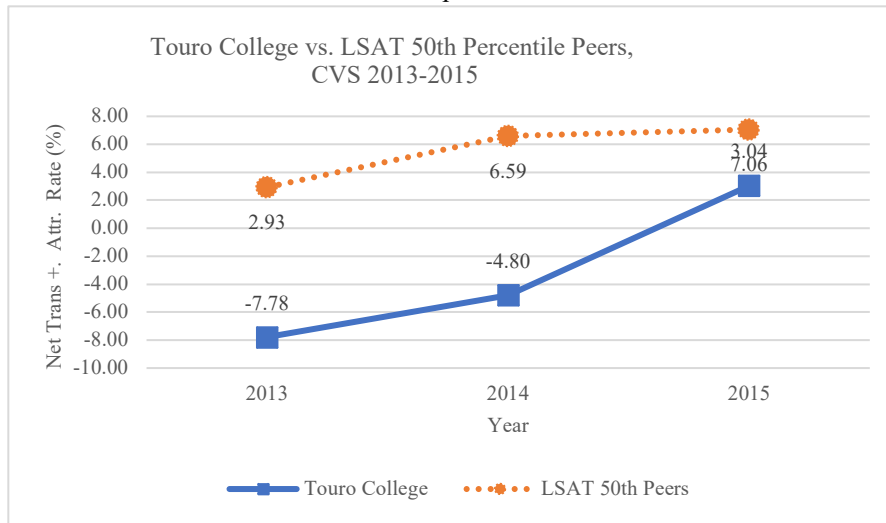
270. *Id.*

271. *Id.*

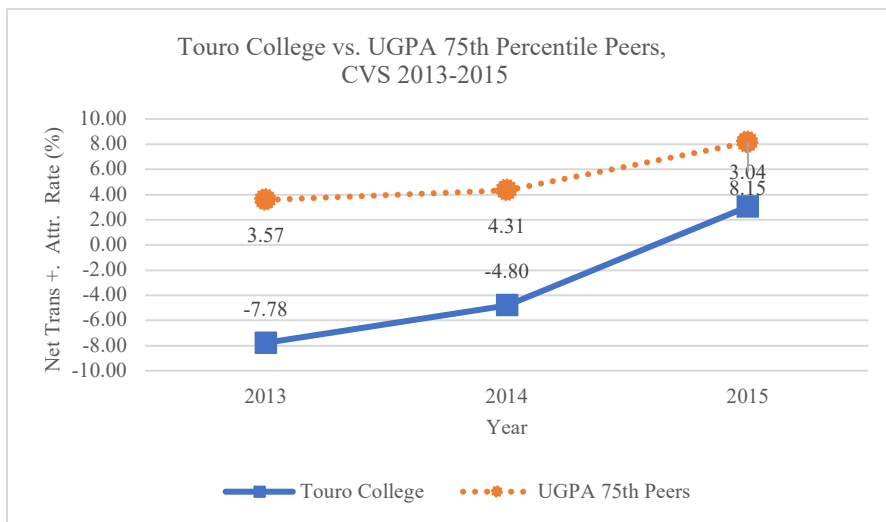
272. *Id.*

273. *Id.*

Graph 65



Graph 66



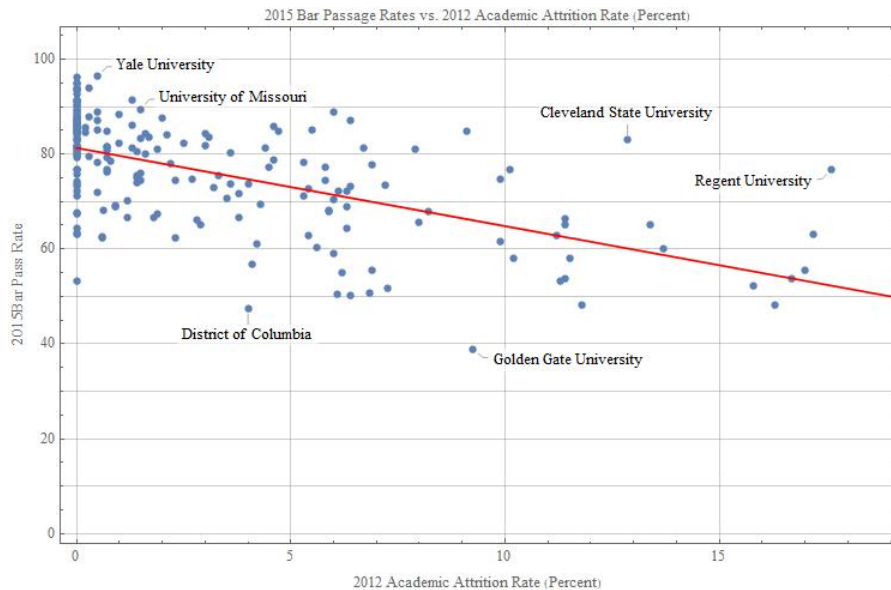
V. A BRIEF NOTE ABOUT AN IRRELEVANT DISTRACTOR

This article demonstrates that academic attrition has, especially when combined with net transfer, a clear and undeniable effect on bar passage.²⁷⁴ However, linear-regression analysis of the relationship between academic attrition for 2012 matriculants and bar performance in 2015 fails to correlate positively—appearing to undermine the findings of this article. This linear-regression result—an irrelevant

274. See *supra* Part IV.C.

distractor—is superficial, misleading, and possibly the product of various factors which we identify. The graph below is the linear regression of academic-attrition rates for 2012 matriculants compared with bar passage in 2015.

Graph 67

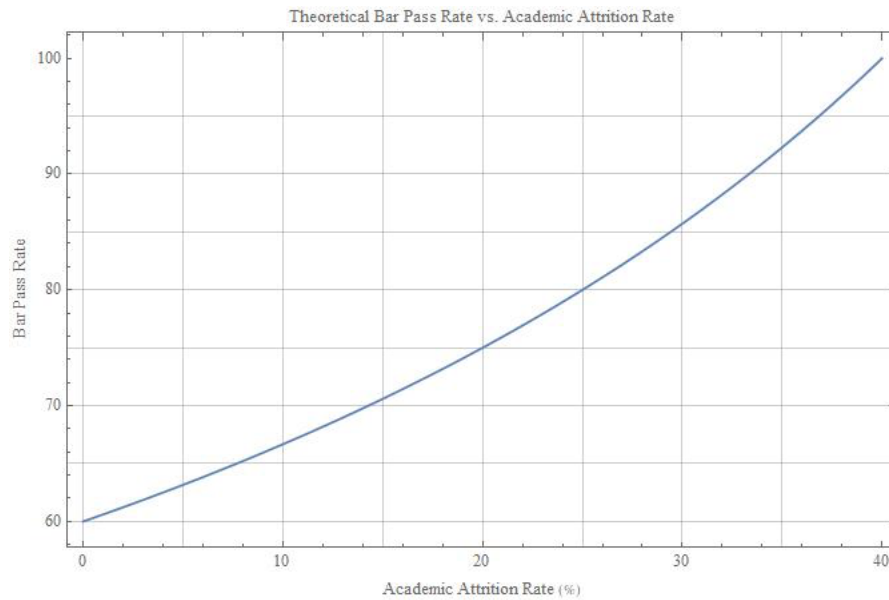


The following hypotheticals help illustrate that unaccounted factors must contribute to the result of the above graph. First, consider a school that matriculates 100 students who will take the bar exam three years later, and assume that, if no students attrite, then sixty of the 100 students (60%) will pass the bar exam. Next, consider that the twenty students who have the lowest 1L GPAs—which indicates low probability of passing the bar exam²⁷⁵—attrite at the end of the first year. Assuming that none of the twenty, attrited students would have passed the bar examination, then sixty of the remaining eighty students (75%) will pass the bar exam. Comparatively, the second scenario represents a 15% increase in bar passage (60% to 75%).

The increase in bar passage in these hypotheticals which academic attrition causes is significant. In the Kinsler rankings, a 15% increase in bar performance can be the difference between a middle-of-the-pack school and a top-fifteen, overperforming school. The following graph displays the effect that varying, academic-attrition rates would have on bar passage, assuming all attrited students would have failed the bar exam.

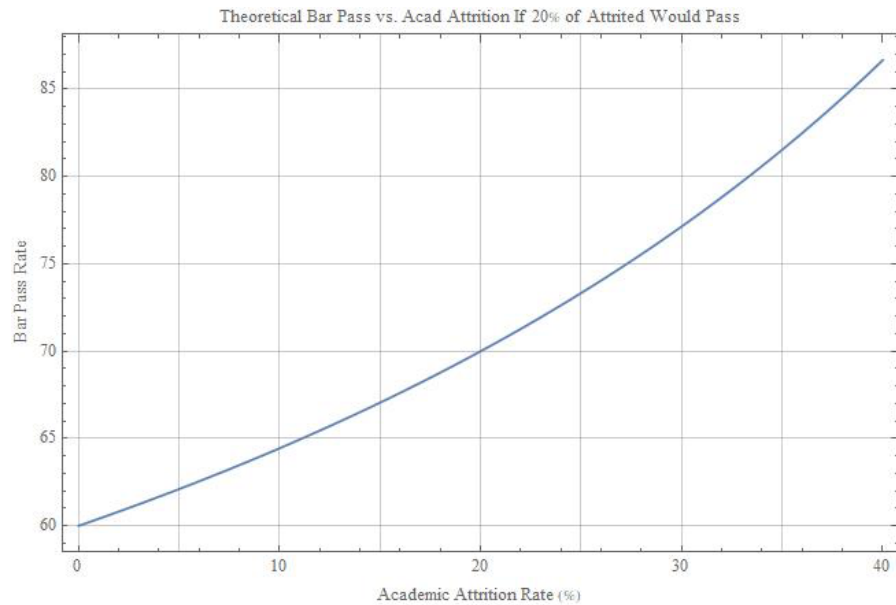
275. See *supra* Part IV.A.

Graph 68



Academic attrition significantly affects bar passage even if some attrited students would have passed the bar exam. Assume that four of the attrited and non-attrited students have opposite bar passage results from the previous hypothetical. Four of the twenty attrited students (20%) would have passed the bar, and fifty-six of the eighty remaining students (70%) will pass the bar exam. Recall that, if zero students attrite, then this hypothetical school's bar-pass rate is 60%. Even when 20% of the twenty attrited students would have passed the bar exam, then the school's bar-pass rate increases to 70%. Ten percent higher bar passage is a significant increase. The following graph displays how varying, academic-attrition rates would affect bar passage of this hypothetical school, assuming that 20% of the academically attrited students would have passed the bar.

Graph 69



The results of these hypotheticals do not accord the linear-regression scatterplot of academic-attrition rates for 2012 matriculants compared with bar passage in 2015. The hypothetical results evidence a strong, positive relationship between academic attrition and bar passage; the scatterplot for 2012 matriculants compared with bar passage in 2015 shows no correlation or possibly a weak, negative relationship. Something must create this discrepancy, and we identify various, reconciliatory explanations.

First, low matriculating credentials can affect academic attrition and bar passage. Schools that have low LSAT scores typically have high, academic-attrition rates. Recall that low LSATs is a reliable predictor of low bar passage.²⁷⁶ Schools that matriculate students who have low LSATs—students who have a low probability of passing the bar—have high, academic-attrition rates. For such schools, the relationship between academic attrition and bar passage should be negatively correlated because high academic attrition indicates low entering credentials, and low credentials typically results in low bar passage.²⁷⁷

A second factor is that academic attrition might affect particular schools differently. Schools might have dissimilar, academic-attrition standards, such as different grading curves and academic-dismissal policies. These distinct attrition standards would mitigate a regression trend when the data of multiple schools is examined. The causes of academic attrition for a particular school might uniquely

276. See *supra* Part IV.A.

277. Interestingly, some schools with middle and higher median-matriculating-LSAT scores have academic-attrition rates that are significantly higher than the attrition rates of peer schools. Whether students who have relatively high credentials and attrite from these schools would have graduated and passed the bar exam had they attended a different school is questionable.

affect the bar passage of that school. Although linear regression reveals no relationship between academic attrition and bar passage when multiple schools are evaluated, that does not indicate that academic attrition has no impact upon the bar passage of an individual school.

Other variables might significantly mask the impact that academic attrition has upon bar passage. Variables such as LSAT scores, UGPAs, costs of living off-campus, student-section size, and the percentage of minority student matriculants might have a greater effect on bar passage than does academic attrition.²⁷⁸ Consequently, the effect that academic attrition has upon industry-wide, bar-pass rates might appear less significant.

Confounding variables are an additional factor that likely skew the relationship between academic attrition and bar passage. A confounding variable is a variable that closely relates to the independent and dependent variables of a study. A variable must meet two conditions to be a confounder, it must: (1) correlate with the independent variable, and (2) causally relate to the dependent variable.²⁷⁹ Exercise is an example of a confounding variable in the context of human weight and bone density.

Exercise can confound the typical relationship between a person's weight and bone density. Generally, bone density and weight are positively correlated—increasing the weight of a person causes higher bone density. Confounding this relationship, exercise usually lowers body weight and increases bone density. Thus, if exercise is not factored, then the data for weight and bone density might show no correlation or a negative correlation. Similar to exercise, matriculants' entering credentials can confound the relationship between academic attrition and bar passage.

High LSATs and UGPAs can confound the impact that academic attrition has upon bar passage. High LSAT scores and UGPAs typically result in high bar passage and low academic attrition. Thus, high LSATs and UGPAs are partly responsible for academic attrition and bar passage appearing to have no relationship. However, we (correctly) assert that academic attrition correlates positively with and *causes* high bar passage at an individual school.

Overall, many factors obscure the positive correlation between academic attrition and bar passage. Future studies discerning whether changes in attrition rates coincide with changes in bar performance should focus on the effect of such distractors upon individual schools over a period of years.

VI. CONCLUSION

Ultimately, the purpose of this article is two-fold. First, this article intends to continue the progress that Kinsler made in developing quantifiable metrics to best understand the factors impacting institutional, bar passage rates. Second, this article unapologetically aims to protect many untenured, academic-support faculty and bar-preparation professionals. Such professionals face unnecessary pressure when bar

278. The BARBRI study supports this assertion. *See supra* Part IV.A.

279. Lauren Thomas, *Understanding Confounding Variables*, (Apr. 2, 2021) SCRIBBR <https://www.scribbr.com/methodology/confounding-variables/>.

success is exclusively attributed to their job performance. Other variables that are unrelated to pedagogy and likely contribute to bar performance should be considered.

This article does *not* argue that academic support and bar-preparation programs are irrelevant; they certainly matter. Many brilliant, hard-working faculty contribute significantly to bar preparation. However, these faculty members should not be expected to magically improve their schools' bar-pass rates. Pedagogy alone is not responsible for bar passage, and such a belief puts these faculty members in an untenable position. Factors beyond the control of such faculty are substantial ingredients in the bar passage recipe.

This article demonstrates that academic attrition and transfer rates—evaluated as a single, independent variable which we termed the CVS—affect bar passage even though they are unrelated to the performance of legal educators. Of the fifteen schools that Kinsler identified as most-overperforming on the bar exam, the relatively high CVSs of the majority of these schools are a plausible explanation for their bar performance. These results indicate that primarily attributing bar-pass rates to the efficacy of faculty and bar programs is premature and unjustifiable. Although the CVSs of three of the fifteen most-overperforming schools—Duquesne, LSU, and New Hampshire—support that bar preparers most affect bar performance, variables such as academic attrition, student transfer, and other factors unrelated to legal pedagogy likely have some impact on bar performance.

Additionally, the CVSs of the most-underperforming schools support that academic attrition and student transfer affect bar passage. Five of the schools that Kinsler identified as most-underperforming have conspicuously low CVSs, relative to LSAT and 75th-percentile peer-schools, when compared with the CVSs of the most-overperforming schools. Two of these schools, Hastings and American, have CVSs which are significantly lower than the CVSs of peer-schools. These results strongly indicate that students' attrition and transfer can significantly impact the bar performance of schools. Our analysis omitted three of the fifteen most-underperforming schools because of model misspecification.

Kinsler pioneering the use of statistics in the study of bar performance is laudable; however, model misspecification lessens the validity of his inferential conclusions. Linearity and homoscedasticity are two of the four conditions founding the reliability of linear-regression analysis. Kinsler applied linear regression to datasets which are neither linear nor homoscedastic. This model misspecification manifested mathematical bias which distorts Kinsler's results for schools' relative bar performance. Kinsler integrated science to the study of bar performance, and, ironically, the issues that we identify for Kinsler's statistical analysis and inferential conclusions highlight the importance of scientific scrutiny.

Overall, the scientific study of bar performance has and should continue to improve our understanding of this field. Statistical analysis and peer review mitigate biases and unsupported claims, such as the fallacy that legal pedagogy and bar programming primarily drive bar passage. Future studies should account for the fact that student attrition and transfer rates, which are beyond the control of vulnerable, untenured faculty, contribute to bar performance and can be manipulated by institutions. Because, *inter alia*, the careers and reputations of such faculty are at stake, the study of bar performance should be objective, accurate, and holistic.

Finally, when studying bar performance, the emerging scholarly reality that the bar examination ineffectively assesses the ability of applicants to succeed in law school²⁸⁰ should not be discounted. The bar exam is extant likely because of the monopolistic nature of the NCBE.²⁸¹ Whether the ABA inexplicably maintains the status quo as though standard 316 is more than a convenient placeholder that permits the ABA to pretend, without labor or investigation, that it is assessing the adequacy of schools is beyond the scope of this article.²⁸² However, a fact that is not beyond the scope of this article is that standard 316 perpetuates the exclusion of minorities from the legal profession because it targets schools that traditionally have high, minority student populations.²⁸³ We sincerely hope that this article encourages others to begin or continue discovering answers to the questions that we have raised about bar passage.

280. See *Bar Ninja*, *supra* note 7, 275–76 n.193 and accompanying text explaining the serious problems with the bar exam as an assessment tool.

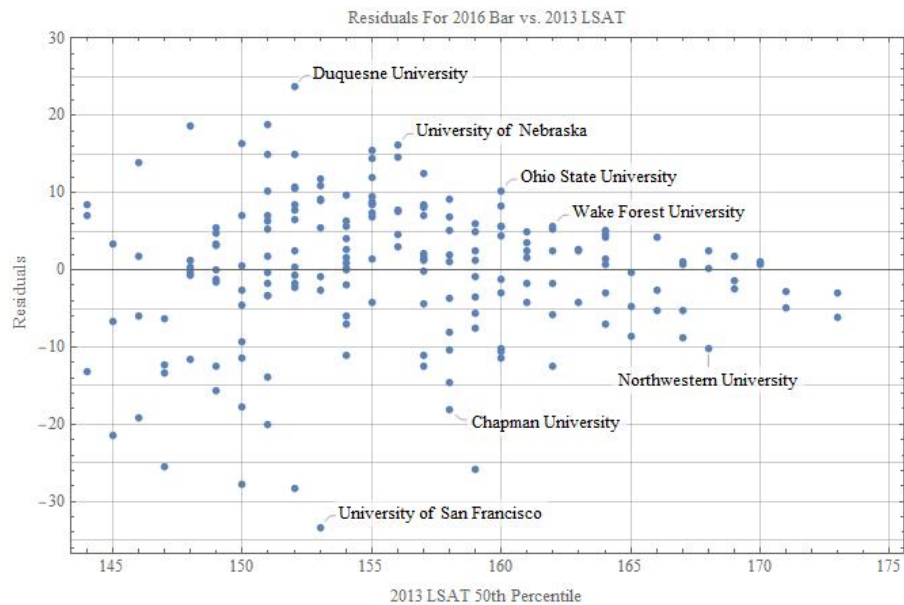
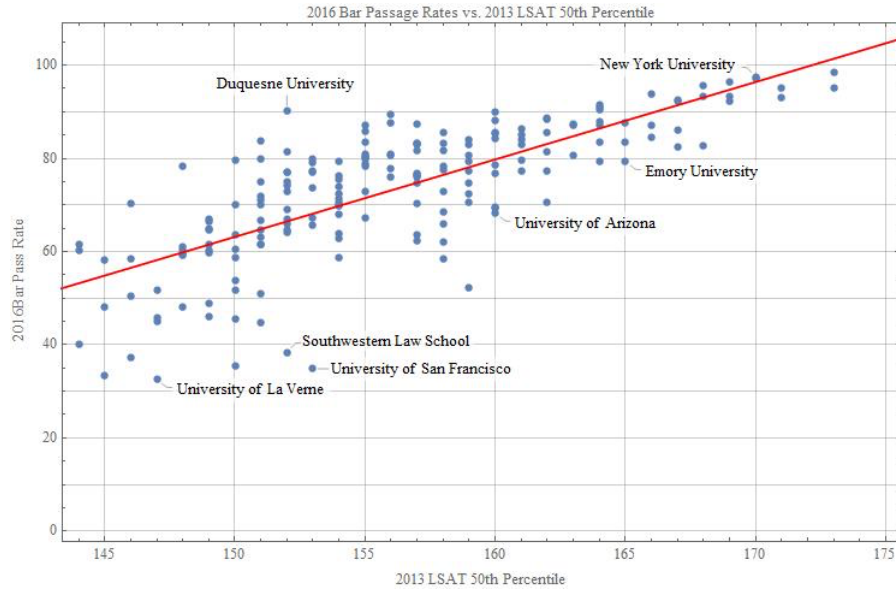
281. See Griggs, *supra* note 25 (describing the almost monopolistic hold the NCBE has on the Bar Examination).

282. See *Bar Ninja* *supra* note 7, at 274–75 (illustrating the arbitrary and capricious nature of standard 316 in Florida. “That these private schools provide a feeder system for FIU at the end of the first year of law school is also documented on the 509 forms. For example, in 2013, sixteen of the twenty-two students who transferred to FIU came from one of these two private institutions, and in 2014, thirteen of the twenty-four students transferring to FIU came from the other. A separate article might consider how FIU’s and other schools’ siphoning off the better students from Nova and St. Thomas in the numbers mentioned would presumably reduce the bar passage percentage at these schools. While FIU’s transfer policy lowers the bar passage at these schools, it also presumably increases FIU’s bar pass rates, thereby increasing the difference between FIU’s bar pass rate and the state average. FIU’s “above state average” results need to be evaluated in this light as well. In a future study, it may be also worth discussing the arbitrary nature of applying the ABA 316 standard to schools in South Florida because of the high intrastate transfer numbers.”).

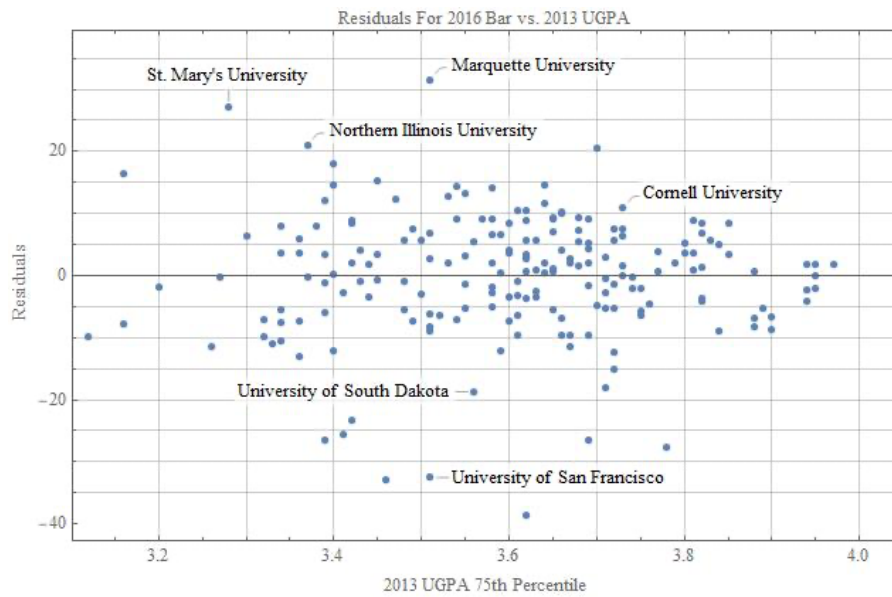
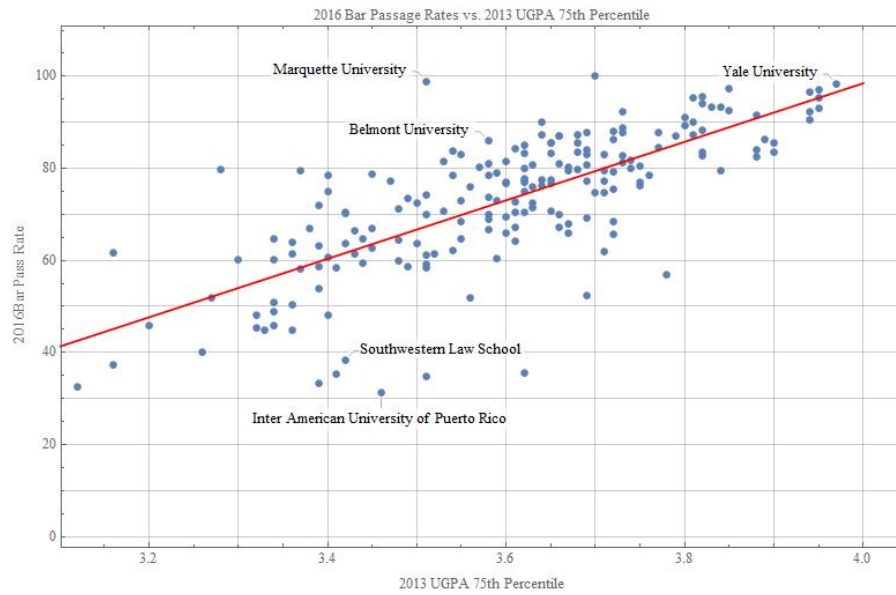
283. See generally Robert L. Green & Robert J. Griffore, *The Impact of Standardized Testing on Minority Students*, 49 J. NEGRO ED. 238 (1980); see also Megan McArdle, Opinion, *Crack Down on Law Schools That Don’t Pass the Bar*, BLOOMBERG, Aug. 8, 2016, <https://www.bloomberg.com/opinion/articles/2016-08-08/crack-down-on-law-schools-that-don-t-pass-the-bar> (“Minorities tend to have lower scores on standardized tests. So schools that serve a high percentage of minorities are going to be hit hard if the ABA enacts this accreditation policy. These schools would include dodgy for-profit outfits, yes, but also some morally upright historically black colleges and universities. Meaning that some minorities will be denied a shot at becoming a lawyer.”).

VII. APPENDIX A

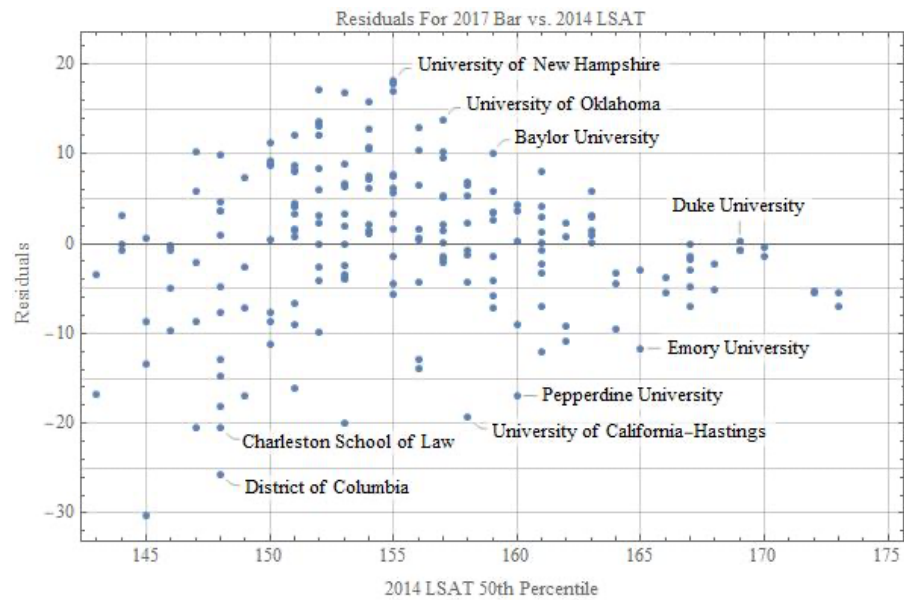
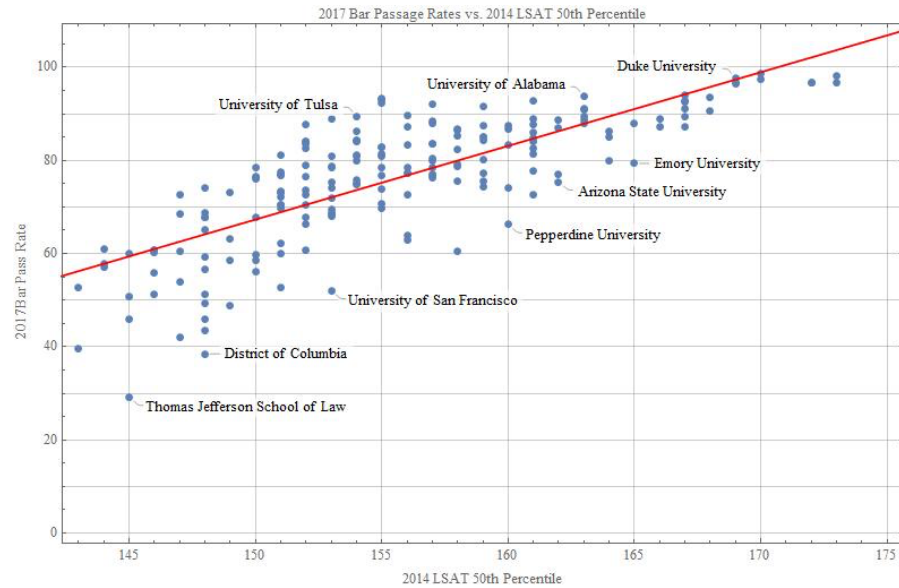
Scatterplots and residual plots for 2013 median LSAT and 2016 bar passage results



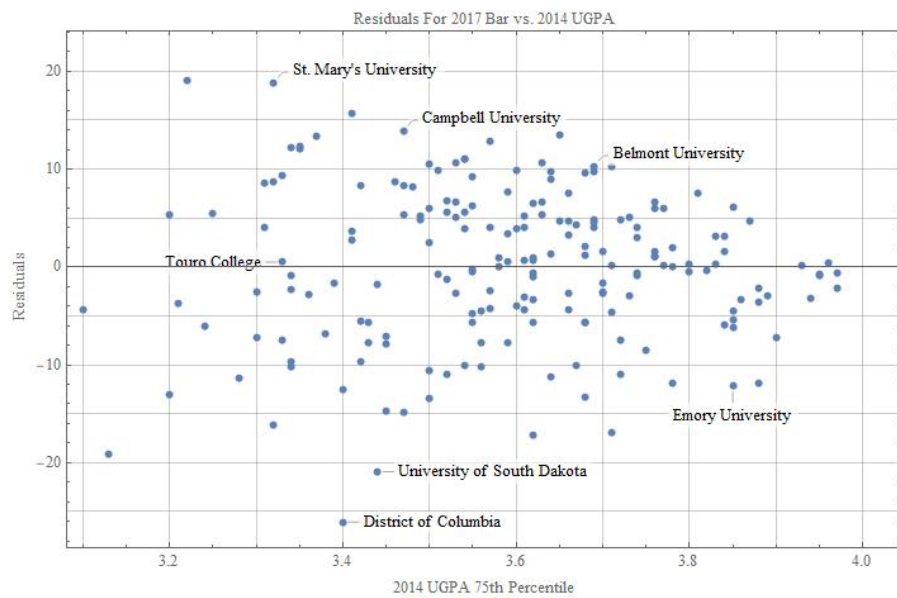
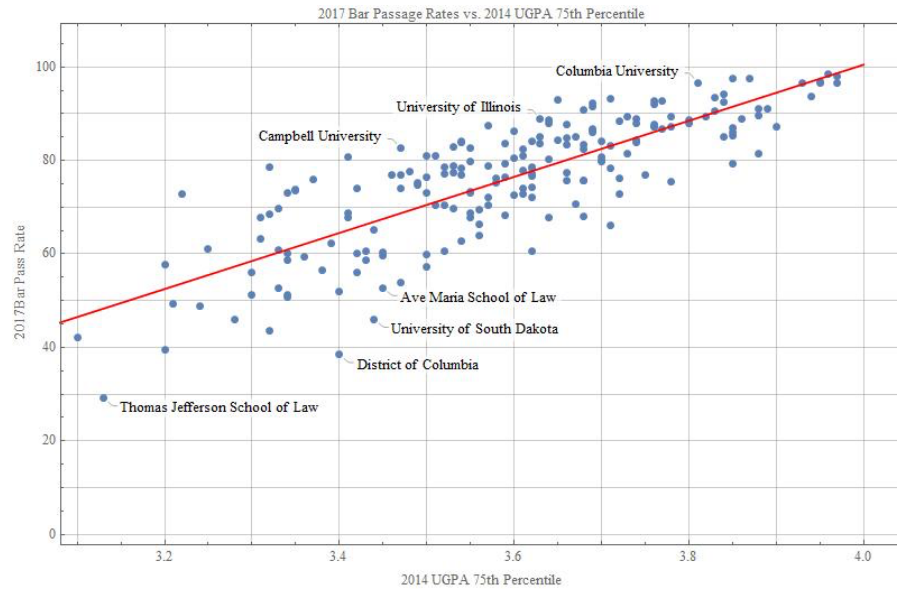
Scatterplots and residual plots for 2013 75th UGPA percentile and 2016 bar passage results



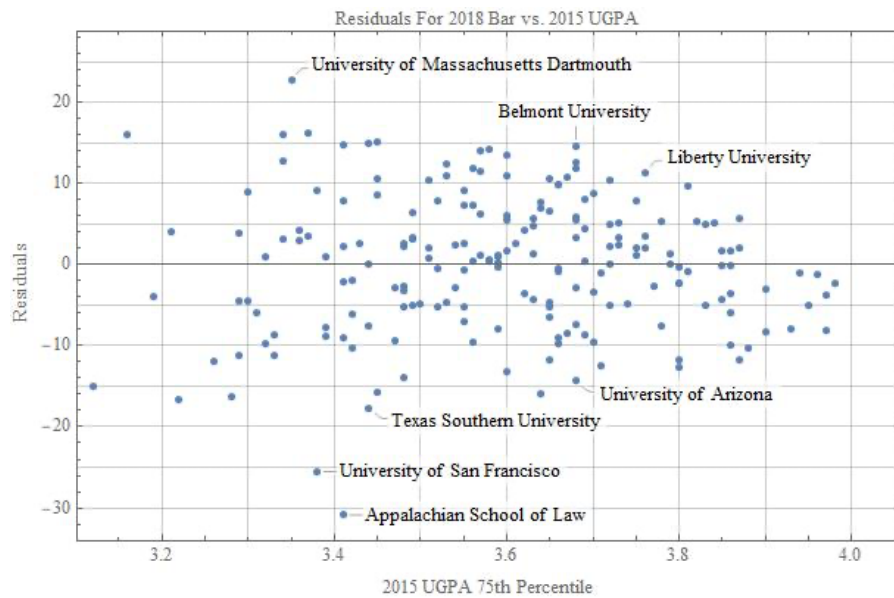
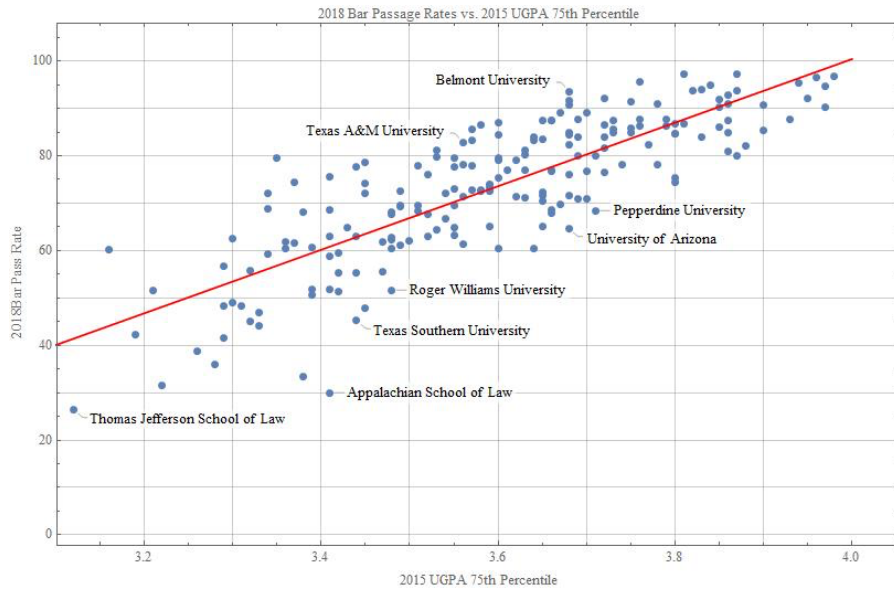
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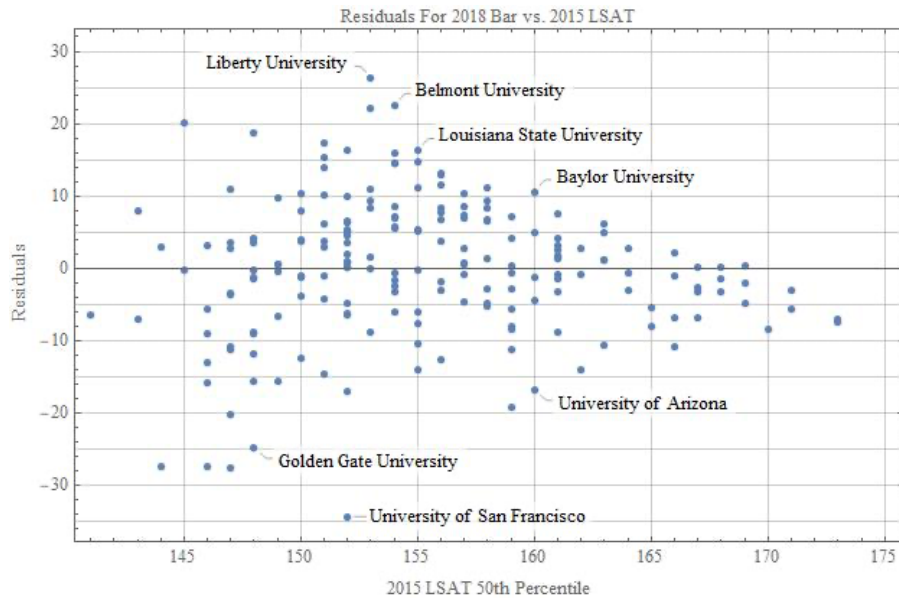
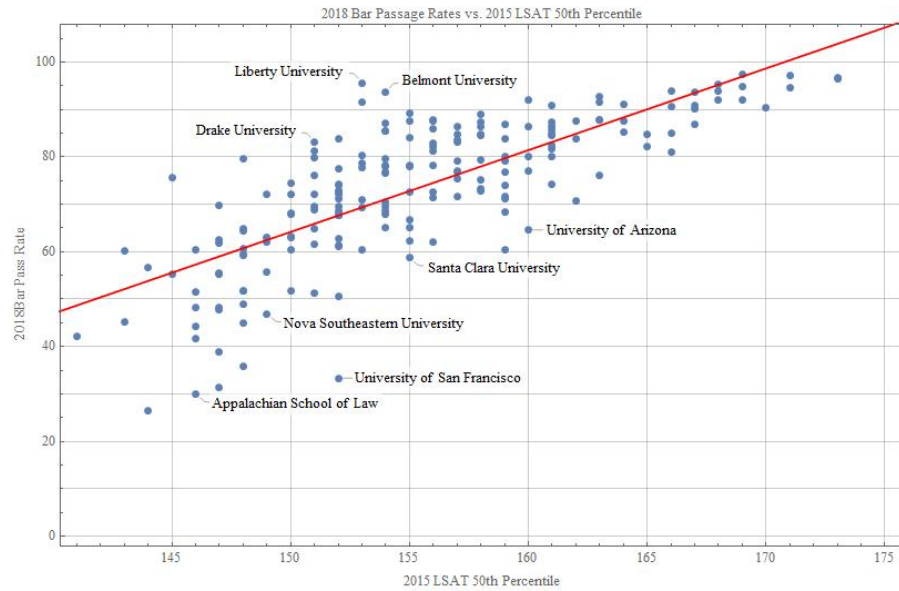
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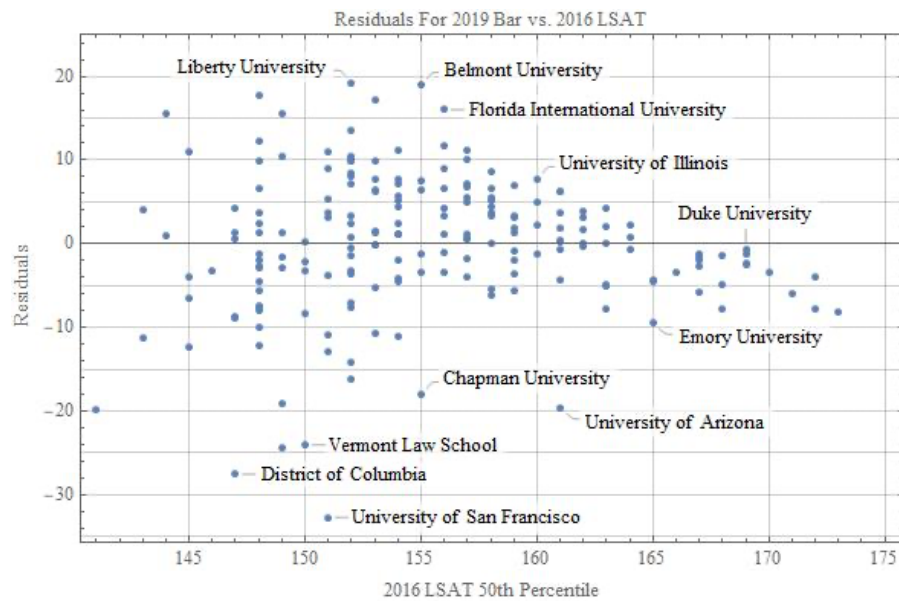
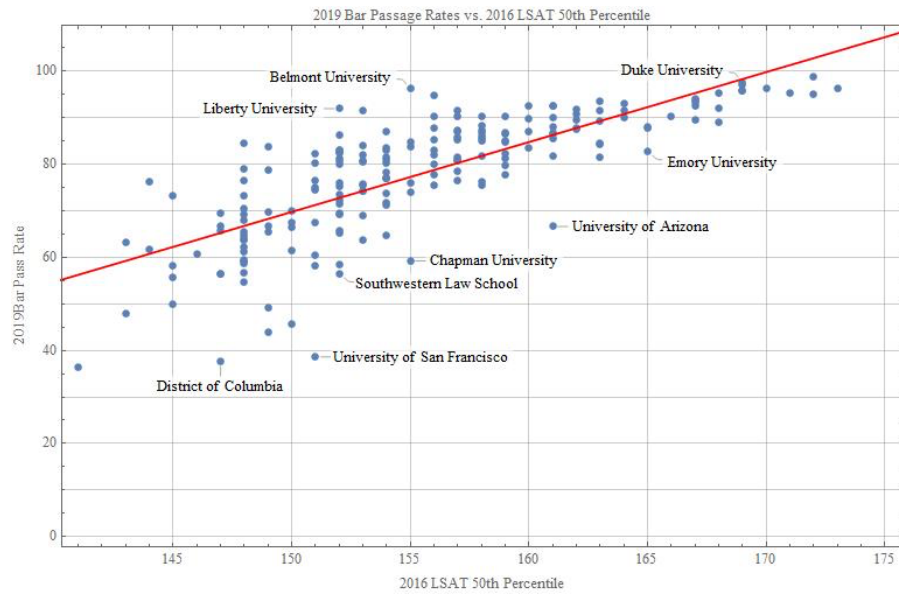
Scatterplots and residual plots for 2015 median LSAT and 2018 bar passage results



Scatterplots and residual plots for 2015 75th UGPA percentile and 2018 bar passage results



Scatterplots and residual plots for 2016 median LSAT and 2019 bar passage results



Scatterplots and residual plots for 2016 75th UGPA percentile and 2019 bar passage results

