Are Law Schools Cream-Skimming to Bolster Their Bar Exam Pass Rates?

A Multilevel Regression Approach to Estimate How Attrition and Transfer Rates Affect Bar Passage

WORKING PAPER[1]
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INTRODUCTION

What drives bar exam success? For law schools, most empirical research has focused on admission factors (Georgakopoulos, 2013), law school academic performance (Thomas, 2003), bar preparation (Klein, 1991), and environmental factors (Taylor et al., 2021). Essentially, the extant research has focused on who enters law school and what they do while they are there (and during that brief period between graduation and sitting for the bar exam). However, little research examines the institutional admission and retention policies that ultimately determine who graduates and therefore sits for the bar exam at a given school.

Using multilevel regression methods, we rigorously test the novel supposition described in a recent paper by Bahadur et al. (2021), which posits that a school's bar passage rates are affected by the rate at which schools both lose students to academic attrition (presumably those students with the lowest grades and lower likelihoods of passing the bar exam) and gain students as a result of transfer (those students with higher grades and greater likelihoods of passing the bar exam)—a process which therefore inexorably alters the composition of law school cohorts. As a result, a school's low or high pass rate—according to Bahadur et al.—is not driven by "pedagogy but rather prestidigitation. When law schools manipulate their matriculant pools via academic attrition and transfer, that sleight of hand improves their bar performance rates" (Bahadur et al., 2021, p. 2).

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[1] As a working paper, feedback is welcomed and encouraged; please email comments and questions to jscott@accesslex.org.

This open question is an important one—do law school attrition and transfer processes perhaps explain improved bar passage rates when other factors or programmatic interventions are credited with that success? Some interventions are heralded as the "silver bullet" for improving bar passage, and since schools expend considerable finite resources to help improve their students' chances of passing the bar exam, it is important to identify whether the claims of a panacea might have more to do with attrition and transfer rates than with the program itself.

Moreover, transfers have two effects: one school typically benefits from the addition of a generally higher performing student, while the other loses said student in whom it had invested substantial resources. Recognizing that first-year (1L) performance is a strong predictor of bar success (Taylor et al., 2021), transfer removes from the originating school a student who is likely to pass the bar exam and could therefore decrease that institution's bar exam performance. Further, when bar passage rates are tallied, the originating school receives no credit or recognition for its investment; on the other hand, the receiving school receives full credit without the expenditure of resources on that student's formative 1L year. Indeed, many of the doctrinal topics taught in the 1L year are tested on the bar exam.

Looking at transfers nationally, schools with lower median LSAT scores and lower *U.S. News & World Report* rankings tend to lose more students to transfer, with those students typically enrolling at institutions with higher median LSAT scores and rankings. In light of this trend, we posit whether or not these transfer rates explain differences in school bar success.

To examine how attrition and transfer rates relate to bar passage, we seek to answer the following questions:

1. On average, to what extent do attrition, transfer-in, and transfer-out rates affect institutional first-time bar passage performance? (RQ1)
2. Does transfer activity vary by institutions' geographic proximity to other law schools with higher or lower rankings? And, if so, how? (RQ2)
3. Are the effects of attrition and transfer rates on institutional first-time bar passage rates moderated by whether a law school is in close proximity to others with higher or lower rankings? (RQ3)

BACKGROUND

Predicting first-time bar passage rates, whether for students or for schools, is tricky business—the elements involved are not simple and straightforward. Instead, bar passage is driven by a complex network of factors and their interplay, including those at administrative level, within the classroom, at home, and intrinsic to test takers themselves (for example, their level of comfort with taking standardized tests, particularly those with professional and financial ramifications).

Given that bar passage is the result of a complex interweaving of factors, it is critical to recognize that any single factor undoubtedly moves in tandem with others. This makes it difficult to isolate and disentangle what is responsible for a school's changing bar passage rate; hence the need for careful consideration of control variables.[2]

Adding a layer of complexity are the high stakes associated with the bar exam, not only for students but for law schools themselves. According to the American Bar Association (ABA), bar exam performance "is likely the single best outcome measure to consider in assessing whether a law school is maintaining a 'rigorous program of legal education'" and "is one of the critical pieces of consumer information that prospective law students should consider in deciding where to study law" (American Bar Association Section of Legal Education and Admissions to the Bar, 2019, p. 1). Hence, there are strong regulatory and financial incentives tied to bar passage.

In 2019, ABA Standard 316, which sets a minimum threshold for bar passage, became more stringent. It now mandates that:

> At least 75 percent of a law school's graduates in a calendar year who sat for a bar examination must have passed a bar examination administered within two years of their date of graduation. (American Bar Association Section of Legal Education and Admissions to the Bar, 2021, p. 25).

Noncompliance results in public notice and can, ultimately, lead to loss of accreditation. Historically, the loss of ABA accreditation leads to school closure. Thus, these revisions to ABA Standard 316 increased the threat of punitive action.

Taken together—the financial incentives, accreditation standards, and the limited locus of control law schools have on standardized test performance—schools face tremendous pressure to improve their bar passage rates.

Research predicting school first-time bar passage rates is nascent. Early research on the topic tended to rely solely on school-level LSAT scores and undergraduate GPA (UGPA) to explain and predict variation in bar passage. (See for example, Ryan, 2019; Kinsler & Hudson, 2017; Kinsler & Usman, 2018; and Kinsler, 2021.) Although research has consistently demonstrated a link between student-level LSAT scores and UGPA and future bar success, Taylor et al. (2021), Georgakopoulos (2013), and Farley et al. (2018) find that the effect is modest, particularly relative to the predictive ability of law school GPA. Moreover, relying only on LSAT scores and UGPA ignores the inherent complexity of the factors driving school pass rates (Ryan et al., 2021; Ryan & Muller, 2022). Nonetheless, these early attempts lay an important foundation for research such as ours.

A 2021 paper by Professor Rory Bahadur and his colleagues presented a novel explanation for what might be driving institutional first-time bar exam performance: high attrition and transfer-in rates at some schools might explain their high bar passage rates, and concomitantly low attrition

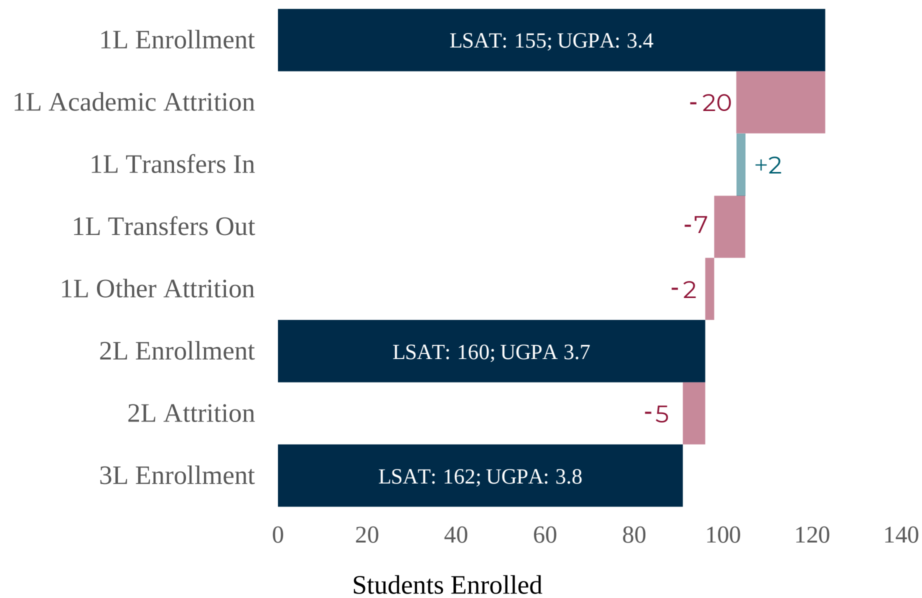
[2] Control variables are those items added to a model which are related to the outcome of interest (e.g., bar passage rate) as well as the variable(s) of interest, i.e., "explanatory variables." Failing to include these confounding factors can yield unreliable results, which may over- or understate the effect of a program, policy change, or other variable of interest.

and high transfer-out rates at others might explain their lower bar passage rates. As a result, the composition of a school's given cohort changes, as illustrated in Figure 1.

Figure 1

As a Result of Attrition (red bars) and Transfer (green bars), the Median LSAT and UGPA of a Cohort Can Change Substantially

Hypothetical Class Composition Over Three Years



According to Bahadur et al. (2021), students with the lowest grades are dismissed from the law school via academic attrition. These students happen to be those who have the lowest probability of passing the bar exam (Taylor et al., 2021); thus, these schools presumably increase their bar passage rate by dismissing their lowest performing students. While every school has a formal attrition process that involves dismissing particularly poor performers after the first year, the authors contend that rather than use attrition as a last resort, some schools are using it as a regular tool to improve their overall rate, unnecessarily dismissing large numbers of poor 1L-performers.

This is a novel explanation of attrition in both legal and higher education scholarship. Traditionally, research on attrition has focused on examining its causes, including academic performance (e.g., Spady, 1970), intellectual development (Tinto, 1975), integration with peers and the institution (Spady, 1970; Tinto, 1975), and external finances and support systems (Bean & Metzner, 1985). Far from considering attrition as the culmination of forces driving poor academic performance, Bahadur et al. (2021) posit that it is partly driven by (at least some) schools' calculation that their ranking or accreditation will be improved by increasing the number of students they dismiss for academic performance. But this fails to account for the fact that some institutions take chances on students that might not have stellar resumes. As such, these institutions might be expected to attrit more students as ABA Standard 501 requires that schools admit only students that "appear capable of satisfactorily completing its program of legal education and being admitted to the bar." It is reasonable to assume that schools, particularly mission-driven institutions, admit some students with lower LSAT scores or UGPAs, giving them a chance to succeed in law school rather than denying them the possibility outright.

The second arm of Bahadur et al.'s supposition it that many schools with higher rankings on the *U.S. News & World Report's Best Law Schools* list replace those attrited students with transfer students who exceled in their first year at institutions with lower rankings. These transfers, given their high level of academic performance in their first year, are more likely to pass the bar exam (Taylor et al., 2021).

But student transfers have two effects: on one hand, they benefit the school to which the higher-performing student transfers; on the other, they diminish the pool of high performing students at the originating institution that invested substantial resources in the transfer student's first year. And in the end, when bar passage rates are tallied, the original school, which invested those resources early on, is not credited with the student's (likely) bar passage. In theory then, it seems that higher-ranked schools might be advantaged at the expense of lower-ranked schools that have fewer endowments and resources.

It is important to consider, however, that students have agency in the decision to transfer, and ultimately make their determinations for myriad reasons, some unrelated to academics. Most germane of these is that students seek transfer to higher-ranked schools to bolster their prospects of obtaining competitive clerkship, internship, and employment opportunities, as well as other postgraduate outcomes. Postgraduate employment opportunities are often tied to the national or local prestige of the law school, which is generally greater for higher-ranked institutions, and have substantial earnings implications for students.

Hence, just as schools act in their best interest, so too do students. Therefore, although transfer-in rates at higher-ranked schools may appear greater than other schools, this is likely due to student and market preferences rather than strategic or underhanded transfer admission practices at these institutions.

These two factors—dismissing many poor performers and transferring in the best students from lower-ranked schools—may, according to Bahadur et al., mean that some schools are receiving or taking credit for outstanding bar passage outcomes that exceed jurisdictional averages, and erroneously attributing this to exceptional academic and bar success programming (e.g., they figured out the "secret sauce"). (For example, see Kinsler & Hudson, 2017; Ruiz, 2020; and Ryan & Muller, 2022.)

To support their theory, Bahadur et al. (2021) provide several graphs that compare the attrition and transfer rates (combined as the sum of a school's attrition and transfer-in rates) at each of the top-15 schools (as rated by Kinsler & Usman, 2018) to an average of similar[3] schools. The figures presented indicate disparities between these top-15 schools and their peer institutions, but they do not indicate whether these differences are related to bar passage. In fact, in examining

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[3] The comparison group of schools comprised schools with "either median LSAT scores within… two, or 75th-percentile UGPAs within… 0.1 of the entering credentials" (Bahadur et al., 2021, p. 36).

the information reported by Bahadur et al., we find that, in more cases than not, when a school's combined attrition and transfer-in rates increase, its first-time bar passage rate decreases or remains unchanged, which is contrary to the theory.

METHODS

Data

We use data disclosed and publicly available in accordance with ABA Standard 509. These data are self-reported annually to the ABA by accredited institutions, with publicly available data going back to 2011. They capture myriad student and institutional characteristics. Our sample includes all ABA-accredited law schools (as of February 2021), except for those schools located in Puerto Rico, as its bar exam contains an English proficiency component, which renders it sufficiently dissimilar to the remaining jurisdictions.

In addition, we dropped Marquette University School of Law and the University of Wisconsin Law School because their graduates are granted diploma privilege in Wisconsin; that is, their graduates are admitted to the Wisconsin bar without taking the bar exam. These schools, therefore, have bar passage rates of 100 percent and are not of interest when investigating outcomes related to bar passage.

We use data for student cohorts entering law school between 2013 through 2016 and assume the typical three years to graduation. Thus, in our sample, students would have graduated and taken the bar exam between 2016 and 2019.[4]

Our primary outcome variable[5] is the first-time bar exam passage differential of each law school (hereafter "pass differential"), which is calculated by differencing:

- a school's average first-time pass rate across all jurisdictions in which its students took the bar exam for the first time, weighted according to the proportion of its students who sat for the exam in each jurisdiction; and
- an average of the jurisdictional first-time pass rates of these jurisdictions, applying the same weights as above. (See Figure A.1 for an illustration.)

This preference to use pass differential over pass rate is due in large part to the fact that each jurisdiction sets its own cut score, the minimum exam score needed to pass the bar, which has led to variation in what score constitutes minimum competence throughout the country. For example, California's high cut score makes it one of the most difficult jurisdictions in the country, which has produced some controversy (Hunter, 2020). To account for this, rather than use first-time bar passage rate, we use pass differential, as described above.

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[4] We elected to not include the 2017 entering cohort because of the COVID-19-related postponements and other changes those graduates would have encountered when taking the bar exam in 2020. Our earlier research suggests that as a result of these changes, the group of graduates taking the bar exam in 2020 was systematically different than those in previous administrations.

[5] Bar pass differential is our main outcome variable of interest, but RQ2 uses the counts of transfers in and transfers out (separately) as outcome variables.

Our primary variables of interest are law schools' attrition, transfer-out, and transfer-in rates. If Bahadur et al.'s theory is correct, we would expect to see pass differentials increase with higher attrition and transfer-in rates.

When calculating transfer rates, we remove from each school those students that entered as a result of a school closing (for example, Indiana Tech Law School and Arizona Summit Law School, which closed in 2017 and 2018, respectively). Thus, the transfer figures we use should reflect typical annual transfers between schools.

To address RQ2, we use the counts of transfers in and transfers out as the outcome variables in two separate models. We then examine whether *transfer markets*—geographic areas of high transfer activity between law schools—predict higher transfer activity, even when including controls which account for other factors associated with attrition and transfers. This research question allows us to determine if simply being near several high-ranked schools has an effect on transfer activity, independent of other factors associated with transfers in and out.

For RQ3, we explore whether proximity to other law schools moderates the effects of attrition and transfer rates on pass differential. Specifically, we investigate the extent to which schools might be clustered regionally in such a way that they gain or lose students to nearby schools. For example, a middle-ranked law school in a sparsely populated area like North Dakota will have few law schools nearby, so high performers looking to transfer to a higher-ranked school after their first year may be less likely to transfer simply because of the geographic distance. On the other hand, a school in the Northeast region is more likely to be within close proximity to another law school, particularly one with a higher ranking, and therefore appeal to high-performing students. Hence, this would make transferring more practical in terms of logistics and geographic preference.

For RQ1 and RQ3, accounting for schools' median LSAT scores and UGPAs is important given those variables' relationships with bar passage. Failing to account for these variables would produce results that are unreliable and biased if they also happen to be correlated with the explanatory variables (e.g., transfer or attrition rates). Moreover, to capture a wider range of these variables, we create an index that combines a school's 25^{th}, 50^{th}, and 75^{th} percentile LSAT scores and UGPAs. This is constructed by converting the 25^{th}, 50^{th}, and 75^{th} percentile LSAT scores and UGPA into a proportion (total points out of a possible 180 for LSAT score and 4.0 for UGPA). We then regressed our outcome by these combined variables. We compared the relative size of the coefficients, using the relative size to weight the variables before adding them and scaling the weighted sum to range between 0 and 1. The result is a more comprehensive measure of a school's entering students (our approach is an adapted version of that developed by Ryan and Muller [2022]). We also consider a wide range of additional control variables, as described in Table A.3.

Models

We employ two similar approaches in order to investigate RQ1 and RQ3, both of which use pass differential as the outcome of interest. (See Table A.2.) RQ2, on the other hand, uses transfer-in and transfer-out rates as the outcomes.

RQ1

To explore the extent to which attrition and transfer rates affect pass differential, we employ a fixed effects approach, such that generally:

$$y_{ij} - \bar{y}_j = \beta\left(x_{ij} - \bar{x}_j\right) + \alpha_i + \left(\varepsilon_{ij} - \bar{\varepsilon}_j\right)$$

where:

$y_{ij} - \bar{y}_j$ is the difference between a given school's weighted average first-time pass differential (across all years of the analysis) and its first-time pass differential in year *i*;
β is a series of coefficients for each explanatory variable (x), which are attrition, transfer-in, and transfer-out rates;
$\left(x_{ij} - \bar{x}_j\right)$ is the difference between a given school's average value for a particular explanatory variable across all years of the analysis and its value in year *i*;
α is a cohort fixed effect; and
ε_{ij} is the difference between the error terms.

Through this approach, we compare how changes in each school's attrition, transfer-in, and transfer-out rates relate to its respective changes in pass differential over the period 2013 to 2016. In essence, holding all else constant, we are testing whether a particular law school's bar pass rate increases concomitantly with years in which it attrited more students than average. We then do this for each school individually.

These individual results are averaged across the 189 schools to arrive at the estimated average effect attrition and transfer rates each have on pass differential. This approach allows us to control for those factors that do not change (or change very little) over time at law schools. For example, the school's geographic location, the size of its student body, and the cost of attendance. It cannot, however, given the data we use, account for programmatic changes that occur at these schools. For example, if a school implements a new academic support program during the study period. If this were to happen *and* the school were to also significantly increase or decrease its attrition or transfer rates, then size of the effect might be either exaggerated or diminished. However, because the estimates are the result of averaging across 189 schools, the likelihood is low that the bias would be sizable and practically important.

For RQ1, our preferred model is a panel linear model which examines how attrition and transfers affect first-time pass differential, holding constant several additional time-varying control variables. This method allows us to compare each school to itself and account for changes in the school's enrollment, section size, and other factors. Since we are comparing schools to themselves, we are therefore able to account for peculiarities that exist across the various jurisdictions. We also interact attrition rate and transfer rate, a decision predicated on Bahadur et al.'s supposition that these variables will co-vary. Indeed, we do find that the model better fits the data when this interaction is included.[6]

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[6] The models we present were chosen according to model fit using Bayesian information criterion (BIC) and Akaike information criterion (AIC) values, as well as theoretical considerations by the researchers. The preferred model is the one which 1) aligns most with the predictors that are theoretically justified, and 2) produces the smallest errors with the fewest variables such that the model is not overfitted.

RQ2
Our second set of models examines whether geographic proximity to law schools with a higher (or lower) rank influences transfer activity. It is plausible that, aside from all other factors that may impact transfer activity, simply being located near a higher-ranking law school makes a given school more likely to lose students to that higher-ranked school, since the transfer would presumably involve less of a logistical challenge for the student. Put simply: if a student attends law school in Chicago, it is easier for that student to move to another location in Chicago than it would be to move to California—especially if transferring to another Chicago law school does not necessitate the student change their living location at all.

The models for RQ2 use the counts of transfers in and transfers out, separately, as dependent variables. For models of both transfers in and transfers out, we determine the effect that our set of independent and control variables have on each, where our primary independent variables of interest are proximity to law schools of different ranks.

RQ3
Our third set of models are an adaptation of fixed effects, which separate the effect of a particular variable into two components (a within-school estimate and a between-school estimate), as such:

$$y_{ij} - \bar{y}_j = \mu + \beta\left(x_{ij} - \bar{x}_j\right) + \gamma_j + \alpha_i + \varepsilon_{ij}$$

where:

$y_{ij} - \bar{y}_j$ is the difference between a given school's average first-time pass differential and its first-time pass differential in year *i*;
β is a series of coefficients for each explanatory variable (x), which are attrition, transfer-in, and transfer-out rates;
$\left(x_{ij} - \bar{x}_j\right)$ is the difference between a given school's average value across the years of analysis for a particular explanatory variable and its value in year *i*;
α_i is a cohort fixed effect;
γ denotes a random effect parameter—a random intercept assigned to each school *j*; and
ε_{ij} is the error term.

This is commonly referred to as a between-within model and allows us to explore the extent to which a school's presence in a competitive transfer market moderates the effects of attrition and transfer rates (Allison, 2009).

The resulting within-school estimate is similar to that obtained in the first model; it compares changes in a school's attrition and transfer rates to changes in its first-time pass differential. The between-school estimate is an estimate of how differences in each school's average attrition and transfer rates relate to differences in its first-time pass differential.[7] In practical terms, this means we separate our explanatory variables into (1) an average for each school (between-school

[7] These between-school estimates should not be interpretated in isolation. We do not include any control variables for what other differences might exist between these schools, so these values are likely biased. This is not a problem for our analysis, which focuses on the within-school variance. The presence of the between-school estimates are what enable us to examine the effect of presence in transfer market—and are treated as such here and throughout.

component), across the years in our sample and (2) the difference between the school's average and its attrition or transfer rate in a given year (within-school component). (See Table A.2.)

FINDINGS

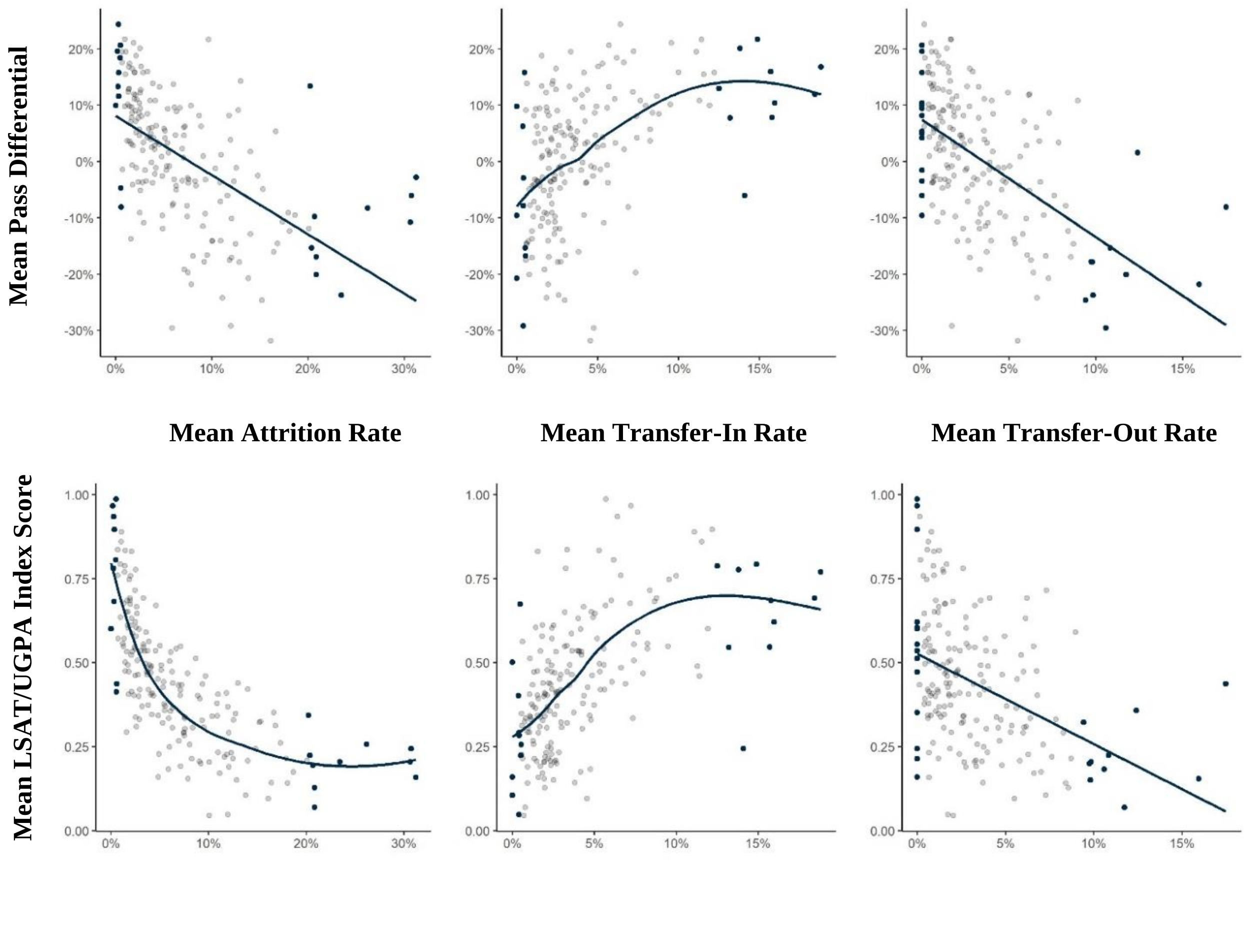
The initial phase of investigating Bahadur et al.'s claim is to examine whether relationships exist between a school's attrition and transfer rates and both its pass differential and LSAT/UGPA index score.

At first glance, there does appear to be a relationship between a school's first-time pass differential and its rates of attrition and transfer (see Figure 1). Furthermore, there is evidence of a relationship (albeit curvilinear for transfer-in rates) between a school's median LSAT/UGPA index score and both its attrition and transfer rates.

Figure 2

Attrition and Transfer-Out Rates Are Negatively Associated with Pass Differential and LSAT/UGPA Index Score; Positively for Transfer-In Rates

(Entering Cohort 2013–2016)



Moreover, the number of students attriting and transferring is not inconsequential. On average, from 2011 to 2020 the number of 1L law students attriting and transferring was approximately 33,000 (8.4 percent of total JD enrollment for the period) and 18,000 (4.9 percent), respectively. This suggests that although a minority, these students represent a significant proportion of the total law school student population. Furthermore, lower-ranked schools lose more students than they gain via transfer and, conversely, higher-ranked schools bring in more students than they lose. (See "Transfer Markets" below for a larger discussion of student transfers.)

Thus, it seems that attrition and transfer rates might be confounding variables in Kinsler (2021) and Kinsler and Usman's (2018) models and therefore that Bahadur et al.'s hypothesis deserves further investigation.

Attrition and Transfer Rates

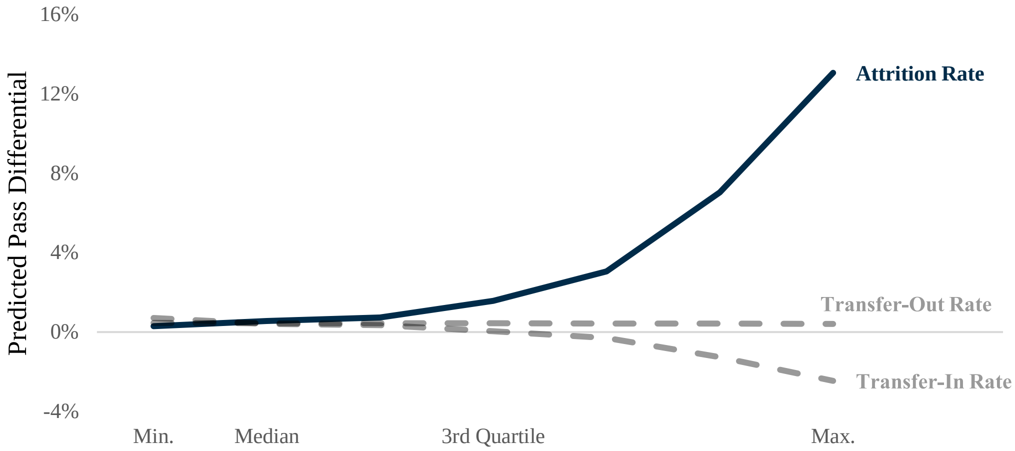
Changes to a school's attrition and transfer rates do not appear to have practically meaningful effects on its pass differential. For attrition, a school that increases its academic attrition from the minimum (0 percent) to the maximum (48 percent) would be expected to increase its pass differential by 13.1 percentage points. Although this is a statistically significant finding ($p < 0.05$), it requires an unrealistic increase in attrition in order to realize the large gain in pass differential. A more plausible yet still substantial increase from 7 to 14 percent attrition is predicted to increase pass differential by only 0.6 percentage points.

The relationship between changes to a school's transfer-in rates and its pass differential is negative, albeit considerably weaker than that for attrition. Increasing a school's transfer-in rate from the minimum (0 percent) to the maximum (24 percent), is expected to yield a 3.2 percentage point decrease in pass differential. Like with attrition, realizing this pass differential gain would require an improbably large increase in transfer-in rate. A more plausible increase from 5 percent to 10 percent is predicted to decrease pass differential by only 0.3 percentage points.

There does not appear to be a relationship between changes in a school's transfer-out rates and its pass differential. A change in a school's transfer-out rate from the minimum (0 percent) to the maximum (32 percent) would be predicted to decrease pass differential by less than 0.1 percentage points.

Figure 3

A School's Pass Differential is Affected Only with Large Swings in Attrition and at the Middle-to-Top of the Distribution; it is Largely Unaffected by Changes to its Transfer-In, or Transfer-Out Rates



Despite the small effects of attrition and transfer-in rates on pass differential, we posit that if Bahadur et al.'s supposition were to be true, perhaps attrition rates might moderate transfer-in rates—and vice versa. We, therefore, explore this possibility by interacting attrition and transfer-in rates. We find that adding this interaction to the model improves model fit, to a small degree.

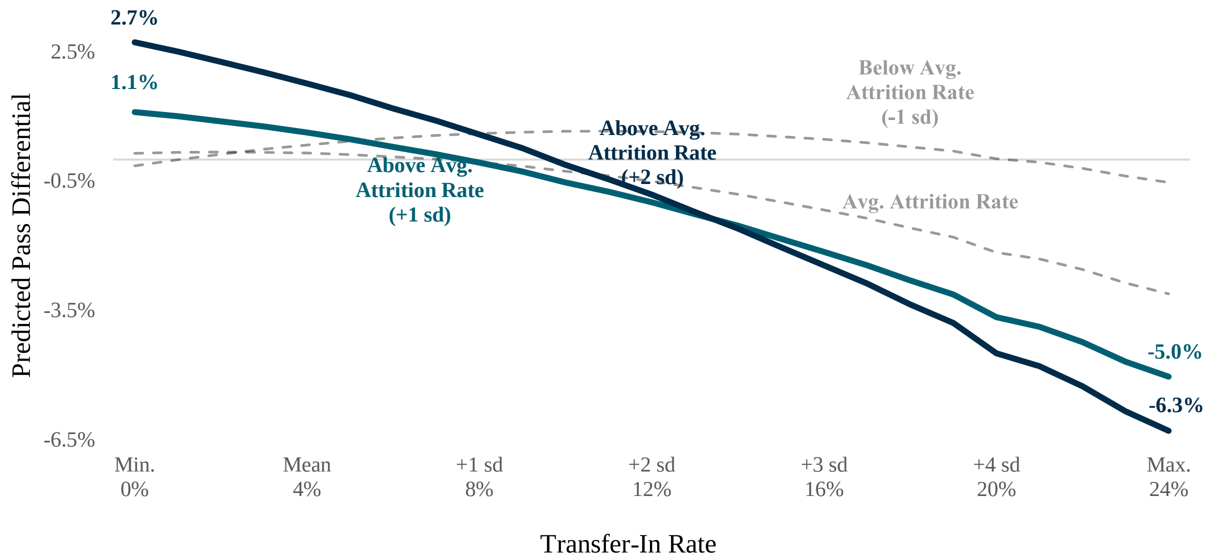
Potential Moderating Effects of Transfer-In and Attrition

There does appear to be some evidence that attrition may moderate the effect of changes to a school's transfer-in rate on pass differential. That is, the effect of transfer-in rates on pass differential varies by a school's attrition rate.

For schools with average or above average attrition, an increase in transfer-in rates is negatively associated with pass differential, with the effect being largest for those schools with above average attrition rates. For a school with an attrition rate of 14 percent (1 standard deviation above the mean), we would expect that an increase in transfer-in rates from the minimum (0 percent) to the maximum (24 percent) would yield a 6 percentage point decrease in pass differential; for a school with an attrition rate of 21 percent (2 standard deviations above the mean), we would expect a decrease of 9 percentage points. We, therefore, consider this moderating effect surprising, but fairly inconsequential.

Figure 4

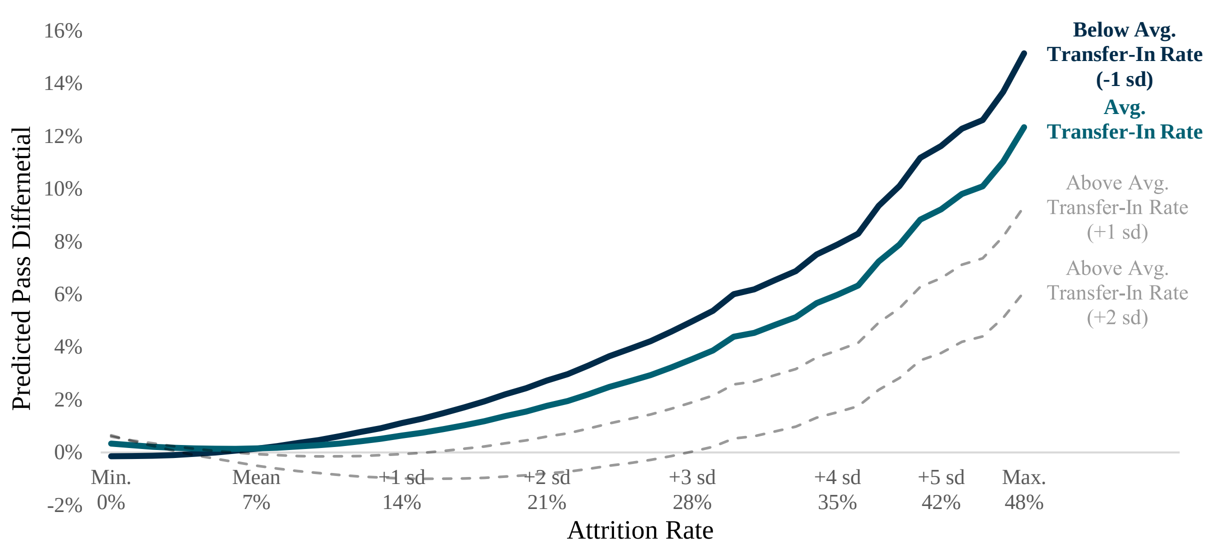
Transfer-In Rates More Negatively Affect Pass Differential for Schools with Above Average Attrition Rates



Transfer-in rates do not appear to meaningfully moderate the effect of changes to a school's attrition rate and its pass differential. As shown in Figure 5, the shape of the curves is fairly similar regardless of the level of a school's transfer-in rate. Nonetheless, there are some differences, most notably that the effect of attrition on pass differential is larger for schools with average or below average transfer-in rates.

Figure 5

Attrition Rates More Positively Affect Pass Differential for Schools with Average and Below Average Transfer-In Rates



To better illustrate these effects, Figure 6 compares five schools with varying levels of attrition and transfer-in rates. The accompanying dotted line notes the predicted pass differential for each school. Note that the confidence intervals beyond 21 percent attrition and 12 percent transfer-in are considerable and are presented here for illustrative purposes only. For this reason, they are presented separately from those figures above for which we have more narrow confidence intervals.

School A with average attrition (7 percent) and below average transfer-in rates (0 percent, or one standard deviation below the mean) would be expected to have a pass differential of 0 percent.

School B with average attrition (7 percent) and average transfer-in rates (4 percent) also has a predicted pass differential of 0 percent.

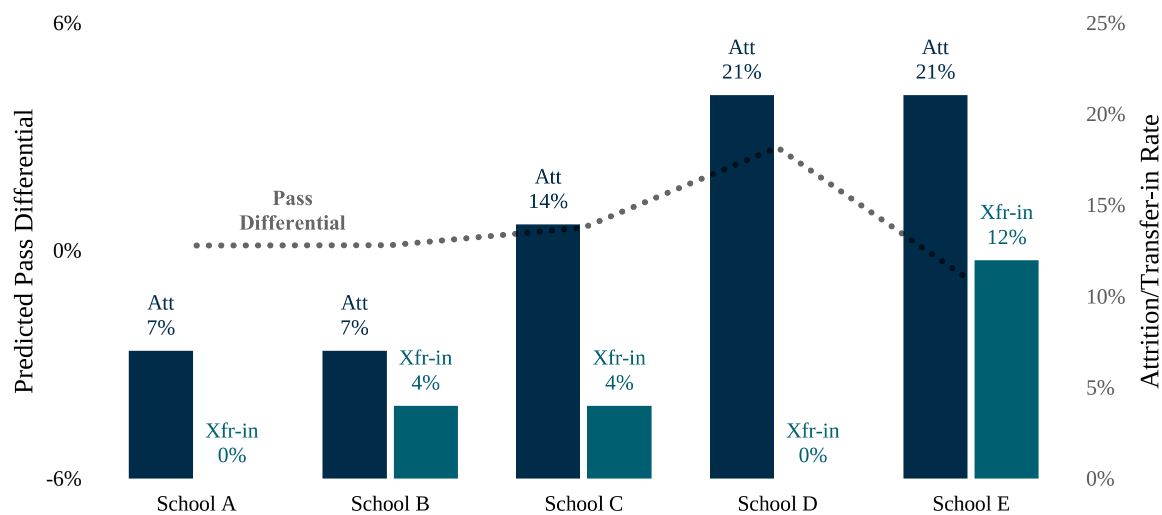
School C with above average attrition (14 percent, or one standard deviation above the mean) and average transfer-in rates (4 percent) sees a slight increase in predicted pass differential at 1 percent.

School D with above average attrition (21 percent, or two standard deviations above the mean) and below average transfer-in rates (0 percent; one standard deviation below the mean) has a predicted pass differential of 3 percent.

School E with the same above-average attrition rates as school D but correspondingly high transfer-in rates (12 percent; two standard deviations above the mean) sees a drop in predicted pass differential at -1 percent.

Figure 6

Attrition is Generally Associated with a Higher Pass Differential; Especially When Transfer-In Rate is Low



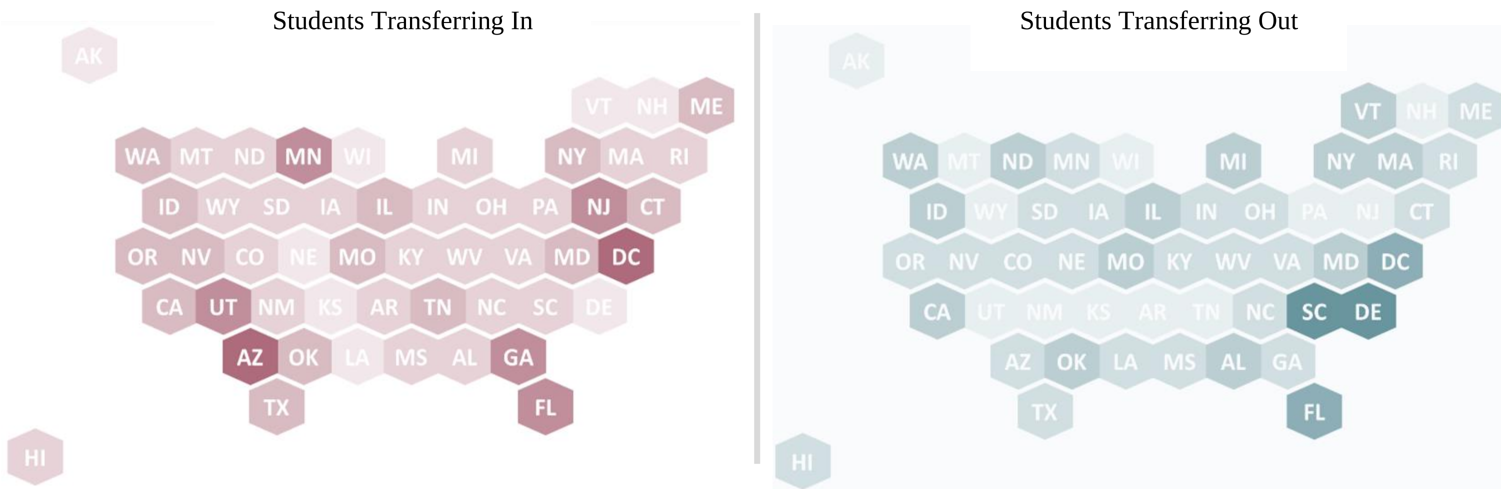
Transfer Markets

At a national level, those schools with lower median LSATs and lower *U.S. News* rankings tend to lose more students to transfer, with those students typically enrolling at institutions with higher median LSAT scores and rankings. Conversely, those schools with the highest median LSAT scores almost exclusively have the lowest (or in many cases, zero) transfer-out rates.

Moreover, transfer rates do appear to some extent to be related to the geographic location of a law school. Most notable is the geographic clustering of students transferring into schools in Washington, D.C., and the Georgia-Florida region of the southeast. Also, Arizona sees some of the highest transfer-in rates of any jurisdiction in the country. Transfers out also cluster in the Mid-Atlantic and southeast regions, with Florida, South Carolina, Delaware, and the District of Columbia seeing the highest transfer-out rates.

Figure 7

Transfer Activity Tends to Cluster in Some Geographical Regions Creating Possible "Transfer Markets"



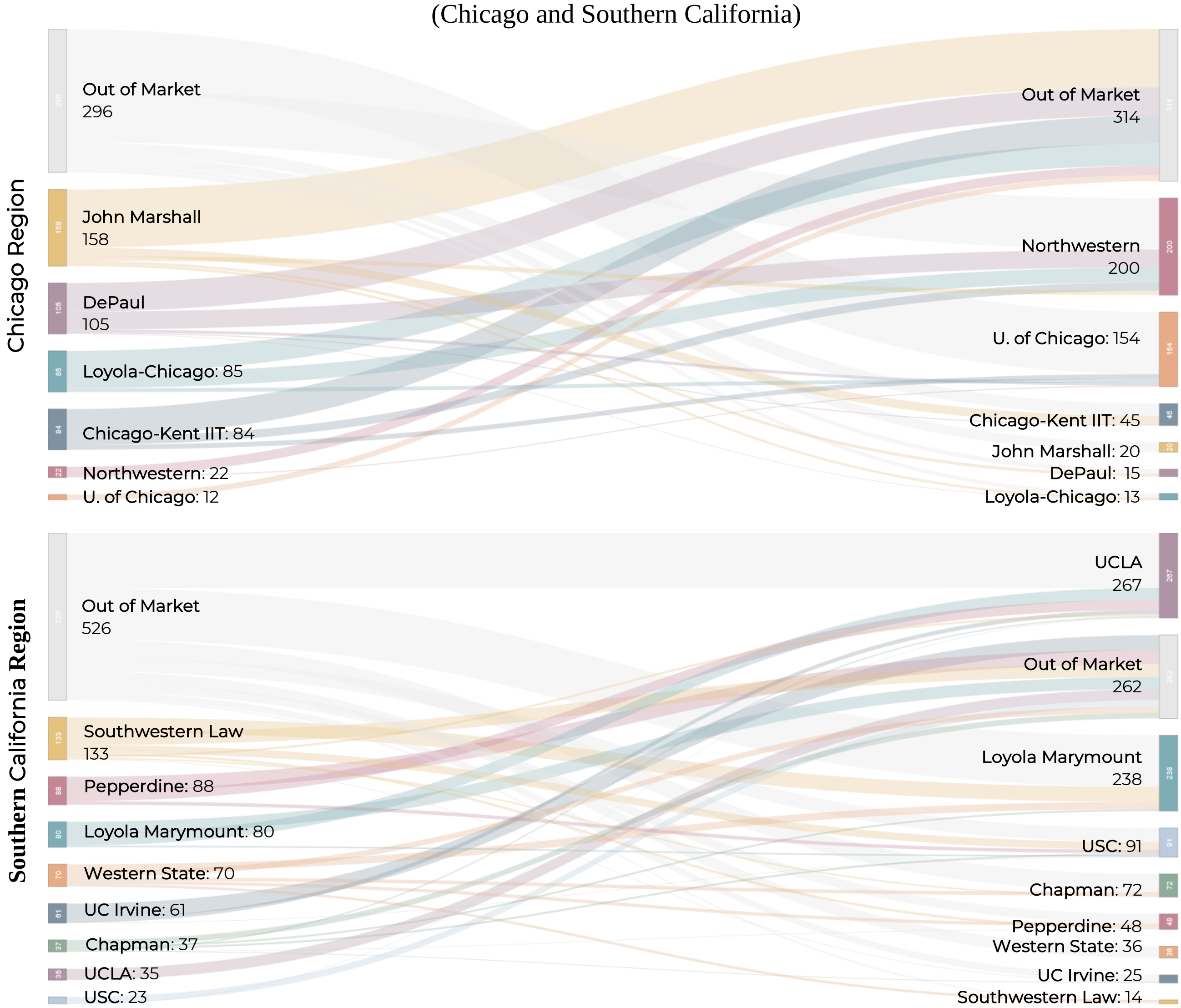
We have developed an interactive map of each law school's transfers. This tool details, for each school, to where and whence its students transfer. It is available on our webpage: https://accesslex.shinyapps.io/law_student_transfer_pathways/.

At a more granular level, examining some of these hotspots, it appears that many transfers occur in-region. For example, a majority of transfers in Chicago transfer to other Chicago schools; Northwestern Law, a nationally renowned law school, sees nearly half of its transfer students coming from other Chicago schools. The regions where this pattern appears to be most notable are: Chicago, the District of Columbia, Florida, New England, Southern California, and Texas. (See Table A.5 for a list of schools included in these regions.) Figure 8 illustrates, for each school in the Chicago and Southern California regions, the origins and destinations of student transfer. Typically, students stay within the region and transfer to a school with a higher ranking. For schools such as the University of Chicago, which are close to many other schools but not near one with a higher ranking, students transferring out tend to move to different jurisdictions altogether to enter a higher-ranked J.D. program.

Figure 8

Within Some Regions, Many Transfer Students Stay Within-Region, Transferring to Higher-Ranked Schools

(Chicago and Southern California)



Transfer Index Effects on Transfer Rates

We utilize a transfer index variable to examine the extent to which transfer rates are themselves affected by whether the school is located in proximity to other law schools. We created this index by grouping schools into 22 regions using each school's geographic coordinates. Employing a 100km radius around each school, we identify schools with overlapping circles to be part of the same region. We also made minor adjustments after the fact when necessary[8], and some schools do not fall into a geographic market with any other schools.

Within each of these regions, we assigned each school its *U.S. News* ranking for a given year and calculated the difference between the total number of schools and the number of schools with a lower ranking in a given year. Schools that were not assigned to a region were assigned the average index value for the given year (because this variable was standardized within each year with mean 0 and standard deviation 1, the value is 0). As a result, a larger index number means that a school is more likely to transfer-in students and less likely to transfer-out students.

We find that the higher the transfer index value, the more likely a school is to transfer-in students and less likely to transfer-out students, holding each school's LSAT-UGPA index constant. A one-point increase in transfer index is associated with a 92 percent increase in a school's transfer-in rate and a 32 percent decrease in transfer-out rate.

Thus, overall location in close proximity to other schools appears to favor higher-ranked schools by increasing the number of students transferring into the institution while decreasing the number transferring out.

Transfer Market Moderation

With our between-within modeling approach, we are able to explore how the effect of being in one of the most active transfer markets moderates the effects of changes in transfer-in and attrition rates on pass differential. For these models, we include the transfer index variable. We find that the effects of a school's average attrition and transfer-in rates on pass differential are not moderated by the school's transfer index; the size and direction of the effect is the same regardless of whether a school is located in close proximity to others with higher, similar, or lower rankings.

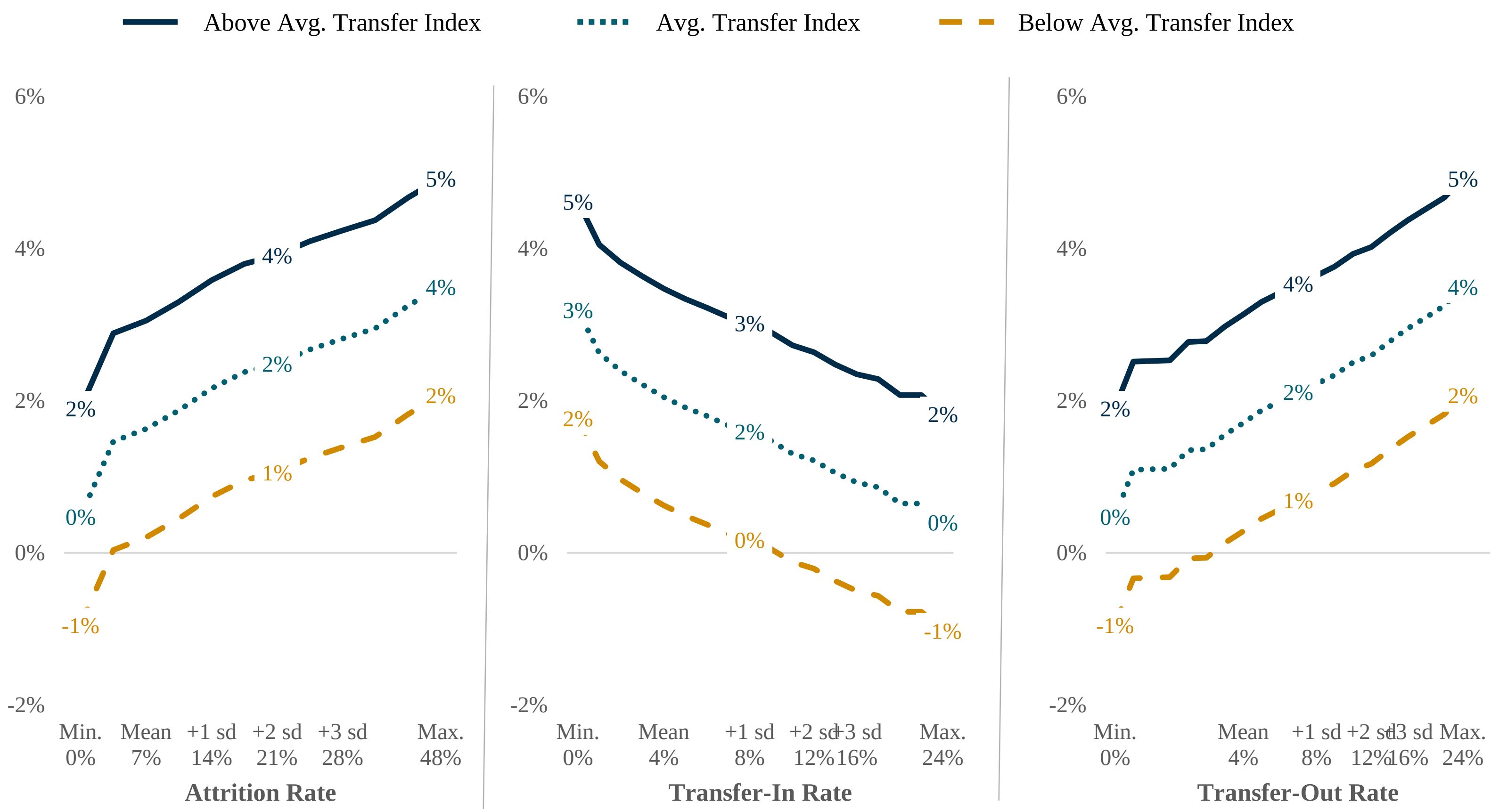
As seen in Figure 9, the slope of the lines for attrition (left figure), transfer-in (center figure), and transfer-out (right figure) rates do not vary by a school's transfer index, which is displayed at three levels: one standard deviation below the mean (dark blue line), the mean (teal line), and one standard deviation above the mean (orange line). If a moderating effect were to be present, the slopes of the lines would differ across the various levels of transfer index.

The difference in the lines is due to the different starting points for schools at the various transfer index levels—recall that higher transfer index values mean that the school has a higher *U.S. News* ranking relative to the schools within a 100km radius. On average, high-transfer-index schools have higher pass differentials, so they intercept the y-axis at a higher point. This does not, however, mean that the effect of attrition or transfer rates is any different than it is for schools with lower transfer index values.

[8] For example, a school could be moved to a different cluster if it was in close proximity (yet just outside of the 100km radium) and it tended to either receive or lose transfer students from/to the nearby cluster.

Figure 9

A School's Transfer Index Does Not Affect the Relationships Between Changes in its Attrition, Transfer-In, and Transfer-Out Rates and its Pass Differential



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DISCUSSION

Among the vast majority of schools (those with attrition and transfer rates less than two standard deviations above the mean), variation in a school's rates of attrition and transfer does not appear to meaningfully affect pass differential. Schools typically experience variation in all three rates from year to year, especially schools with relatively small cohorts in which changes of only a few students attriting or transferring can produce a noticeable shift in attrition and transfer rates. However, the limited influence of attrition and transfer on institutional bar exam performance does not negate the notion that the loss of students from one school and the gain of those students by another does no harm or provides no benefit; rather, it suggests that transfers and dismissals do not appear to substantively affect a school's bar exam performance when attrition and transfer-in rates are less than two standard deviations above the mean.

That said, the interaction effect between attrition and transfer-in rates suggests that that decisions regarding transfer-in policies may influence attrition policies, or vice versa—we cannot disentangle the direction of the moderation. For example, a school might transfer-in more students to compensate for attriting more students. Or it might attrite more students so that it can have more open seats for transfer-in students. Therefore, the existence of this interaction might provide early circumstantial evidence to support Bahadur et al.'s hypothesis.

However, although this moderating effect exists, on average, it appears to run contrary to the theory posited by Bahadur et al.: the pass differential for schools with high attrition rates decreases as the transfer-in rate increases (according to Bahadur et al.'s theory, the pass differential should increase) and the effect of higher attrition for schools with above average transfer-in rates is negligible (whereas, Bahadur et al.'s theory predicts that this combination would yield an appreciable increase in pass differential).

With respect to transfer index, we find that a school's proximity to others and its relative ranking among this group of regional peers influences the number of students transferring both in and out. This relationship does not, however, appear to moderate or alter the effect of changes in a school's attrition, transfer-in, or transfer-out rates on its pass differential. This finding appears to be contrary to Bahadur et al.'s hypothesis. We would expect, given Bahadur et al.'s hypothesis, that schools with above average transfer index values would benefit more by higher attrition and transfer-in rates.

We also looked descriptively at those schools with above average (1) attrition rates, (2) transfer-in rates, and (3) transfer index values. Only two schools met these criteria: Florida International University (FIU) and Seton Hall University. Both of these schools are mentioned prominently in Kinsler and Usman (2018) and Bahadur et al. (2021). Kinsler (2021) ranks FIU second overall and Seton Hall University thirteenth. Due to their rankings in Kinsler (2021), much attention is given to these two schools by Bahadur et al.

Looking more broadly, nine schools (FIU, Seton Hall University, and seven others; see Table 1) have both above average transfer-in rates and attrition rates. The majority of the schools in Table 1 either award degrees to minority candidates at a higher-than-average rate, enroll more part-time students than average, or have a more racially diverse faculty. Most notably, FIU encompasses all the above. This may suggest that these schools are “mission-driven,” meaning they consciously admit underrepresented students at higher rates, including those with lower LSAT scores who are less likely to pass the bar exam, in order to broaden access to legal education and the profession. This is *not* to say that underrepresented students should generally be expected to perform poorly on the bar; it is an acknowledgment of extant evidence that underrepresented minority students have lower odds of passing the bar exam (see, e.g., Taylor et al., 2021; American Bar Association, 2021). This is a barrier that encourages some law schools to admit students of color at lower rates.

Combining our statistical results with a descriptive look at those schools with average or above-average attrition and transfer-in rates, there is only limited and, in some ways, contradictory evidence to support the supposition that, on average, schools leverage their attrition and transfer rates to bolster their bar performance substantively affect a school’s bar passage rates.

Table 1

Comparison of Nine Schools with Higher than Average Attrition and Transfer-In Rates

School Name (Attrition/Transfer-In Rate)	Bar Pass %	Pass Differ-ential	Median LSAT	Median UGPA	Adm it Rate	% Full-Time	% Minority Degrees	% Minority Faculty
Appalachian School of Law (Att: 16%; Xfr-in: 5%)	43%	-32%	145	2.97	49%	99%	12%	9%
City U. of New York (Att: 11%; Xfr-in: 4%)	78%	-4%	153	3.31	40%	90%	34%	36%
Florida International U.[a] (Att: 10%; Xfr-in: 11%)	89%	22%	156	3.61	28%	76%	64%	48%
Hofstra U.[b] (Att: 8%; Xfr-in: 7%)	62%	-20%	153	3.33	58%	97%	28%	9%
Lincoln Memorial U. (Att: 30%; Xfr-in: 11%)	76%	-2%	150	3.07	53%	60%	9%	20%
Seton Hall U.[a] (Att: 8%; Xfr-in: 8%)	85%	10%	157	3.45	50%	68%	22%	12%
St. Thomas U. (Florida) (Att: 19%; Xfr-in: 4%)	58%	-10%	147	3.06	61%	95%	79%	29%
U. of Idaho (Att: 8%; Xfr-in: 4%)	73%	-4%	152	3.20	59%	98%	20%	12%
U. of Toledo (Att: 13%; Xfr-in: 5%)	75%	-1%	152	3.33	61%	79%	13%	8%
Avg. Across All Schools (Att, 7%; Xfr-in, 4%)	76%	1%	156	3.39	50%	89%	26%	15%

[a]School was identified as a top 15 school by Kinsler (2021); [b]School was identified as a bottom 15 school by Kinsler (2021).

LIMITATIONS

This research relies upon publicly available data that is reported annually to the ABA by each accredited law school. Since the data is self-reported, there are occasionally inconsistencies in the data. These inconsistencies are likely the result of data entry error. In rare cases, intentional misreporting has been alleged. For example, in a March 2022 *New York Times* article, a professor at Columbia University challenged the school's undergraduate *U.S. News* ranking, charging the university with manipulating the data it reports to increase its ranking. Moreover, in 2021, a former dean of Temple University's business school was convicted of intentionally misreporting data in order to improve the school's ranking and revenue.

We have taken great care to identify and correct any observed abnormalities. We find no evidence of data manipulation in the data we use in this analysis. Notwithstanding, one common error we observed involves the reporting of attrition and transfer rates. Schools often adjust attrition rates reported for previous years to account for changes in their first-year class sizes. In light of this, we have calculated the attrition and transfer rates for each school using their reported enrollment, attrition, and transfer counts, rather than rely on the reported rate values.

Schools may also misreport attrition, attributing what should be first-year attrition to the second year. We have carefully examined the dataset and corrected those instances where this error was apparent. This is tricky, however, as academic attrition policies vary widely across institutions, with some placing students on academic probation following the first-year and then attriting them only after they fail to meet a required benchmark in the third or fourth semester. Thus, a large number of second-year transfers may not necessarily indicate a data entry error.

From year-to-year, the ABA reporting requirements related to attrition and transfer have been modified. Due to these changes, we do not include data from the first two years of available ABA data.

We also deliberately exclude data for graduates who took the bar exam in 2020 or 2021. Although this allows us to avoid issues related to inconsistency with the bar exam due to the various adjustments and alterations in response to the COVID-19 pandemic, the downside is that we do not capture more recent changes in enrollment trends (e.g., increased admission rates for women, increases in matriculation).

CONCLUSION

Some researchers have expressed concerns about schools using attrition and transfer policies to inflate bar passage rates (Bahadur et al. 2021), an interesting thesis worthy of attention considering the implications for academic and bar success professionals whose efforts to prepare law students for the bar exam could be undermined if certain institutions are found to take shortcuts to bar passage improvement. However, our research only finds limited evidence to support this notion: attrition rates are positively associated with pass differential; transfer-in rates are negatively associated. (Transfer-out rates do not appear to have a meaningful impact on pass differential.)

When examined in combination, high transfer-in rates counter the effects of high attrition rates in predicting an institution's first-time pass differential. Transfer index, however, does not moderate the effect of attrition and transfer-in rates.

Finally, some actors in legal education have proposed that lower-ranked schools face undue difficulty complying with ABA accreditation standards because they are vulnerable to losing their top performers to higher-ranked schools via transfer (e.g., Garcia et al., 2016; Society of American Law Teachers [SALT], 2019). Given that lower-ranked schools are inherently more vulnerable to being harmed by this dynamic, some have suggested that a type of credit-sharing or acknowledgement of transfer students' original law school in bar passage statistics is in order (Garcia et. al, 2016; SALT, 2019). The ABA also acknowledges in its Standard 316 Guidance Memo that some students may transfer out of a school and pass the bar exam as a graduate of another law school, and it enables noncompliant institutions to use evidence of such trends to demonstrate "good cause" to extend the time they are given to reenter compliance with the Standard (ABA, 2019, pg. 3).

Our results suggest that, on average, transfer-out rates generally do not significantly harm pass differentials, nor do transfer-in rates significantly bolster pass differentials. And although we find that institutional bar passage rates fall as transfer rates increase, the reduction only lowers the pass differential by a percentage point or less. Nonetheless, law schools that fall only a percentage point short of the 75 percent benchmark may use our results to show that there is a high probability that losing students to transfer reduced their passage rate just enough to fall out of compliance. This argument is likely effective for schools with smaller cohort sizes, as a relatively small difference in the number of students passing the bar has a greater impact on their overall passage rate.

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APPENDIX

Descriptive Appendix

Table A.1

Descriptive Statistics

	Mean	**Median**	**Standard Deviation**	**Min.**	**Max.**
First-Time Bar Pass Differential	0.01	0.01	0.12	-0.44	0.27
First-Time Pass Rate	0.75	0.78	0.15	0.30	0.99
Transfer-In Rate	0.04	0.03	0.04	0.0	0.24
Attrition Rate	0.07	0.05	0.07	0.0	0.48
Transfer-Out Rate	0.03	0.02	0.04	0.0	0.24
UGPA (mean)	3.39	3.39	0.24	2.79	3.93
LSAT (median)	156	155	6.63	141	173
Minority Degrees Awarded (%)	0.26	0.22	0.15	0.02	1.00

Table A.2

Multilevel Models Employed

	Method	Obs. (# of Schools)	Explanatory Variable(s)*	Outcome Variable
RQ1: *On average, to what extent do attrition, transfer in, and transfer out rates affect institutional first-time bar passage performance?*	Fixed effects (also referred to as "no pooling")	748 (189)	• Attrition rate • Transfer-in rate • Transfer-out rate	Pass differential
RQ2: *Does transfer activity vary by institutions' geographic proximity to other law schools with higher or lower rankings? And, if so, how?*	Mixed Effects Poisson	748 (189)	• Transfer index	Counts of: Transfers in Transfers out

RQ3:
Are the effects of attrition and transfer rates on institutional first-time bar passage rates moderated by whether a law school is in close proximity to others with higher or lower rankings?
	Between-within random effects (contains both fixed and random effects)	748
		(189)
			• Attrition rate
			  ○ Yearly rate minus mean rate
			  ○ Mean rate
			• Transfer-in rate
			  ○ Yearly rate minus mean rate
			  ○ Mean rate
			• Transfer-out rate
			  ○ Yearly rate minus mean rate
			  ○ Mean rate
			• Transfer index
				Pass differential

Note: *All models include a dummy variable for the year the students matriculated, to account for correlation among observations from the same schools in different years.

Figure A.1

Calculating a School's Pass Differential Through June 2019[9]

Assume School X had 180 graduates in a given year who took the bar exam for the first time, 90 in State A, 45 in State B, and 45 in State C.

The following table illustrates how the weighted averages and pass differential for School X would be calculated.

	State A	State B	State C	Weighted Avg.
School X				
# Takers	90	45	45	
% Takers	50	25	25	
# Passers	81	27	18	
Pass rate (%)	90	60	40	
Weighted pass rate (%)	45	15	10	70
ABA Avg.				
Pass rate (%)	90	80	60	
Weighted pass rate (%)	45	20	15	80
Pass Differential (%)				- 10

The weighted average for the school is calculated by taking the pass rate for the school in the three states and weighting it in proportion to the number of students taking the bar exam in the three states. Here, of the 180 graduates taking the bar exam in these three states, 50% took the exam in State A, 25% took the exam in State B, and 25% took the exam in State C. So, by multiplying the pass rate for the school in each state by its proportional weight, and adding those results together, one arrives at a weighted average pass rate of 70 percent for graduates of the school who took the bar exam in these three states.

By multiplying the overall pass rate in each state by the proportional weight determined by looking at the number of the school's graduates who took the exam in each state (here, 50%, 25%, and 25%), and adding those results together, one arrives at a weighted average pass rate of 80 percent for all first-time takers from ABA-approved law schools in these three states.

The difference of these two weighted averages is the pass differential.

Source: Adapted from American Bar Association Section of Legal Education and Admissions to the Bar, Report to the House of Delegates (February 2008).

[9] Note: The guidelines surrounding this reporting were changed in May 2019 as a result of revisions made to the ABA's accreditation standards. Beginning in Spring 2020, schools are now required to report bar passage outcomes

Table A.3

Description of Model Variables[1]

Variable Name	**Variable Type**	**Description and/or Available Responses**
Admission Rate	Continuous	Percent of applicants admitted to school.
Attrition Rate	Continuous	Non-transfer attrition rate of a given school in a given year
Cohort	Categorical	Indicates which admission year the relevant cohort entered. Four cohorts total in sample.
Full Time JD (%)	Continuous	Percentage of enrolled students who are full-time students.
LSAT/UGPA Index	Continuous	Constructed by converting the 25th, 50th, and 75th percentile LSAT scores into a proportion (total points out of a possible 180) adding them, and doing the same for the 25th, 50th, and 75th percentile UGPA. These sums are then weighted by their respective explanatory power (of pass differential), added, and then scaled between 0 and 1.[2]
Degrees Awarded to Students of Color (%)	Continuous	Percentage of JDs the school awarded to under-represented minority (Black, Hispanic, and Native/Indigenous) students.
Faculty of Color (%)	Continuous	Percent of faculty who are racial/ethnic minorities.
Section Size	Count	Count of number of students in average section of first-year JD course.
School Type	Categorical	Classification of school as either public or private.
Student-Faculty Ratio	Continuous	Ratio of number of students to faculty members.
Transfer Market Index	Count	Count of geographically proximate schools with higher *U.S. News* rankings.
Transfer-In Rate	Continuous	Transfer-in rate (percent of 1L cohort) of a given school in a given year
Transfer-Out Rate	Continuous	Transfer-out rate (percent of 1L cohort) of a given school in a given year

Note: [1]Not all variables are employed in all models, see the regression outputs in the appendix for the list of variables included in each model; [2]when adding the proportioned LSAT and UGPA measurements together, UGPA is weighted by its affect when our dependent variable, bar pass differential, is regressed by the LSAT and UGPA measures. Since the coefficient on UGPA is 22 percent that of LSAT, UGPA is weighted by 0.22 when it is added to the LSAT measure.

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for all students. In addition, the use of the weighted average is no longer calculated, reported, nor relied upon for compliance purposes.

Table A.5

RQ1 Model Results

	No Interaction (n = 749)	Interaction (n = 749)
Attrition Rate	-0.019	-0.001
	(0.050)	(0.050)
Attrition Rate (squared)	0.147***	0.154***
	(0.053)	(0.053)
Transfer-In Rate	-0.009	0.038
	(0.037)	(0.041)
Transfer-In Rate (squared)	-0.023	-0.040
	(0.045)	(0.045)
Interaction Term: Attrition Rate Given Transfer-In Rate		-0.200**
		(0.078)
Transfer-Out Rate	-0.001	-0.012
	(0.020)	(0.020)
LSAT/UGPA Index	0.504***	0.516***
	(0.088)	(0.088)
Degrees Awarded to Graduates of Color (%)	-0.134	-0.133
	(0.083)	(0.083)
Degrees Awarded to Graduates of Color (%; squared)	0.014	0.018
	(0.127)	(0.126)
1L Section Size	-0.039**	-0.041**
	(0.018)	(0.018)
R^2	0.155	0.165

Note: *p<0.10; **p<0.05; ***p<0.01

Table A.6

RQ2 Model Results

	Transfers In	Transfers Out
	(n = 749)	(n = 749)
Transfer Index	0.650***	-0.384***
	(0.063)	(0.068)
Public School	-0.021	-0.377***
	(0.099)	(0.107)
2014 Cohort	-0.081	-0.081
	(0.054)	(0.055)
2015 Cohort	-0.211***	-0.183***
	(0.055)	(0.056)
2016 Cohort	-0.307***	-0.702***
	(0.056)	(0.061)
Akaike Inf. Crit.	3,967.739	4,007.802
Bayesian Inf. Crit.	4,004.689	4,044.752

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.7

RQ3 Model Results

	Between-Within Models	
	No Interaction (n = 749)	Interaction (n = 749)
Mean Attrition Rate (square root)	0.029	0.030
	(0.035)	(0.035)
Attrition Rate (difference)	-0.004	-0.005
	(0.047)	(0.047)
Attrition Rate (squared difference)	0.108**	0.150***
	(0.047)	(0.050)
Mean Transfer-In Rate (square root)	-0.021	-0.028
	(0.028)	(0.028)
Transfer-In Rate (square root difference)	-0.011	-0.010
	(0.015)	(0.015)
Mean Transfer-Out Rate (square root)	-0.088***	-0.078***
	(0.022)	(0.022)
Transfer-Out Rate (difference)	-0.009	-0.012
	(0.018)	(0.018)
Transfer Index	0.016**	-0.008
	(0.007)	(0.012)
LSAT/UGPA Index	0.909***	0.899***
	(0.074)	(0.077)
LSAT/UGPA Index (squared)	-0.419***	-0.397***
	(0.069)	(0.073)
Percent Faculty of Color (square root)	0.044*	0.045*
	(0.023)	(0.023)
1L Section Size	-0.044***	-0.045***
	(0.015)	(0.015)
School Type: Public School	0.009	0.009
	(0.008)	(0.007)
2014 Cohort	0.018***	0.018***
	(0.005)	(0.005)
2015 Cohort	0.020***	0.021***
	(0.005)	(0.005)
2016 Cohort	0.022***	0.024***
	(0.005)	(0.005)
Interaction: Attrition Rate (difference) Given Transfer Index		0.074**
		(0.031)
Interaction: Transfer Index Given Transfer-In Rate (difference, square root)		0.031*
		(0.018)
Akaike Inf. Crit.	-2,176.235	-2,175.124
Bayesian Inf. Crit.	-2,088.479	-2,078.130

Note: *p<0.10; **p<0.05; ***p<0.01; all continuous variables are scaled 0-1, except transfer index, which is normalized with mean 0 and a standard deviation of 1.

Table A.8

Interacting Effect of Attrition Rates Given Various Levels of Transfer-In Rates

	Attrition Rate	Predicted Bar Pass Differential	Confidence Interval
Transfer-In Rate: 0%	0%	-1%	[-2%, 1%]
	5%	0%	[-1%, 1%]
	10%	1%	[-0%, 2%]
	15%	3%	[2%, 4%]
	20%	4%	[3%, 5%]
	25%	5%	[3%, 7%]
	30%	6%	[4%, 9%]
	Attrition Rate	**Predicted Bar Pass Differential**	**Confidence Interval**
Transfer-In Rate: 4%	0%	0%	[-1%, 1%]
	5%	0%	[0%, 1%]
	10%	1%	[1%, 1%]
	15%	2%	[2%, 3%]
	20%	3%	[2%, 4%]
	25%	4%	[2%, 5%]
	30%	5%	[3%, 7%]
	Attrition Rate	**Predicted Bar Pass Differential**	**Confidence Interval**
Transfer-In Rate: 8%	0%	0%	[-1%, 1%]
	5%	0%	[-1%, 1%]
	10%	1%	[0%, 1%]
	15%	2%	[1%, 3%]
	20%	2%	[1%, 4%]
	25%	3%	[1%, 5%]
	30%	3%	[1%, 6%]

Table A.9

Interacting Effect of Transfer-In Rates Given Various Levels of Attrition Rates

	Transfer-In Rate	Predicted Bar Pass Differential	Confidence Interval
Attrition Rate: 0%	0%	-1%	[-2%, 1%]
	5%	0%	[-1%, 1%]
	10%	0%	[-2%, 1%]
	15%	0%	[-2%, 2%]
	20%	0%	[-3%, 3%]
	25%	1%	[-3%, 5%]
	Transfer-In Rate	**Predicted Bar Pass Differential**	**Confidence Interval**
Attrition Rate: 5%	0%	1%	[0%, 2%]
	5%	1%	[0%, 1%]
	10%	0%	[0%, 1%]
	15%	0%	[-1%, 2%]
	20%	0%	[-2%, 2%]
	25%	0%	[-3%, 3%]
	Transfer-In Rate	**Predicted Bar Pass Differential**	**Confidence Interval**
Attrition Rate: 10%	0%	3%	[2%, 4%]
	5%	2%	[1%, 3%]
	10%	1%	[0%, 2%]
	15%	0%	[-2%, 2%]
	20%	0%	[-3%, 2%]
	25%	-1%	[-5%, 2%]

Table A.10

The Effect of Various Transfer-Out Rates on Pass Differential

Transfer-Out Rate	Predicted Bar Pass Differential	Confidence Interval
0 %	0.46 %	-0.57%, 1.50%
1 %	0.46 %	-0.51%, 1.43%
2 %	0.46 %	-0.46%, 1.38%
3 %	0.46 %	-0.43%, 1.34%
4 %	0.45 %	-0.41%, 1.32%
5 %	0.45 %	-0.41%, 1.31%
6 %	0.45 %	-0.42%, 1.32%
7 %	0.45 %	-0.45%, 1.35%
8 %	0.45 %	-0.49%, 1.39%
9 %	0.45 %	-0.55%, 1.44%
10 %	0.45 %	-0.61%, 1.50%
32 %	0.41 %	-2.96%, 3.79%