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Comparing Campus Discipline Rates: A Multivariate Approach for Identifying Schools with Significantly Different than Expected Exclusionary Discipline Rates

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Introduction

Campus behavior issues are a significant obstacle for successful student academic and social outcomes.[1] Campus behavior management strategies vary widely across school districts and campuses, and these strategies help structure similar variation in exclusionary discipline rates across campuses, even those with statistically similar students, teachers, and campus contexts.[2] Skiba and Edl[3] find that differences across campus approaches to discipline as well as differences across school principals' attitudes about discipline influence exclusionary discipline rates. Dahir[2] finds that these differences in campus discipline strategies can impact other student outcomes such as academic achievement, dropout, and retention. In addition, recent research has shown that the disproportionality in discipline outcomes that exists across various sub-populations (e.g., race, gender, or disability) can be explained by campus discipline strategies and administrators' attitudes.[1,2,4,5]

For these reasons, policymakers and education agencies are interested in monitoring and assisting school districts in behavior management strategies in order to reduce unnecessary exclusionary discipline. For instance, in Texas in 2010 the Legislative Budget Board (LBB) conducted reviews of the student behavior management systems at various campuses in order to help monitor and evaluate campus discipline strategies.[6] These campus reviews assessed the campus context, student characteristics, and discipline strategies in order to give campuses recommendations to improve the administration of disciplinary actions. The goal of these, and similar, reviews is to help campuses change their use of exclusionary discipline in ways that will help improve their overall academic performance.

Currently, there is no tool or metric for systematically identifying schools with discipline rates that are significantly higher than expected given a campus's characteristics.[7] Common explanations for excessive discipline rates at a campus include the campus socioeconomic context, student demographics, or teacher characteristics. However, controlling for these factors can allow for the comparison of discipline rates across campuses with statistically similar student and campus characteristics.

Policymakers and education agencies would benefit from a tool that can identify schools with different than expected discipline rates—controlling for student, teacher, and campus characteristics—so that they can plan appropriate monitoring or interventions by targeting schools with troublesome patterns or outcomes. Similar tools do exist for comparing and monitoring schools based on academic achievement and school resource allocation while controlling for campus characteristics.[8,9] The

Relative Rate Index (RRI) calculation—often used by federal agencies such as the Office of Juvenile Justice and Delinquency Prevention (OOJDP) to determine sub-group differences in juvenile justice contact—has been used to compare aggregate discipline rates and outcomes among sub-groups at campuses; however, this metric does not control for other covariates that help explain discipline rates and outcomes.[10,11]

Texas is a good context for examining the differences in campus discipline rates. About 1 out of every 5 students in the United States is educated in Texas. The student population in Texas is demographically diverse, including 33% white students, 14% black students, and 49% Hispanic students.[12] Texas public schools have locally determined student codes of conduct and discipline strategies, and Texas has discipline rates comparable to other large states like California and Florida. In this study, we compiled a longitudinal dataset that includes every student in 7th grade in Texas during the 2001 to 2003 period and tracks those students for at least six post-7th grade years.[i] The dataset compiled for this analysis includes the individual student academic records, discipline records, teacher characteristics, and campus characteristics for over 6.6 million student-years. Also, these school and campus records were linked to the Texas juvenile justice system records in order to control for students' prior juvenile justice contact. We utilize a multivariate model to compare how campus discipline rates differ across schools with statistically similar students, teachers, and campus characteristics.

We find that campuses with statistically similar characteristics, composition, resources, and challenges have significantly different rates of discipline. These findings are important for identifying schools with significantly different than expected exclusionary discipline rates. Policymakers, education agencies, and school district personnel can use this methodology and these data to identify campuses where the extant campus behavior management strategies should be examined. The data used in this paper are readably accessible, and the multivariate methods used to compare campuses is easy to employ.

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[i]Portions of this analysis and a fuller description of the dataset are available in the report: Fabelo T, Thompson MD, Plotkin M, Carmichael D, Marchbanks MP III, Booth EA. *Breaking Schools' Rules: A Statewide Study of How School Discipline Relates to Students' Success and Juvenile Justice Involvement.* Council of State Governments Justice Center Publications. Accessible at: http://justicecenter.csg.org/resources/juveniles

Campus Monitoring and Assessment

Public bureaucracies, including school campuses, are unique in that they possess monopoly power.[13] Most individuals who are dissatisfied with their school are unable to receive no-cost education without “voting with their feet” and moving to another school zone.[14] Further, unlike businesses, schools and other public bureaucracies lack a single measure of effectiveness: profit.[13] Judging the effectiveness of a waste collection company is relatively easy—what is its profit margin? Rating a municipality’s waste collection is more difficult. Is it providing services to all citizens? Is it controlling costs? Is it providing the services well?

For years, decision makers have sought mechanisms to hold schools accountable,[15(p1)] and usually do so through academic performance and high-stakes testing. As methodologies and data collection have improved, some are utilizing advanced statistical techniques to better examine high-stakes testing outcomes by also considering a variety of factors, such as wealth, that could affect academic achievement in a school.[9,16,17] So monitoring and assessment tools for student outcomes, such as academic performance, and campus outcomes, such as campus financial allocations, exist and are useful to policymakers and education agencies. One example in Texas is the Financial Allocation Study for Texas (FAST) tool, which produces reports that assess and compare campuses’ academic progress and financial efficiencies across Texas.[8] This monitoring tool uses individual-level student data as well as campus and district data to model outcomes like academic progress using a multilevel model.[9]

The literature on school monitoring indicates that the central goal of this process is to make campus comparisons that control for context,[7] and studies like the FAST reporting tool allow this kind of monitoring to occur in a way that can inform policymakers and decision makers in education agencies at every level. Heck[18] outlines a monitoring and assessment system based on school report card grades, controlling for some student demographic characteristics in order to make within-district campus comparisons. Statewide tools for monitoring or assessing academic progress do exist, and their increasing use by state educational agencies is, in part, due to the emphasis on accountability in the 2001 No Child Left Behind (NCLB) legislation. Further, the NCLB legislation calls schools to monitor and report school safety data; yet there is no tool or set of criteria that has emerged for assessing progress on school safety, discipline, or violence as there is for student academic achievement.[7,19]

Recent research has established that discipline issues are an important predictor of academic success.[1,2] Astor et al[7] discuss how school safety and school violence are important determinants of academic success. They suggest that district-based monitoring of school violence could be an important tool for improving student outcomes,[7] yet these recommendations do not consider monitoring campus exclusionary discipline. Campus discipline is often dispensed inequitably;[2,20] this has deleterious academic consequences. Yet despite this, there is no established methodology for assessing or monitoring discipline rates at campuses.

One lesson for monitoring and assessment of student behavior outcomes comes, predominantly, from a metric widely used in juvenile justice research. Metrics such as the Relative Rate Index (RRI) do perform the function of monitoring and gauging juvenile justice outcomes like disproportionality in sub-group contact with various parts of the juvenile justice system. A major criticism of the RRI is that it does not account for individual and contextual factors when calculating juvenile justice contact rates. Despite this, the RRI is an important tool for assessing behavior patterns and behavior management within the juvenile justice system.[10,21] Taken together, tools like RRI that assess juvenile behavior and tools like the FAST methodology that assess other outcomes while controlling for individual and contextual factors offer guidance for a methodology to assess and compare exclusionary discipline rates across campuses.

Recently, the degree to which students are being disciplined within schools has received attention from policymakers,[22,23] government agencies at the state and federal level,[24] and interest groups.[25,26] While interest in holding schools accountable for their discipline rates has been growing, the methodologies for assessing campuses have remained relatively unsophisticated. In order to properly identify campuses that are potentially over- or under-disciplining their students, one must take into account the situation that a campus faces such as district wealth, teacher experience, or student challenges.

Predicting School Discipline Rates

Research on school discipline and school violence shows that behavior issues become more prominent in middle and high school.[16] Predictors of student behaviors that spur exclusionary school discipline have commonly included the following: student characteristics like socioeconomic status, special education status, gender, and race; student academic outcomes like test performance and attendance; teacher characteristics like years of experience and race; and the campus context such as campus wealth and campus safety.[16,26,27,28] While much of this literature focuses on school records at just a few campuses or on survey data for student self-reported behavior, our study includes the school and teacher records for all these explanatory factors across every school in Texas for our cohorts.

Other research has pointed to the importance of prior juvenile justice contact for explaining school discipline outcomes.[29] Students who have been in contact with the juvenile justice system are thought to have been labeled (or have self-labeled) as trouble children, or they have patterns of behavior that were not corrected by the juvenile justice system, and these often lead to further issues at schools in terms of academic and behavioral outcomes.[10,26,29] One obstacle for studying the effects of juvenile justice involvement on school discipline outcomes is that school-based assessments usually do not access the juvenile justice data. In this analysis, we incorporate all these individual student, teacher, and campus attributes, including juvenile justice records, from existing state databases in order to compare school discipline rates across campuses in Texas.

Data and Variables

Our longitudinal dataset for this study includes 3 cohorts of every student in 7th grade in Texas from 2001 to 2003 and follows them for at least 6 years. This dataset includes the individual student academic records, discipline records, teacher characteristics, and campus characteristics for over 6.6 million student-year observations. This includes data across this period from about 3,900 public middle and high schools.

For our study cohorts, about 14% were African American, 40% Hispanic, and 43% white/not Hispanic. Moreover, 51% of our study was male. Over 13% of the students were designated as having received special education at any time during the study period. About 60% of the students in our cohorts were classified as economically disadvantaged (e.g., eligibility for free or reduced-cost meals) during this study period.

The campus discipline rates analyzed below come from the students' exclusionary discipline placement records. Exclusionary discipline (i.e., discipline punishments where students are removed from the classroom) includes suspensions (either in-school or out-of-school), expulsion from campus, or expulsion and placement at an alternative education program.[ii] Texas does not require campuses to report discipline that does not rise to the level of formal punishment. For instance, if a

[ii] In Texas, there are two types of alternative behavior programs (not available in all areas): the Disciplinary Alternative Education Program (DAEP), which is used for expulsions for more than 3 days, and the Juvenile Justice Alternative Education Program (JJAEP), which is available in some of the larger counties in Texas for students accused of juvenile delinquency or statutory offenses under Title 3 of the Texas Family Code.

student is asked to stay after class by a teacher to discuss his or her classroom behavior, that event would not be reported in our dataset.

There are 2 types of exclusionary discipline punishments in Texas schools—mandatory offenses and discretionary offenses. Mandatory offenses are specific criminal behaviors (e.g., assault) that require mandatory removal of the student from school grounds. Discretionary offenses are offenses (e.g., criminal mischief or student code of conduct violations) for which school administrators have discretion about whether the student should be removed from the classroom or campus. The latter offense category amounts to more than 92% of all discipline offense during our study period. The fact that an overwhelming majority of offenses are discretionary helps explain why the campus discipline rates from campus to campus can vary so much with different campus behavior management strategies, even when campuses have very similar student and campus contexts.

In order to predict discipline rates, we use a large set of explanatory variables for the individual students, their teachers, and their campuses. For individual students, we control for student demographic characteristics (e.g., race, ethnicity, and gender), individual student attributes (e.g., economically disadvantaged, limited English proficiency, or disability), student academic performance (e.g., standardized test performance, retention, and gifted/talented), and prior student discipline contact. Importantly, we also link to individual student records in the Texas juvenile justice database and account for prior juvenile justice system contact while modeling campus discipline rates. We also include predictors for students' campus and teacher characteristics such as campus accountability rating, student-to-teacher ratio, teacher salary, teacher experience, and racial congruity between teacher and student. A full list of variables and controls are included in the Appendix.

Taken together, these variables measure the gamut of factors thought to structure discipline outcomes for students in the aforementioned literature. The difference here is that we are able to include all these factors into the same model for several cohorts of all secondary students across an entire state tracked across time.

Methods

The methodology for our study utilized involves 4 basic steps that will be discussed in greater detail:

1. Estimate the probability that each student will be disciplined within the school year.

2. Utilize the individual estimates to form a predicted discipline rate for each campus.
3. Identify the actual discipline rate for each campus.
4. Examine the extent to which each campus discipline rate is greater (less) than predicted by the model and assess whether that difference is statistically significant.

Individual Estimation

In order to determine individual estimates for the model predicting student discipline, the research team utilized binomial logistic regression (Logit).[30] Logit allows researchers to identify the effect that a given variable has on the probability an event occurs while isolating the effect of all other measures in the model. For instance, African American students routinely have a higher discipline rates than their white peers. However, socioeconomic status is also predictive of discipline. Logit allows for the independent effect of race on the probability that a student is disciplined while controlling for the effect of socioeconomic status.

One challenge in modeling school data is that students are nested within groups like classrooms and schools. Often, this type of education data is modeled using mixed or hierarchical level modeling (HLM) to account for this nesting; however, given the size of the dataset and the computational demands of HLM procedures, we instead used clustering of student observations within campuses to account for dependence of student observations within schools. Primo et al[31] find that clustered standard errors produce the same point estimates as HLM, require fewer distributional assumptions than HLM, and is less computationally intensive. These authors suggest that "calculating standard errors is a more straightforward and practical approach, especially when working with large datasets."[31(p446)] Therefore we clustered sandwich estimator of variance at the campus level following these authors' suggestions.

An additional benefit of Logit, particularly useful for this project, is that it facilitates the calculation of individual probabilities of an event (in this case being disciplined) after accounting for the individuals' characteristics, their teacher's characteristics, and the campus characteristics.[iii] Figure 1 shows the conceptual design of this model where individual and campus factors help predict discipline involvement.

For this paper, we calculated the individual probabilities of being disciplined in the 2004-2005 school year[iv] for each student in our cohorts,

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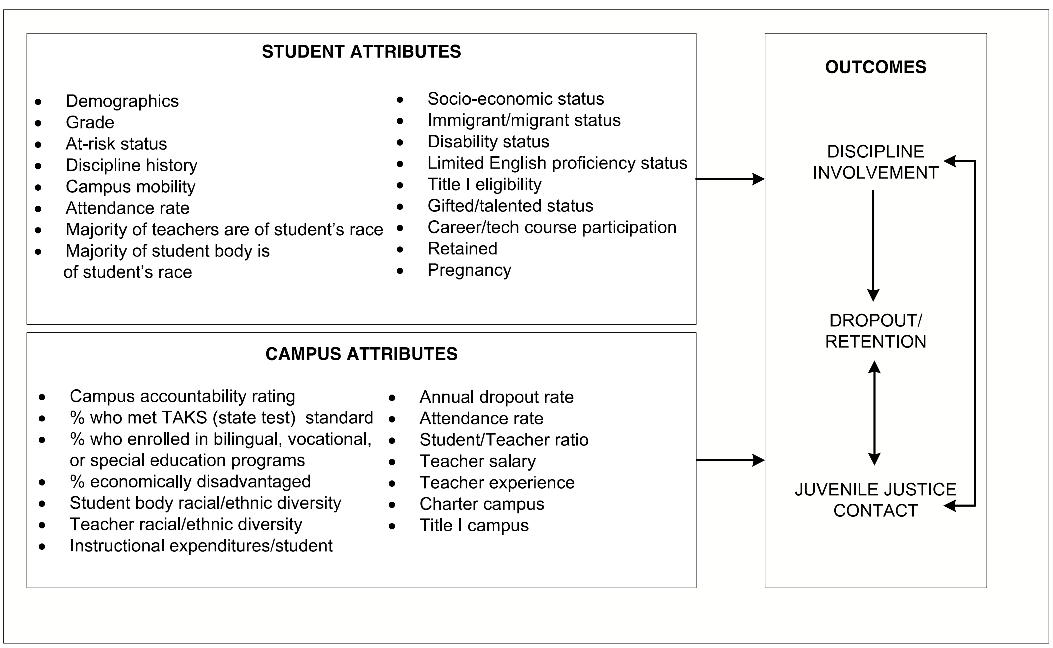
[iii]See Long[30] for a discussion calculating individual probabilities using Logit.

[iv]We chose to include all of the campuses' single school year from our cohort in order to get clean counts of the number of campuses that experience higher or lower than

using Logit and accounting for over 80 separate factors recorded in the Texas Public Education Information Management System (PEIMS) data. In order to provide a more complete picture, both individual-level and school-level characteristics are utilized. Also, for this model, we used the predictor variables of prior juvenile justice contact, dropout, and retention to predict discipline involvement for each student. For instance, a student's race and gender are utilized as are her academic performance, disability status, economic status, and discipline history. At the same time, the model accounts for the schools' overall demographic portfolio, indicators of academic programs, and district wealth as well. The Appendix displays the full list of the individual and campus level attributes as well as the summary statistics showing the operationalization and variation for each variable in the model shown in Figure 1.

Figure 1. Overview of statistical model predicting campus discipline rates



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expected discipline rates. Had we presented the distribution for all cohort years, the same campus could move from, for example, having higher-than-expected discipline in one year and then as-expected discipline in the next.

Predicted Campus Discipline Rate

After predicting the probability of discipline for each student, the overall predicted campus discipline rate is calculated. This value is simply the average probability of discipline across all students converted to percentages. For instance, if a campus has 10 students with a 0.50 probability of discipline and 10 more with a 0.60 probability of discipline, the average probability would be 0.55. As such, we expect a discipline rate of 55% at this hypothetical campus.

Actual Campus Discipline Rate

The actual campus discipline rate is simply the percentage of students from our cohort who were disciplined at their respective campuses. Importantly, we only utilize those students who are in our cohort for all these calculations. It is possible that there are unique differences in the students who moved into the state after our sample was developed. To the extent that these differences lead to distinctive discipline rates, usage of simple campus discipline rates published in the Texas public school reports (e.g., the Academic Excellence Indicator System) could produce a different picture of discipline than what the students in our cohort experienced.

Campus Classification

After identifying the actual and predicted levels of discipline in each of the schools, the research team determined if the difference between these values achieved statistical significance utilizing a basic t-test for proportions. Campuses were then classified as having discipline that was:

- Lower Than Expected
- As Expected
- Higher Than Expected

If a campus is classified as having a discipline rate that is lower or higher than expected, then the actual level of discipline differed from the predicted level by a statistically significant amount.

Results

In 2004-2005 for our study, approximately 50% of campuses in the analysis disciplined their students at rates consistent with what the multivariate model predicted. At the same time, students at 23% of campuses experienced discipline rates statistically higher than expected. Finally, 27% of the campuses reported lower discipline rates than predicted by the model.

One important consideration is that the differences are based on the students' characteristics at a given campus. Because of this, schools that have an extremely difficult student population and very few resources can still discipline at lower-than-expected rates. At the same time, a wealthy district with a less challenging population may have higher than expected discipline. This methodology allows the research team to account for these resources and challenges and compare these schools more fairly.

Regardless of the advantages a school has, there remains a high level of variation in the rates of discipline. The research team divided the schools into 3 categories based upon their expected discipline rate.[v] As depicted in Figure 2, 24% of schools that are predicted to have low discipline rates actually had lower-than-expected discipline. At the same time, 32% of campuses that were expected to have high discipline rates actually discipline their students at rates beyond the predicted levels.

Also noteworthy, considerable variation existed within districts. Table 1 summarizes the campus classifications at 5 of the largest school districts in the state of Texas. In order to maintain anonymity of the districts, the districts are listed in random order rather than in order of their relative size. Across each of these districts, there were substantial differences in the proportion of schools within a district that disciplined higher or lower than their expected levels. In no district were 80% of the campuses of a single classification. District behavior management policies and codes of conduct are usually static across a district, yet across most districts in Texas there is considerable variation in discipline rates, even after controlling for the context.

Figure 2. Actual versus predicted campus discipline rates

[v] The percentage of students disciplined at campuses where the model predicted low discipline is .7% to 21.5% of students; 21.6% to 29.3% of students were disciplined at average predicted discipline rate campuses. Finally, for campuses with higher predicted discipline rates, the percentage of students disciplined was 29.3% or more.

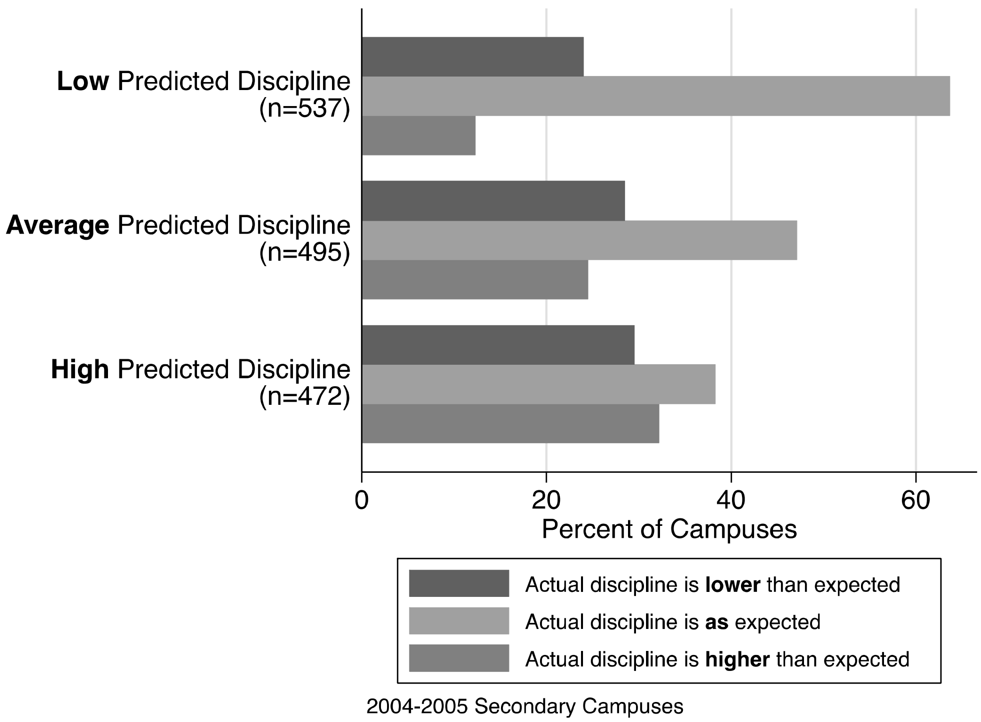

Table 1. Comparison of discipline rate variability across 5 large Texas school districts

	Actual Discipline Is **Lower Than Expected**	Actual Discipline Is **As Expected**	Actual Discipline Is **Higher Than Expected**
District 1	64.3%	14.3%	21.4%
District 2	55.6%	27.8%	16.7%
District 3	76.9%	15.4%	7.7%
District 4	20.0%	33.3%	46.7%
District 5	23.7%	39.5%	36.8%
Total Number of Campuses	51	34	31

Discussion and Policy Recommendations

The results of this analysis are an indicator that, despite differences in the resources and challenges across districts and campuses, there is substantial variation in the rates at which campuses choose to discipline students. The data and methodology for this analysis are accessible for educational agencies, policymakers, and local school districts to be able to compare and assess how their discipline rates compare with statistically similar campuses elsewhere. Where policymakers and educational agencies are interested in further examination or interventions with campuses with different-than-expected rates of exclusionary discipline, this methodology provides an assessment tool similar to ones used in assessing academic performance or financial efficiency.

The results of this analysis are important for identifying school campuses and districts that are handling exclusionary discipline at unexpected rates. Similar to the aforementioned actions or interventions by SEAs in Texas, these findings can help to identify and compare school campuses' discipline performance after controlling for myriad factors. Educators need to access this information in order to understand and make informed changes regarding local discipline strategies. Additionally, this type of discipline analysis and comparison can allow policymakers to make more informed and better targeted policy and budgeting decisions for districts, thereby reducing budgeting waste and tailoring policies or interventions to specific districts given their local context and challenges. It could help campuses and districts become accountable for the exclusionary discipline use in the same way that districts are compared and evaluated by academic, dropout, or funding outcomes.

It is important to note that this method does not capture the local differences that matter for discipline rates, such as campus leadership decision making, classroom management policies, or local positive behavior interventions and supports. So using this tool, much as with other educational monitoring tools, would be a first step for identifying schools that may need technical assistance or other site-based interventions. Collection and analysis of these data in the manner discussed above would be useful to educational agencies, policymakers, and local school districts for assessing campus discipline performance. Systematic collection of other attributes, such as positive behavior interventions and supports, campus behavior management characteristics, or student ticketing would provide better information for this model if it were made available. Finally, since exclusionary discipline has an impact on future academic outcomes, entities concerned with supporting academic success should consider whether the campus discipline rates are different than the model suggests.

Appendix

The variables used in our model for this analysis are listed and described below, broken out by type of variable:

Student Demographics					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
African American	Student is African American.	0.145	0.353	0	1
Latino	Student is Hispanic.	0.397	0.489	0	1
Other Race	Student is not a white, Hispanic, or black student.	0.031	0.174	0	1
Male	Student is male.	0.511	0.500	0	1
African American in a non-African American Majority School	Student is African American in a school with a majority of students who are non-African American, must be a clear majority of another race.	0.056	0.229	0	1
Hispanic in a non-Hispanic Majority School	Student is Hispanic in a school with a majority of students who are non-Hispanic, must be a clear majority of one race.	0.082	0.275	0	1
Other Race in a non-Other Race Majority School	Student is "Other Race" in a school with a majority of students who are non-"Other Race," must be a clear majority of one race.	0.019	0.138	0	1
White in a non-White Majority School	Student is white in a school with a majority of students who are non-white, must be a clear majority of one race.	0.043	0.203	0	1
Student Attributes					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Title I Indicator	Student receives Title I services.	0.007	0.085	0	1
Economically Disadvantaged	Student is eligible for free or reduced-price lunch or other public assistance.	0.450	0.497	0	1
Limited English Proficiency	Student is classified as having limited English proficiency.	0.066	0.248	0	1

Immigrant	Student is classified as an immigrant.	0.013	0.115	0	1
Migrant	Student is classified as a migrant.	0.017	0.129	0	1
Ever Pregnant	Student was pregnant in any previous year.	0.006	0.075	0	1
Student Racial Majority	Majority of students on the campus are of the student's race.	0.603	0.489	0	1
Teacher Racial Majority	Majority of teachers on the campus are of the student's race.	0.557	0.497	0	1
Number of Schools Attended	Number of schools the student attended in the year	1.084	0.332	0	20
Autism	Student is diagnosed with autism.	0.002	0.044	0	1
Emotional Disturbance	Student is diagnosed with an emotional disturbance.	0.011	0.105	0	1
Learning Disability	Student is diagnosed with a learning disability.	0.083	0.275	0	1
Mental Retardation	Student is diagnosed with mental retardation.	0.008	0.088	0	1
Physical Disability	Student is diagnosed with an orthopedic impairment, auditory impairment, visual impairment, deaf-blind, speech impairment, non-categorical early childhood or other health impairment.	0.020	0.138	0	1
Traumatic Brain Injury	Student is diagnosed with a traumatic brain injury.	0.000	0.018	0	1
Student Academic Performance					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
At-Risk of Dropping Out	Student is at-risk of dropout (TEA designation).	0.410	0.492	0	1
Gifted	Student is classified as gifted.	0.111	0.314	0	1
Vocational Education	Student is in a vocational education class.	0.342	0.475	0	1

Has Failed a TAKS Test	Student has failed a TAAS/TAKS test (state test) before or during our study period.	0.471	0.499	0	1
Failed Last TAKS Test	Student failed at least one section of the TAAS/TAKS test (state test) at least one time the last year s/he took the exam.	0.415	0.493	0	1
Retained	Student was retained in the previous year.	0.047	0.211	0	1
Years Behind	Number of years student is behind expected grade level	0.260	0.542	0	8
Attendance Rate	Student's attendance rate	95.500	5.745	1.764	100
Student Discipline Contact					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Disciplined	Student was disciplined.	0.249	0.432	0	1
Encountered juvenille justice system in the Past	Student was referred to juvenille justice system in the past.	0.060	0.237	0	1
Number of ISS Disciplinary Actions	Total number of discipline events where the action taken was in-school suspension	0.000	0.013	0	12
Number of OSS Disciplinary Actions	Total number of discipline events where the action taken was out-of-school suspension	0.549	1.622	0	76
Number of DAEP Disciplinary Actions	Total number of discipline events where the action taken was referral to a DAEP	0.046	0.299	0	25
Number of JJAEP Disciplinary Actions	Total number of discipline events where the action taken was referral to a JJAEP	0.001	0.034	0	3
Number of Expulsion Disciplinary Actions	Total number of discipline events where the action taken was expulsion	0.001	0.023	0	3

Number of Fine Disciplinary Actions	Total number of discipline events where the action taken was truancy-related fines	0.011	0.123	0	16
Number of No Action Disciplinary Actions	Total number of discipline events where no action was taken	0.000	0.002	0	1
Number of Unknown Disciplinary Actions	Total number of discipline events where the action taken was not reported	0.168	0.732	0	41
Number of juvenille justice system referrals	The number of juvenille justice system referrals that the student had in the year	0.048	0.342	0	23
Cohort Measures					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
7th Grade	Student is in the 7th Grade.	0.184	0.388	0	1
8th Grade	Student is in the 8th Grade.	0.178	0.383	0	1
9th Grade	Student is in the 9th Grade.	0.198	0.399	0	1
Ninth Grade * Held Back	Student is in the 9th Grade and is at least two years behind expected grade level.	0.015	0.122	0	1
10th Grade	Student is in the 10th Grade.	0.162	0.368	0	1
11th Grade	Student is in the 11th Grade.	0.142	0.349	0	1
Cohort Year	The number of years the student's cohort has been in the study	3.394	1.710	1	8
Cohort Measures					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
African American X Cohort Year	The cohort year for African American students; all other students receive a 0.	0.496	1.369	0	8
Latino X Cohort Year	The cohort year for Latino students; all other students receive a 0.	1.350	1.983	0	8

Other Race X Cohort Year	The cohort year for Other Race students; all other students receive a 0.	0.107	0.668	0	8
Campus Measures					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Charter School	Student attends a charter school.	0.014	0.117	0	1
Title I School	Student attends a Title I school.	0.419	0.493	0	1
Exemplary Campus	Campus accountability rating is "exemplary."	0.033	0.180	0	1
Recognized Campus	Campus accountability rating is "recognized."	0.163	0.370	0	1
Unacceptable Campus	Campus accountability rating is "unacceptable."	0.039	0.193	0	1
Missing Rating	Campus accountability rating is "missing."	0.011	0.103	0	1
Alternative Education Accountability Rating- Acceptable Campus	Alternative education accountability campus rating is "acceptable" (for alternative campuses only).	0.018	0.134	0	1
Alternative Education Accountability Rating - Unacceptable Campus	Alternative education accountability campus rating is "unacceptable" (for alternative campuses only).	0.001	0.039	0	1
Campus Attendance Rate	Attendance rate based on student attendance for the entire school year	94.587	2.534	44	100
Campus Dropout Rate	Annual campus dropout rate (grades 7-12). Includes mobile students in the denominator. See http://www.tea.state.tx.us/index4.aspx?id=4080.	1.286	2.268	0	61.5
Student/Teacher Ratio	The number of students per teacher on the campus	14.962	2.638	0.1	62.03474
Percent Bilingual/ESL Education	Percentage of students at the campus enrolled in bilingual/ESL education	6.180	7.779	0	100

Percent Career and Technical Education	Percentage of students at the campus enrolled in career and technical education	44.987	27.288	0	100
Percent Special Education	Percentage of students at the campus enrolled in special education	12.640	5.299	0	100
Percent Met Standard on all TAKS Subjects	Percentage of students at the campus who met the standard on all TAKS (state test) subjects	62.273	15.927	0	1.00E+02
Percent Economically Disadvantaged	Percentage of students at the campus eligible for free or reduced-price lunch or other public assistance	45.395	26.073	0	100
Average Actual Salaries of Teachers	Average salary paid to each FTE teacher at the campus	41843.640	4620.657	20000	107224
Average Years Experience of Teachers	Average years experience for teachers at the campus	11.913	2.547	0	4.60E+01
Per-Capita Instructional $	Average total instructional expenditures per student at the campus	4137.334	1289.232	1	49941
District Wealth Per Capita	Total taxable property value per student	2.575	1.628	0.2043045	37.89253
Campus Measures					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Diversity Measure (Student)	Measure of student diversity at the campus. Calculated as follows: [0 = perfect homogeneity; 0.75 = perfect diversity]	0.282	0.176	0	0.7482204
Diversity Measure (Teacher)	Measure of teacher diversity at the campus. Calculated as follows:: [0 = perfect homogeneity; 0.75 = perfect diversity]	0.426	0.199	0	0.749125

Student/Teacher Racial Congruence (Higher Value = Less Congruence)	Chi-square based measure indicating the student/teacher racial congruence at the campus. [0= perfect congruence. Higher values indicated less congruence (more differences)]	2319.108	2263.910	0	20000
County Measures					
Label	***Definition***	***Mean***	***Std. Dev.***	***Min.***	***Max.***
Suburban County	Student lives in a suburban county.	0.220	0.414	0	1
Non-Metro Adjacent County	Student lives in a non-metro county adjacent to a metro county.	0.137	0.344	0	1
Rural County	Student lives in a rural county.	0.028	0.164	0	1
Percent Single Parent Families	Percentage of families in the student's county headed by either a father or mother only (2000 US Census)	0.238	0.043	0.0337079	0.3267997
Percent of Population With Diploma	Sum total of the percent of 25+ year olds within the student's county with 1 of the following educational attainments: high school graduate (includes equivalency); some college, no degree; associate degree; bachelor's degree or graduate/professional degree	74.871	8.879	34.70198	112.1969
Percent Homes Rented	Percent of occupied homes in the student's county that are rented by the occupant (2000 US Census)	0.346	0.097	0.1225292	6.57E-01
Average Household Size in County	Average household size in the student's county (2000 US Census)	2.782	0.268	2.13	3.75
Income Per Capita	2006 per capita income in the student's county (Comptroller's Office)	34258.260	8823.797	12971	48644

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