

Quantitative Report

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Promising Practices Project: Exploring Predictors of Achievement and Positive Outlier Status in New Jersey Grades 3–8

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Executive Summary

This quantitative report highlights the measurable factors influencing student achievement in English language arts (ELA) and mathematics, as well as the likelihood of schools being categorized as "positive outliers." District-level influences explain most of the variability in mean achievement, accounting for three-quarters of the variation in both subjects. However, while the research controls for district context, the primary focus is to study the role of school-level factors.

Factors Associated with Mean ELA and Mathematics Achievement

1. In both ELA and math, more than half of the variation in mean achievement is attributable to districts. However, school-level factors also contribute to at least one third of the variability in mean achievement, and the subsequent findings shed light on some of those school factors.
2. The interaction between the ratio of psychologists to students and school need—defined by factors like demographic composition, socioeconomic status, and enrollment of historically disadvantaged populations—is a significant factor in both ELA and math achievement schoolwide. In both subjects, this interaction has a substantial positive effect on achievement, especially in schools with higher levels of need. For instance, in ELA, the effect was more than one third of a standard deviation, while in math, the effect was nearly two thirds of a standard deviation. However, the psychologist-to-student ratio alone does not show a direct impact outside of this interaction, suggesting that its effectiveness is contingent upon the context of school need.
3. The psychologist-to-student ratio also boosts ELA and/or math performance for all subgroups, and it appears to be moderated by either school need and/or percent of students with disabilities, so that the positive influence of the psychologist-to-student ratio is seen when contextual variables increase.
4. The relationship between other support staff ratios and student achievement is mixed in both subjects. While increasing the ratio of psychologists to students interacts positively with the level of school need, other staffing ratios exhibit negative effects. Specifically, both counselor-to-student and social worker-to-student ratios show negative associations with achievement in both schoolwide ELA and math, but positive associations for some subgroups like Hispanic students and economically disadvantaged students. Additionally,

greater teacher-to-student ratios are linked to reduced achievement in both subjects. These findings highlight the complexity of staffing and resource allocation when school context is considered, and suggest that optimal staffing configurations relative to student composition and need should be carefully analyzed.

5. Teacher experience is associated with student achievement in both subjects in a nonlinear fashion. Initially (i.e., during the first years of serving as a teacher), increases in teacher experience are associated with declines in average achievement. This suggests that at lower levels of experience, additional years of teaching may not have a positive impact. Notably, nonlinear relationships can be better understood through the application of a quadratic term. When a quadratic term is applied to teacher experience, this relationship becomes clearer: Once teachers reach a certain level of experience mid-career, further increases in experience are associated with small positive increases in average student achievement.
6. Mean achievement increases with grade level progression in both subjects, with substantial increases observed as students advance from fifth through eighth grades as compared with third grade. However, for multilingual learners and students with disabilities, a “reversed” grade effect shows achievement declines in higher grades.
7. In both ELA and math, school need was consistently associated with lower achievement. This negative influence was most pronounced in the schoolwide analysis, indicating the significant challenges faced by schools with greater shares of students with higher needs. However, the positive influence of staffing and resource allocation was much larger than the negative influence of school need in most instances.
8. Proxy indicators of an unsupportive school climate, as indicated by measures like chronic absenteeism and suspension rates, negatively affect achievement in both ELA and math and for all subgroups. However, its influence is relatively small compared to other factors like staffing and resource allocation.

Factors Associated with the Likelihood of Being a “Positive Outlier” School

1. Findings from ordinal logistic regressions indicate that school climate factors, such as schoolwide out-of-school suspension rates and chronic absenteeism rates, play a prominent role in determining whether schools’ performance warrants inclusion among the “positive outlier” schools. Higher schoolwide out-of-school suspension rates significantly decrease the likelihood of schools being categorized in higher-than-expected performance categories, and increase the likelihood of falling into lower-than-expected performance categories. A similar trend is observed for schoolwide chronic absenteeism rates. These results are consistent with results from the hierarchical linear modeling (HLM) analysis to study factors influencing mean achievement, but are more central predictors in the analysis of factors associated with the likelihood of being a “positive outlier” school.

2. Among school practices related to staffing, teachers' years of experience and levels of support staffing are statistically significant. The average years of teaching experience, along with its quadratic term, reveal nonlinear effects on school performance categories. As with the previous analyses, the data show a decrease in the likelihood of schools being in a positive performance category as teachers' years of experience initially increase; however, greater likelihood of being in positive categories exists, on average, when teachers are at the mid or late career point. Additionally, increasing the counselor-to-student ratio significantly increases the likelihood of schools being categorized in positive performance categories. Specifically, increasing the ratio from 1:100 to 2:100 boosts the likelihood of a school being in a moderately positive category from 9.0% to 17.2% and in a highly positive category from 6.5% to 11.4%. This suggests that greater access to counselors is associated with better student outcomes, likely due to enhanced social-emotional support. In this analysis, psychologist-to-student and social worker-to-student ratios rendered insignificant results in the full logistic regression model.

The findings from the quantitative analyses provide valuable insights into the factors driving school performance, challenging simplistic views of academic performance by uncovering the significant roles of student support staff and school climate. These results suggest important directions for decision-making, practice, and future research.

Section 1: Introduction

Overview

The goal of this report is to quantitatively explore how factors like school climate, resources, staffing, and leadership contribute to student achievement relative to student demographics, in the first year of testing following the COVID-19 pandemic, academic year 2021–22. Understanding these relationships is important to inform policy and replicable models for improving educational outcomes. Initial qualitative findings highlight the complexity of school- and district-based factors, including school culture, leadership, staffing decisions, and teacher collaboration, which may influence student performance and recovery. The quantitative analyses presented here aim to examine similar relationships, where measures are available, and complement the qualitative study. The analysis is grounded in the notion that school- and district-level practices, when examined carefully, can offer insights into how some schools managed to exceed expectations regarding student learning outcomes.

The research team identified variables in the New Jersey Department of Education’s (NJDOE) School Performance Reports data to measure three broad areas: 1) school leadership and teacher experience, 2) staffing and resource allocation, and 3) school climate. Descriptive statistics on these key measures can be found in Appendix 1.

School leadership and teacher experience include teacher retention, administrator retention, teachers’ years of experience in the school, and school leaders’/administrators’ years of experience in the district to provide measures of school stability, which could contribute to an environment conducive to instructional continuity and improvement (Grissom, et al., 2021; Kini & Polodsky, 2016; Schmid, 2018).

Staffing and resource allocation in this study emphasizes access to specialized support staff such as school counselors, social workers, and psychologists, considering the importance of social-emotional learning (SEL), mental health support, children’s well-being, academic intervention, and general teacher and student support (Alvarez et al., 2013; Ding et al., 2023; Education Trust, 2019; López, et al., 2021; National Association of School Psychologists, 2021; National Association of Social Workers, 2024; Zabek et al., 2023). Per-pupil spending is examined to assess how resource availability correlates with performance (Baker, 2018). Teacher-to-student and administrator-to-student ratios are additional indications of resource allocation (Solheim & Opheim, 2019; Theobald & Grits, 1996; Trawick-Smith, 2024).

School climate is proxy-measured through indicators of chronic absenteeism and student suspension practices. High rates of exclusionary discipline (e.g., out-of-school suspensions) could signal that developmental relationships are weak

or non-existent in the school. Chronic absenteeism can indicate a disengaging school climate, triggering negative socio-emotional responses and hindering student learning (Allensworth et al., 2021). Research has shown that high absenteeism rates correlate with lower academic performance, especially for students from disadvantaged backgrounds (Dee, 2024; Rafa, 2017).

School and neighborhood socioeconomic and student demographic composition are examined alongside the three broad study areas to evaluate the extent to which school and district practices can mitigate the historic institutionalized disadvantage that the selected subgroups have experienced.

The study's research questions are as follows:

1. What within-school and district factors are associated with higher New Jersey Student Learning Assessments (NJSLA) performance schoolwide and among subgroups of students (Black students, Hispanic students, multilingual learners (MLs), students with disabilities (SWDs), and economically disadvantaged students)?
 - a. What factors are associated with NJSLA ELA performance?
 - b. What factors are associated with NJSLA math performance?
2. What factors are associated with the odds of being a "positive outlier" school based on the residuals from the phase one quantitative study?

Residuals are the differences between observed school performance (i.e., average ELA and math scores) and the performance predicted based on school and neighborhood characteristics. In this study, residuals highlight how much a school either exceeded or fell short of statistically-based expected performance after accounting for these background factors. Schools with positive residuals performed better than expected and are considered "positive outliers." The analysis for the second research question uses residuals to categorize schools and examine the factors associated with exceeding expectations.

Methods

This study examines factors associated with student achievement among all students schoolwide and among five subgroups of historically disadvantaged students: Black students, Hispanic students, economically disadvantaged students, multilingual learners (MLs), and students with disabilities (SWDs).

Education data were drawn from the NJDOE School Performance Reports and socioeconomic data from the National Center for Education Statistics (NCES). These datasets provided coverage of school-level performance, school demographic composition, and district-level socioeconomic characteristics, enabling an analysis of the factors influencing NJSLA outcomes in both ELA and mathematics.

Neighborhood socioeconomic status was controlled for and operationalized using a vector of variables at the district level: median income, unemployment rate, the proportion of households receiving the Supplemental Nutrition Assistance Program (SNAP), parental education levels, child poverty rates, and the proportion of single-mother households. These variables were centered around the state mean (i.e., grand-mean centered), allowing for interpretation relative to deviations from the statewide average. School-level demographics and NJSLA performance from a previous year (2018–19) were controlled for through the New Jersey School District Need Index. This index is statistically reliable (reliability coefficient = 0.9721) for indicating the extent to which schools are serving historically disadvantaged populations who would normally require additional educational resources to produce equitable outcomes (Campbell, 2022).

The index is based on the percentage of students who are economically disadvantaged, from a home speaking a language other than English, not math proficient, not ELA proficient, English learner, Black, Hispanic, and/or minority. The models also controlled for 2021–22 school demographic characteristics including racial/ethnic groups and those classified as students with disabilities or as multilingual learners in schools. As described, the primary predictor variable domains of interest were those measuring aspects of school leadership and teacher experience, staffing and resource allocation, and school climate.

Missing data in predictor (i.e., independent) variables were addressed according to the expected reason for missingness. Given that districts can report student-to-support staff ratios (e.g., student-to-counselor and student-to-psychologist ratios) at the school and/or district-levels, the variables are consistently scaled (i.e., number of students to one staff member) (NJ Department of Education, 2022). Missing school-level ratios were imputed with district-level ratios. Schools without school- or district-level ratios of students to support staff were assumed to have no staff for that category and were imputed with a value of zero. To aid in interpretation, student-to-support staff ratios were further converted to ratios of staff to students, and scaled to staff per 100 students (e.g., counselor-to-student ratios).

Other predictor variables with partially missing data (generally less than 10%) were imputed with the statewide average of the variable to reduce the number of dropped cases, minimize bias, and allow for use of all available information from the sample. By using this method, fewer cases were dropped. Mean imputation preserves the statistical distribution of the variable and does not change model estimates. All imputed variables, regardless of the method, had a missing data indicator variable to assess the relationship between imputation status and the outcomes. The imputation indicators are not discussed in the narrative, but readers are encouraged to review the regression tables and assess any significant patterns associated with the missing indicators.

Other variable manipulations include the log transformation of variables with very wide ranges and large extreme values (e.g., per-pupil expenditures and school enrollment), to address skewed distributions and to approximate normality. This strategy improves regression estimation by limiting undue influence of variables with very large values. In the case of teaching experience, the use of a quadratic term reflects a recognition of the possibility that its impact on student outcomes is not linear, and that teaching quality may decline or improve over time (Graham et al., 2020).

The final analytic sample consisted of 1,983 public New Jersey schools enrolling grades 3–8, with schools as the primary unit of analysis as requested by the NJDOE team. However, this analytic approach distinguishes between the amount of impact due to school-level and district-level factors, which will be discussed below. A few variables were modeled at the district level.

The first research question employed hierarchical linear modeling (HLM), a regression-based technique that accounts for schools' nesting within districts. The dataset for the HLM model is organized by school and grade level (Grades 3–8), leading to a dataset with 11,898 records. However, the numbers of records vary by model because not all schools have all subgroups or all grade levels, and some schools have missing outcome data that was not imputed to avoid bias.

The HLM approach permitted estimation of how school practices contribute to average student achievement in ELA and mathematics, accounting for school- and district-level characteristics. The dependent variables were the mean achievement for ELA and mathematics schoolwide or for each subgroup of students, expressed as standardized scaled scores (mean = 0 SD = 1). Standardization facilitated comparisons across subgroups and enabled effect sizes to be interpreted in terms of standard deviation units. All models included frequency weights for valid scores contributing to the mean test score; subgroup enrollment was controlled for in the subgroup models.

A series of models examined the relationship between the sets of variables separately then all together (i.e., a stepwise approach). The first model studied school and neighborhood demographic characteristics without the inclusion of variables representing school practices and resources. The second model added school leadership and teacher experience variables, as well as staffing and resource allocation variables (e.g., teacher and administrator experience and ratios of support staff to students) along with demographic variables. The third model examined school climate variables along with demographic variables. The fourth model combined all sets of variables to examine how they vary with one another.

Based on observations from the fourth model, a fifth model looked at interactions between the strongest predictors (mostly support staff-to-student ratios) and school context to further understand mechanisms of variability. A sixth model was added to study support staff variables at the district level, since these data can either be reported at the school or district levels. To manage the number of models, Model 6 was only run for schoolwide achievement and not for subgroup models.

For simplicity and to maintain a focus on the complete picture, the discussion of results focuses on the fourth model; the fifth model is discussed as a point of comparison. The results for all HLM models are presented in Appendix 2 and 3; readers are encouraged to peruse all models and explore the role of sets of variables separately from others.

In addition to the main findings, this report also discusses how variability spreads between districts and schools for additional context when making sense of findings. HLM analysis allows for an assessment of the consistency or variability in the outcome, and how much of the observed variability lies between groups (i.e., districts) or within groups (i.e., between schools). The

statistic providing this information is called the interclass correlation (ICC). The higher the ICC, the greater the variation between *districts*. The lower the ICC, the greater the variation between *schools*. If more of the variation is between districts then, ideally, efforts for improvement would pay close attention to district-level factors. If more of the variation is between schools, then efforts for improvement would ideally pay slightly more attention to levers in schools. ICC results are described at the beginning of the ELA and math HLM results section.

A note for reading the findings from the HLM models: The standardized test score variables (referred to as achievement or performance) range from -4.00 to 4.00 , with a mean of 0 and a standard deviation of 1 . A coefficient of 0.05 to 0.20 can be considered moderately substantial and a coefficient above 0.20 can be considered large (Kraft, 2020). In this report, since many variables are modeled, coefficients described as “substantial” refer to those which are 0.10 or higher, taking the upper half of the moderately substantial range and all above. Coefficients are also described in terms of standard deviation units to allow for assessment of the importance of each variable’s role relative to the range of the outcome measure. For example, a coefficient of 0.10 is one-tenth of a standard deviation whereas a coefficient of 0.66 is two-thirds of a standard deviation. Less substantial but statistically significant coefficients are sometimes discussed if they are central to the research questions.

The second research question builds on prior analyses to understand what sets schools apart as “positive outliers”—those that exceeded expectations in ELA and math performance given their student populations and despite the assorted challenges associated with the pandemic. Given that the residuals that defined “positive outliers” follow an approximate normal distribution, schools were categorized into five groups based on the residuals’ locations relative to the mean and standard deviation (SD) of all sampled schools. Using these residual-based school performance categories and ordinal logistic regression methods, this analysis explores the factors associated with the likelihood of a school performing better than expected (i.e., being “positive outliers” while accounting for potential differences in performance within the “positive outlier” schools).

Essentially, this work aims to differentiate schools that performed *as expected*, those that *moderately exceeded expectations*, and those that *highly exceeded expectations*. Insights from the latter two groups are likely to provide incrementally compelling evidence of effective practices and procedures, as their performance is less likely to be attributable to chance. This analysis is supplementary and exploratory, involving multiple points of comparison, and thus focuses on the school level only. Future analyses will expand to explore district-level factors. For similar reasons, this study examines schoolwide residuals only and not subgroup residuals.

The ordinal logistic regression analysis relies upon the same set of school practices employed in the HLM analysis—variables related to school leadership and teacher experience, staffing and resource allocation, and school climate. The analysis to identify factors associated with the likelihood of being a “positive outlier” school did not model for school and neighborhood background, because that information is already embedded in the residuals (i.e., the residuals from phase one were a result of models based on school and neighborhood background).

The logistic regression analysis similarly took a stepwise approach. The first model looked at school leadership and teacher experience variables and staffing and resource allocation variables (e.g., teacher and administrator experience and ratios of support staff to students). The second model examined school climate variables. The third model was a combination of all variables. The discussion of the results focuses on the third model; the results of all models are detailed in Appendix 4. Readers are encouraged to peruse the details of the models.

To illustrate the findings, an “average school” serves as an anchor, where all independent variables are set to the sample mean. The results are presented based upon statistically significant changes in probabilities of this school’s performance being classified as “better” or “worse” than expected if there is a one-unit change (i.e., positively or negatively) in certain school practices, or “as expected” if the change is less than one unit.

The report closes by summarizing the findings across all models for the two research questions, begins to make sense of what they might mean, and discusses implications and considerations for future research.

Limitations

These methods do not allow for causal inferences. In other words, these methods do not permit the determination of whether a predictor caused the outcome. Pandemic-related disruptions are known to have triggered significant changes in student attendance and assessment, which might confound the relationships being measured. A myriad of other confounders could be identified. However, bias is alleviated by controlling for the school need index, which includes prior (2018–19) performance and other school composition variables. Prior performance is generally one of the strongest controls when studying academic outcomes in contexts where statistical bias is suspected.

A second limitation is that the analysis only studies the school year 2021–22. Longitudinal data extending into future school years would offer more robust insights into the consistency of the findings. While the project request targeted 2021–22 only, future studies could examine how factors change over time. Finally, while efforts were taken to ensure the accuracy of measures and minimize the impacts of missing data, the accuracy of the original New Jersey School Performance Reports data cannot be guaranteed. For example, it is unclear whether schools/districts accurately or consistently reported ratios of staff-to-students and suspension data.

Section 2: Studying Mean Achievement in English Language Arts – HLM Results

Variability between Districts and Schools – A Cross-model Examination

Roughly 74% of the variation in mean ELA achievement in the schoolwide model is between districts based on an unconditional model without any predictor variables. The subgroup models tended to have slightly more variability attributed to schools than the 74% in the schoolwide model, but across all subgroup models more than half of the variability in mean ELA achievement was still due to district factors. For Black students, Hispanic students, economically disadvantaged students, multilingual learners, and students with disabilities, the ICCs (i.e., the measures of variability between groups) were 65%, 64%, 53%, 53%, and 68% respectively. The fact that most of the variability is attributable to districts indicates that all the school factors studied (and those unstudied) will only have the potential to affect about 25%–40% of the variance in mean ELA achievement. It will therefore be important that future research carefully studies the district-level variables which are most consequential for reading outcomes, as the greatest impact will be among district levers.

Schoolwide

This discussion focuses on a comparison of Models 4 and 5 where interactions are added. Numerous variables have a detectable relationship with schoolwide mean ELA achievement, including demographic composition, grade level, school need, neighborhood socioeconomic status, school staffing and resource allocation, and proxy indicators of an unsupportive school climate. However, most do not have a substantial influence on mean ELA achievement. The school need index, which is a composite of several variables related to student demographics and academic proficiency, is the demographic variable with the most substantial influence on schoolwide mean ELA achievement; notably, greater school need is associated with lower mean ELA achievement (from Model 5, coef. = -0.116 , SE = 0.034 , $t = -3.25$).

Support staff variables also have substantial influence on mean ELA achievement, but an interesting picture emerges. In Model 4, the psychologist-to-student ratio has a positive, significant, and substantial influence on mean ELA achievement; on the other hand, higher counselor-to-student ratios in this sample of elementary and middle schools have a negative influence on mean ELA achievement. Controlling for the interaction between school demographic background (i.e., school need and percentage of students with disabilities) in

Model 5, the influence of the psychologist-to-student ratio varies depending on level of school need (Figure 1). The psychologist-to-student ratio and school need moderate one another, so that when the psychologist-to-student ratio increases with increased school need, their interaction has a significant, substantial, and positive influence on mean ELA achievement (coef. = 0.385, SE = 0.087, $t = 4.43$). In other words, for each additional psychologist per 100 students and school need level increase by one unit, that school’s mean ELA achievement increases by more than one-third of a standard deviation. Once this interaction is accounted for, there remains no independent influence of the psychologist-to-student ratio on mean ELA achievement. Again, in Model 5, the counselor-to-student ratio has a negative relationship with schoolwide mean ELA achievement (coef. = -0.460 ; SE = 0.170; $t = -2.70$). Increasing the social worker-to-student ratio also has a negative influence on student ELA achievement as school need increases (coef. = -0.196 , SE = 0.069, $t = -2.84$); (Figure 2, p. 15).

Figure 1: Interaction of School Psychologist-to-Student Ratio and School Need on Schoolwide Mean ELA Achievement

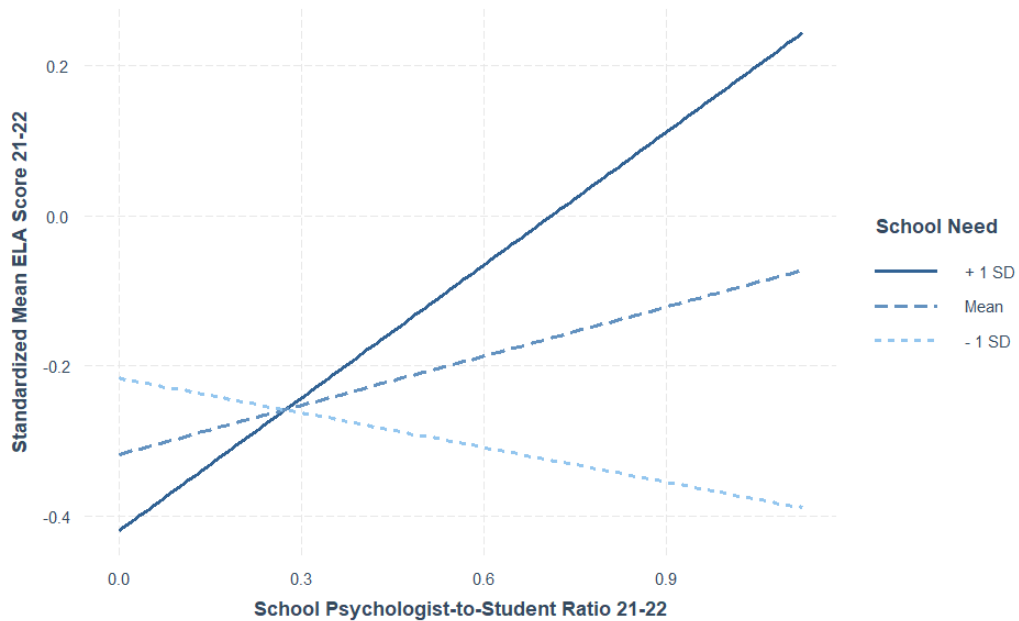
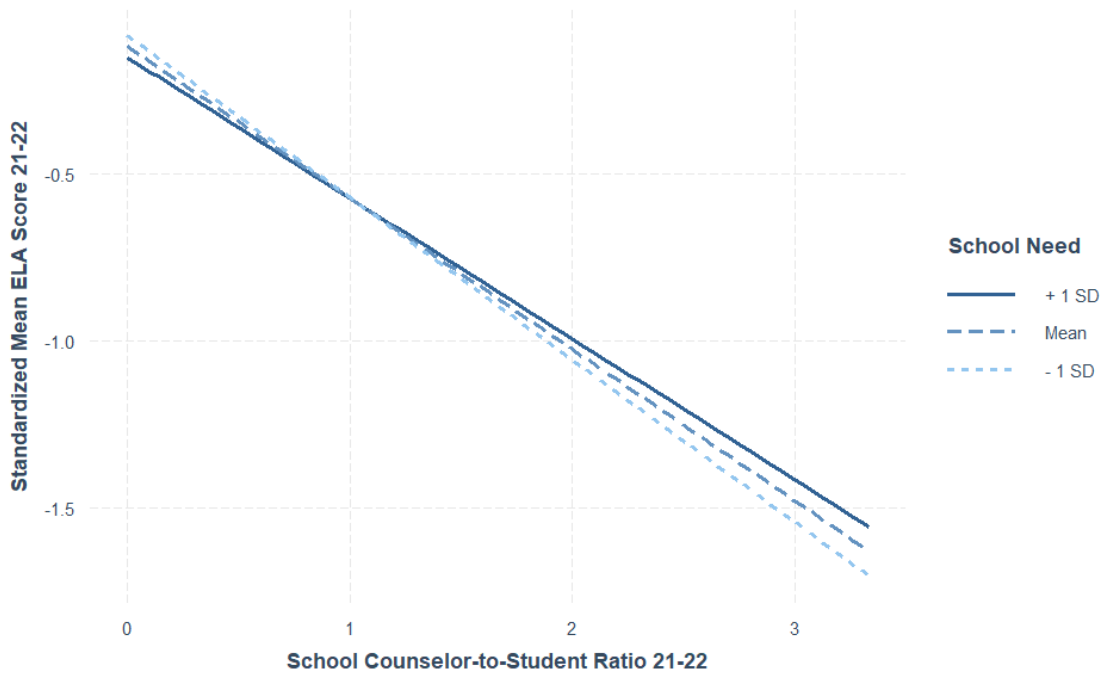


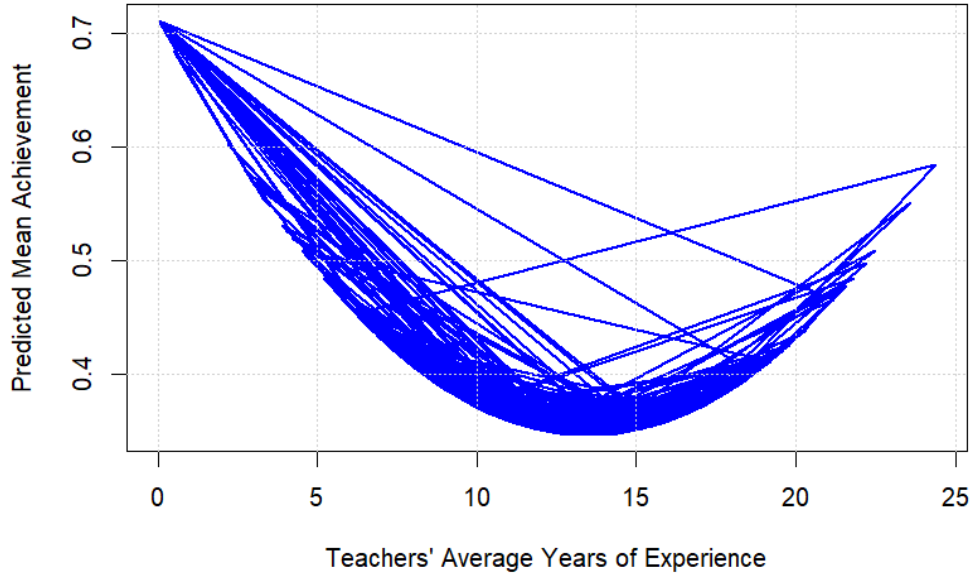
Figure 2: Interaction of Counselor-to-Student Ratio and School Need on Schoolwide Mean ELA Achievement



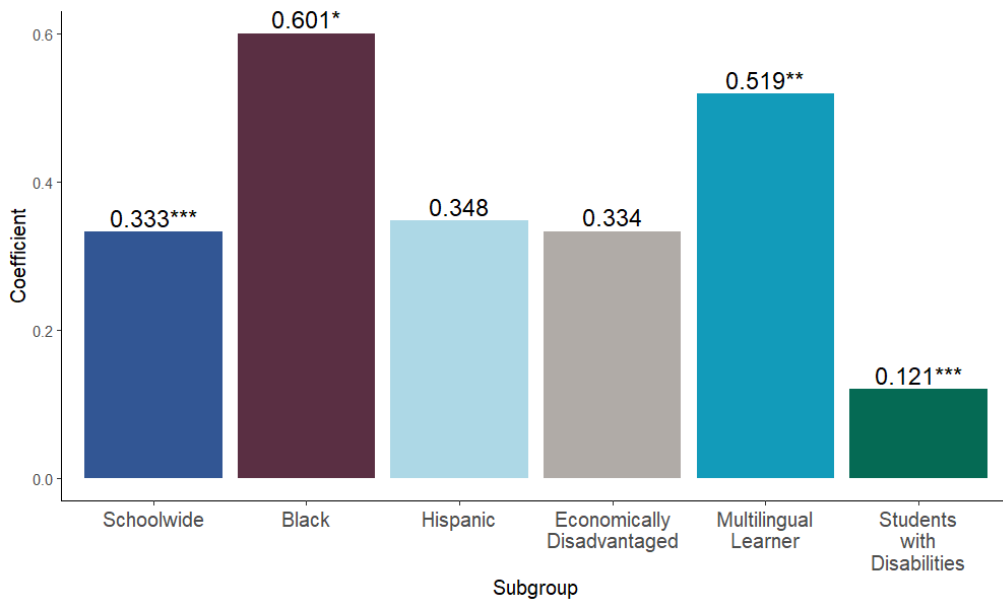
Other variables play a role in predicting mean ELA achievement schoolwide. Besides the psychologist-to-student ratio, increases in other staffing-related variables were associated with reduced mean ELA achievement schoolwide, but the coefficients were less substantial. From Model 4, these include the teacher-to-student ratio and years of teacher experience. The staffing-related variables with positive but less substantial influences are administrator retention in the district for at least one year and the quadratic term for years of teacher experience (i.e., suggesting that teachers at the higher end of the experience distribution have a positive influence on mean ELA achievement; Figure 3, p. 16). ELA mean achievement substantially increased with the grade levels in both Models 4 and 5 (from Model 4, Grade 6: coef. = 0.104, SE = 0.027, $t = 3.85$; Grade 7: coef. = 0.159, SE = 0.030, $t = 5.22$; and Grade 8: coef. = 0.167, SE = 0.030, $t = 5.50$).

Variables serving as proxies for an unsupportive school climate, such as in-school and out-of-school suspension rates and chronic absenteeism rates, were negatively associated with mean ELA achievement, but this inverse association with the outcome was weak. Detailed results for each subgroup will be discussed further below.

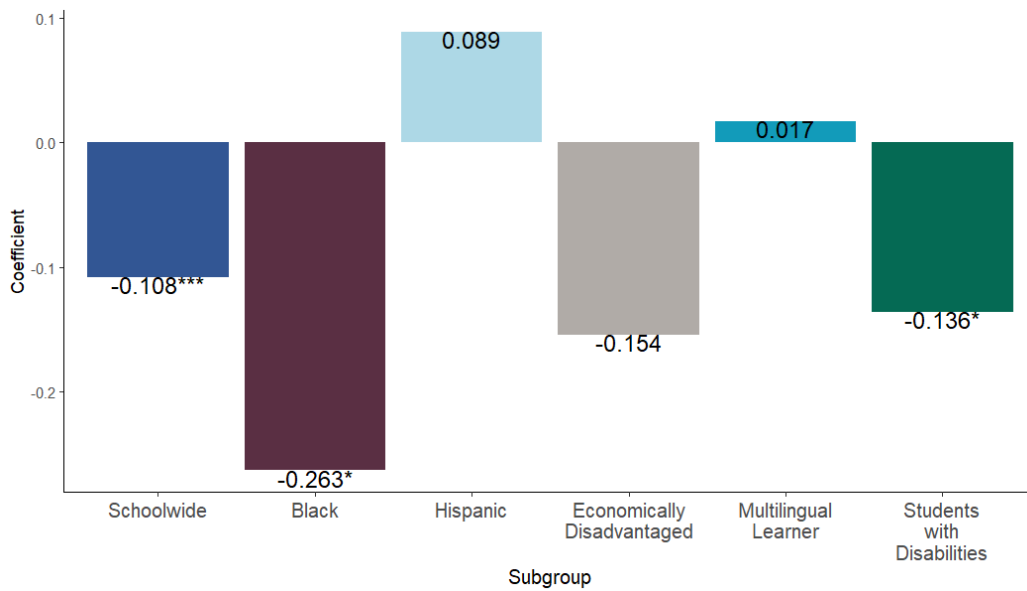
Figure 3: Relationship between Mean ELA Achievement and Teachers' Average Years of Experience



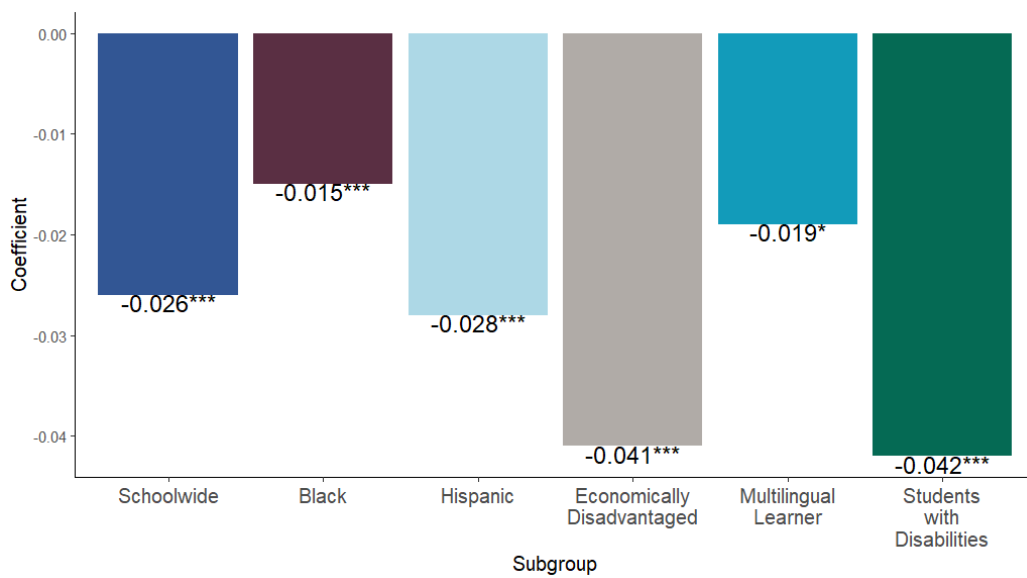
A1. Graph of Coefficients: Relationship between Psychologist-to-Student Ratio and Mean ELA Achievement among Subgroups of Students



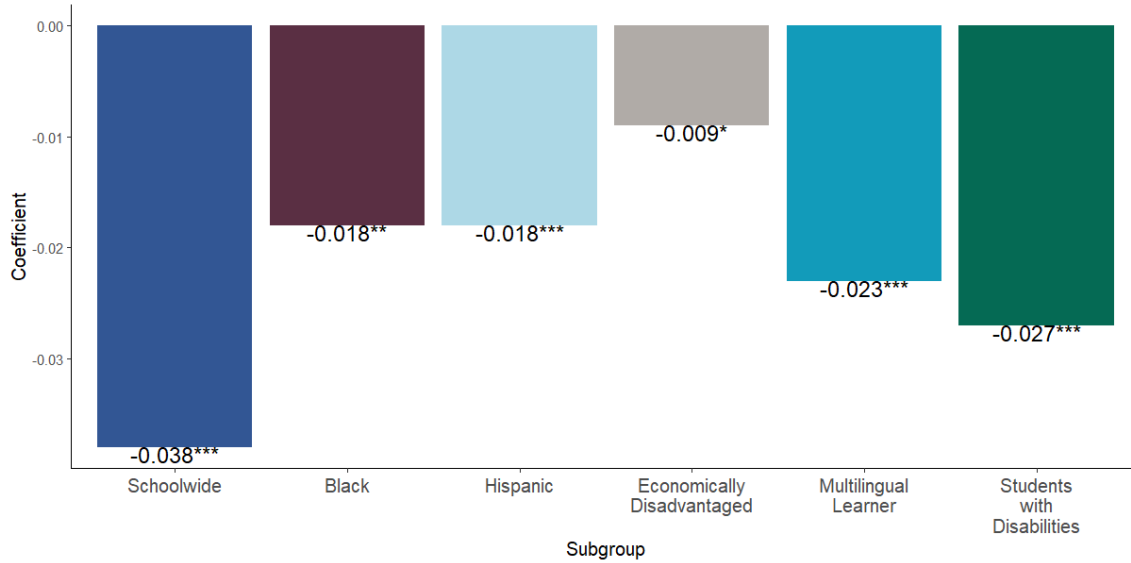
A2. Graph of Coefficients: Relationship between Counselor-to-Student Ratio and Mean ELA Achievement among Subgroups of Students



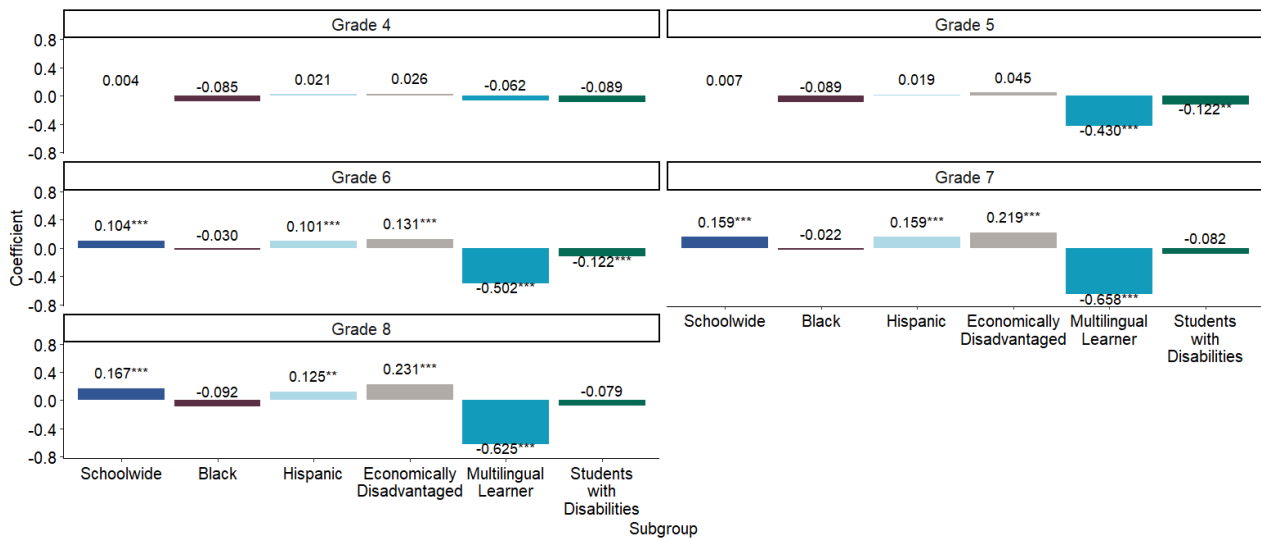
A3. Graph of Coefficients: Relationship between Schoolwide Out-of-School Suspension Rates and Mean ELA Achievement among Subgroups of Students



A4. Graph of Coefficients: Relationship between Schoolwide Chronic Absenteeism Rates and Mean ELA Achievement among Subgroups of Students



A5. Graph of Coefficients: Relationship between Grade Level and Mean ELA Achievement among Subgroups of Students



Student Subgroup Achievement

Black Students

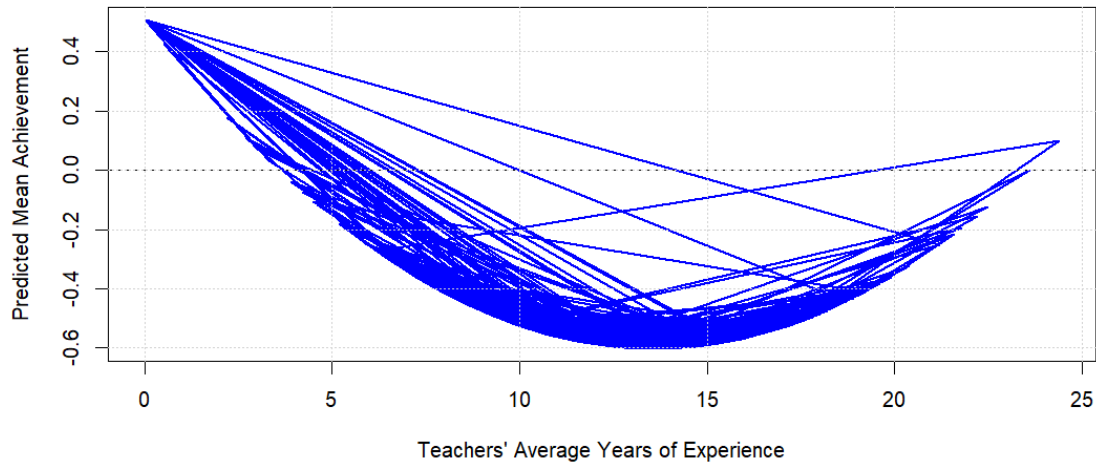
The picture changes somewhat when studying mean ELA achievement for Black students. Based upon the results of Model 4, the psychologist-to-student ratio positively influences Black students' ELA achievement; however, this influence is not at a statistically significant level. Though the result could be due to chance because it has not reached statistical significance, the coefficient would suggest that for every unit increase in the psychologist-to-student ratio (one more psychologist per 100 students), there is nearly one-half of a standard deviation increase in mean Black ELA achievement (coef. = 0.419, SE = 0.224, $t = 1.87$).

Here again, teachers' years of experience matter for mean ELA achievement for Black students; however, only when teachers' experience is at the higher end of the distribution does it have a positive influence (Figure 4, p. 20). This is indicated by the negative coefficient for teachers' years of experience (coef. = -0.163 , SE = 0.066, $t = -2.46$) and its positive quadratic term (coef. = 0.006, SE = 0.003, $t = 2.52$).

Figure 4 shows that initial increases in teachers' years of experience are associated with decreases in mean ELA achievement for Black students; however, when teachers' years of experience cross higher thresholds, the association shifts to a positive one. As with the schoolwide model, proxy indicators of negative school climate play a statistically significant but relatively insubstantial role in predicting mean ELA achievement. School need does not play a significant role for Black students' mean ELA achievement, nor does the increased achievement with grade progression.

Adding in the interaction variables between school context and support staff in Model 5 wipes out the marginal but positive influence of the psychologist-to-student ratio on Black students' mean ELA achievement. A significant interaction between school need and the psychologist-to-student ratio is observed but, unlike the schoolwide model, it is negative. This means that school need cancels out any positive influence of the psychologist-to-student ratio on Black mean ELA achievement. When both increase together, their influence is substantially reductive for Black mean ELA achievement (coef. = -0.583 , SE = 0.217, $t = -2.69$). A similar relationship between teachers' years of experience and Black mean ELA achievement remains in Model 5. The negative, though insubstantial, influence of indicators of unsupportive school climate also remains in Model 5.

Figure 4: Relationship between Black/African American Students’ Mean ELA Achievement and Teachers’ Average Years of Experience



Hispanic Students

As with mean Black students’ ELA achievement, according to Model 4, when studying mean ELA achievement among Hispanic students, proxy indicators of unsupportive school climate (i.e., out-of-school suspension and chronic absenteeism rates) are negatively associated, but their influence is not substantial. Like the models for Black students’ mean ELA achievement, school need does not significantly influence Hispanic students’ mean ELA achievement, nor does the psychologist-to-student ratio. No staffing-related variable emerges as significant for Hispanic students’ mean ELA achievement.

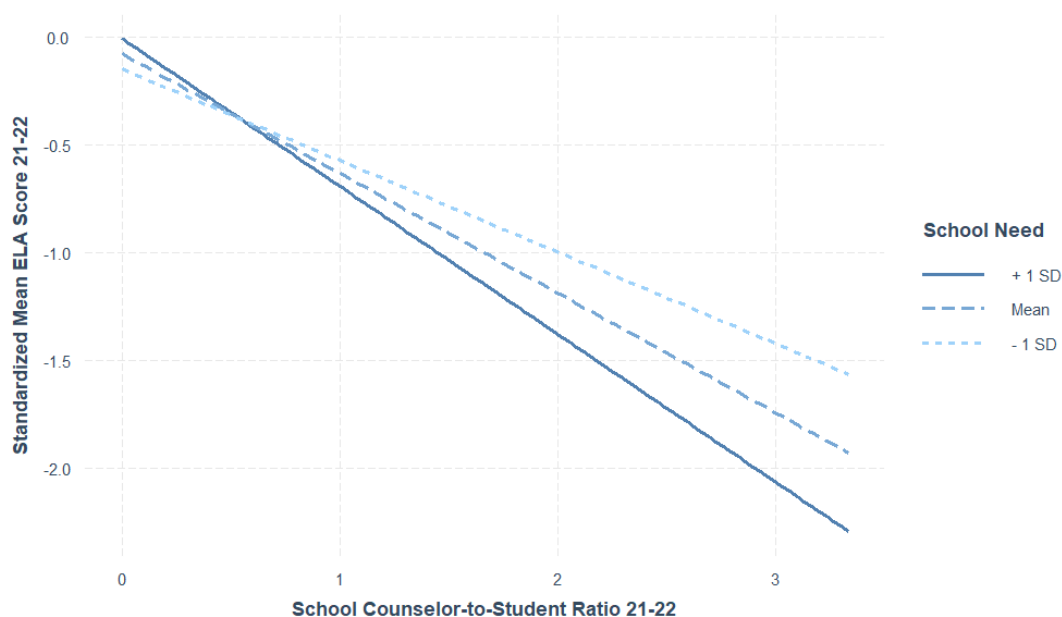
However, teachers’ years of experience approach—but do not reach—statistical significance and follow the same pattern as the other models, where only teachers’ years of experience at the higher end of the distribution have a positive influence. Importantly, the lack of significance means that this finding is not reliable for Hispanic students’ mean ELA achievement; nonetheless, it should be considered as it approaches significance. As with the schoolwide model, Hispanic student ELA achievement increases for the higher grades relative to Grade 3 achievement (from Model 4, Grade 6: coef. = 0.172, SE = 0.064, $t = 2.69$; Grade 7: coef. = 0.237, SE = 0.063, $t = 3.78$; and Grade 8: coef. = 0.141, SE = 0.069, $t = 2.06$).

When the interactions between support staff and contextual variables are added in Model 5, most of the findings remain consistent with a key change. The finding of increased mean achievement as grade level progresses remains, as does the marginal role of teachers’ years of experience. What changes in Model 5 is the addition of a prominent but negative relationship between the increased

counselor-to-student ratio and Hispanic students' mean ELA achievement. For every counselor added per 100 students in the school, Hispanic students' mean ELA achievement decreases by nearly two-thirds of a standard deviation (coef. = -0.596 , SE = 0.247 , $t = -2.42$).

At the same time, the interaction between the counselor-to-student ratio and the percentage of students with disabilities is significant (though not substantial) and positive; this suggests that when the counselor-to-student ratio and percentage of students with disabilities increase together, Hispanic students' mean ELA achievement increases slightly (coef. = 0.033 , SE = 0.012 , $t = 2.76$; Figure 5). This finding again points to the need to qualitatively understand how configurations of support staff influence ELA performance and how that relationship varies with school context. Along with a similar finding for the ratio of social workers to students in the schoolwide model, this finding raises the question of whether these dynamics signal anything about prioritization of resources, proximity of the positions to ELA instruction, and/or other explanations.

Figure 5: Interaction of Counselor-to-Student Ratio and School Need on Hispanic Students' Mean ELA Achievement



Economically Disadvantaged Students

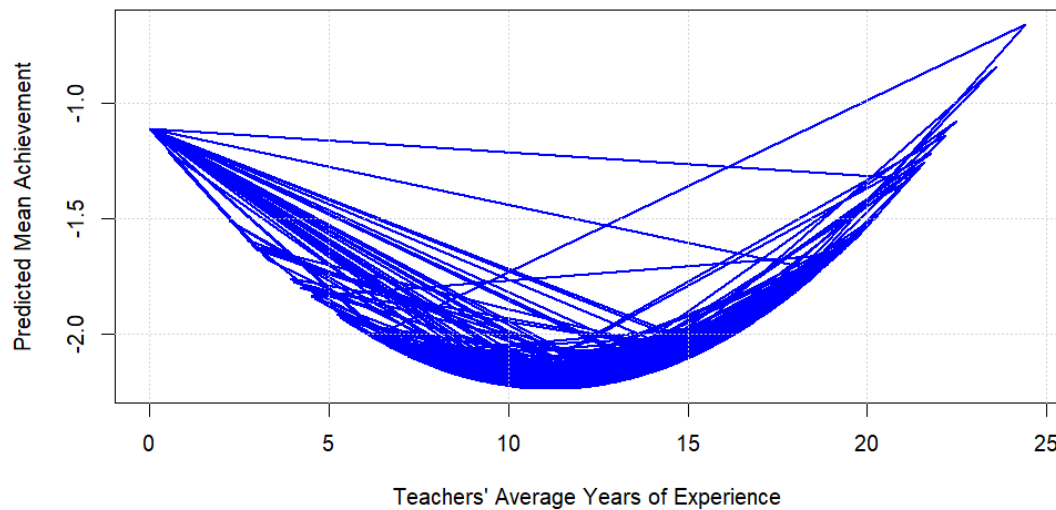
The modeled factors influencing economically disadvantaged students' mean ELA achievement are like the findings sprinkled across the models for schoolwide, Black students, and Hispanic students. Based on Model 4, proxy indicators of a less engaging school climate (i.e., out-of-school suspension and chronic absenteeism rates) have a negative association with mean ELA achievement for economically disadvantaged students—but their influence is not substantial when

all other variables in the model are controlled for. Here, too, ELA achievement for economically disadvantaged students increases at higher grade levels and the coefficients are substantial (Grade 6: coef. = 0.202, SE = 0.080, $t = 2.52$; Grade 7: coef. = 0.371, SE = 0.090, $t = 4.14$; Grade 8: coef. = 0.496, SE = 0.088, $t = 5.64$). School need is not associated with mean ELA achievement for economically disadvantaged students.

The staffing variables also reflect some of the previous patterns, but not always. Teachers’ years of experience had a substantial influence on mean ELA achievement for economically disadvantaged students, but not linearly. While the linear term alone suggests that an initial increase in teachers’ years of experience is associated with decreases in achievement for economically disadvantaged students, adding a quadratic term reveals that more years of experience is associated with slight increases in mean ELA achievement for economically disadvantaged students (Figure 6).

This finding is indicated by the significant negative coefficient for teachers’ years of experience (coef. = -0.201 , SE = 0.049, $t = -4.12$) and the insubstantial but positive coefficient for its quadratic term (coef. = 0.009, SE = 0.002, $t = 4.68$). Unlike the models for schoolwide and other subgroups, the social worker-to-student ratio has a positive influence on mean ELA achievement for economically disadvantaged students in Model 4 (coef. = 0.349, SE = 0.142, $t = 2.46$).

Figure 6: Relationship between ELA Achievement and Teachers’ Average Years of Experience Among Economically Disadvantaged Students



Many of the same associations remain when the interactions between support staff and contextual variables are added in Model 5 (which adds interactions between support staff and two context variables—school need and students with disabilities). For example, the relationships between

teacher experience, grade level, and mean ELA achievement hold in the same manner. There are two notable changes in Model 5, however. First, the influence of the social worker-to-student ratio nearly triples so that for every additional social worker hired per 100 students, mean ELA achievement for economically disadvantaged students increases by one and a half standard deviation units (coef. = 1.500, SE = 0.369, $t = 4.04$). However, when enrollments of students with disabilities increase, the 'effect' of the social worker-to-student ratio is slightly reduced as indicated by the negative interaction term (coef. = -0.054 , SE = 0.017, $t = -3.25$; Figure 7). Second, a moderated influence of the psychologist-to-student ratio emerges so that when the psychologist-to-student ratio increases with the percentage of students with disabilities, a positive influence is present (coef. = 0.075, SE = 0.017, $t = 4.28$); otherwise, increasing the psychologist-to-student ratio has a largely negative influence (coef. = -1.334 , SE = 0.406, $t = -3.29$; Figure 8, p. 24).

Figure 7: Interaction of Social Worker-to-Student Ratio and Percentage of Students with Disabilities and Economically Disadvantaged Students on Mean ELA Achievement

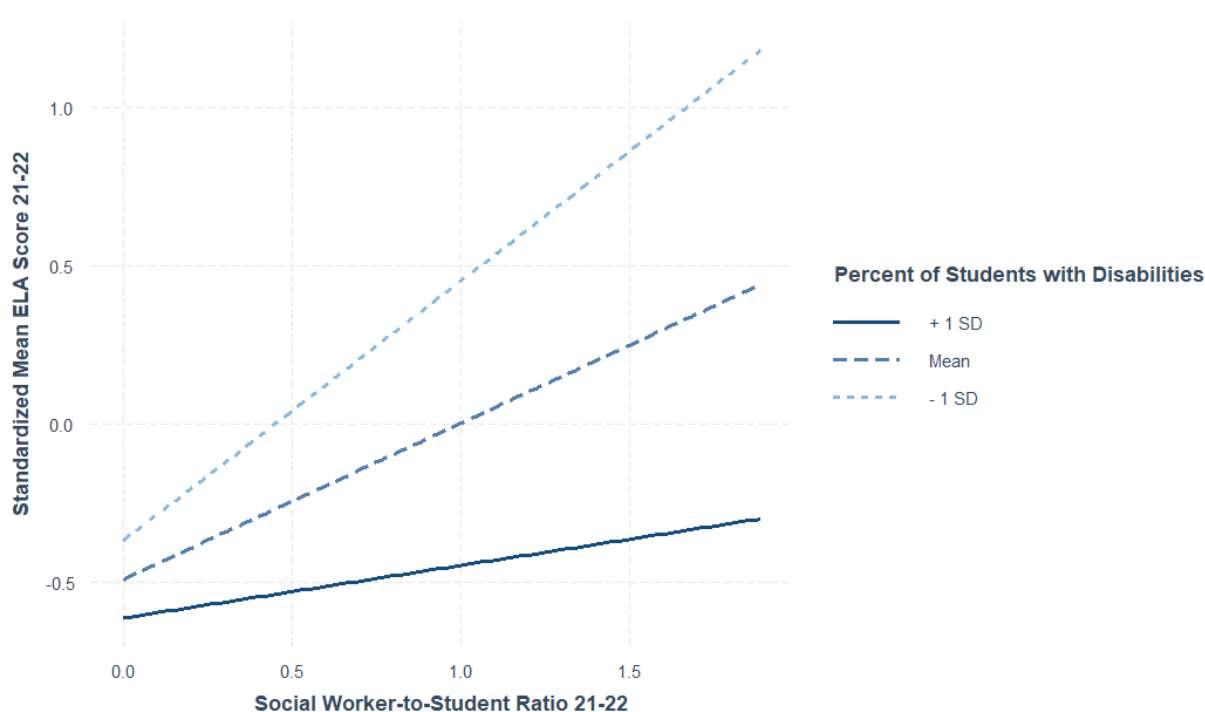
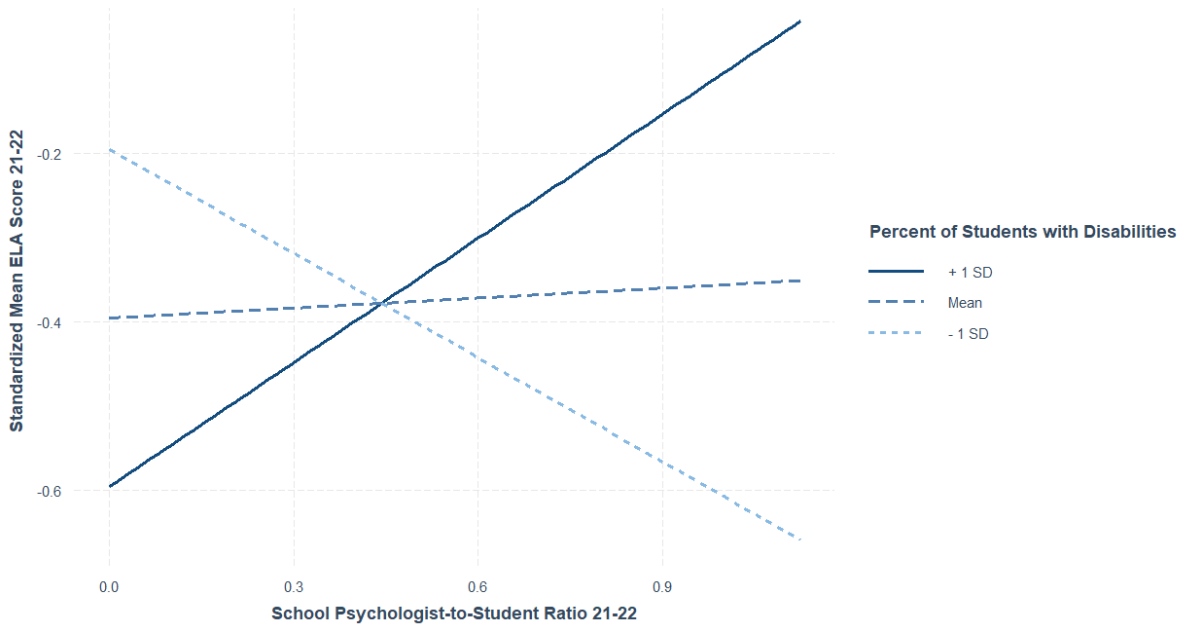


Figure 8: Interaction of School Psychologist-to-Student Ratio and Percentage of Students with Disabilities and Economically Disadvantaged Students on Mean ELA Achievement



Multilingual Learners (MLs)

Based on Model 4, which does not include the interactions between support staff and school context, multilingual learners’ mean ELA achievement is most strongly associated with grade level, administrator-to-student ratio, and psychologist-to-student ratio. In this model, however, ELA achievement for MLs substantially decreased as grade level increased, so that fifth and sixth grades’ ELA achievement was around one-third of a standard deviation below third grade mean ELA achievement, and seventh and eighth grades’ ELA achievement was half of a standard deviation below third grade ELA achievement (Grade 5: coef. = -0.339 , SE = 0.086 , t: -3.96 ; Grade 6: coef. = -0.402 , SE = 0.095 , t: -4.23 ; Grade 7: coef. = -0.515 , SE = 0.108 , t: -4.78 ; Grade 8: coef. = -0.517 , SE = 0.109 , t: -4.73).

Unlike most other models, the administrator-to-student ratio had a significant and substantial negative influence on MLs’ mean ELA achievement (coef. = -0.215 , SE = 0.081 , t: -2.64). The psychologist-to-student ratio is the main positive predictor in this model, having a substantial (nearly half a standard deviation unit) influence on multilingual students’ mean ELA achievement (coef. = 0.455 , SE = 0.223 , t = 2.04). Proxy indicators of a less engaging school climate (i.e., out-of-school suspension and chronic absenteeism rates) have a negative impact on mean ELA achievement among MLs, but their influence is not substantial when all of the other variables in the model are controlled for. Unlike the models for all of the other groups, school need is not a significant predictor of multilingual students’ mean ELA achievement.

In Model 5, where interactions between support staff and school context (i.e., school need and percentage of students with disabilities) are controlled for, the positive influence of the psychologist-to-student ratio is wiped out in that it becomes negative and loses statistical significance. However, it becomes clear that the positive influence of the psychologist-to-student ratio is moderated by the percentage of students with disabilities who are enrolled in the school, so when both increase, mean ELA achievement for MLs also increases by a small margin (coef. = 0.045, SE = 0.024, $t = 1.89$; Figure 9). This finding, however, only approaches and does not reach statistical significance. An interaction between the school need level and the ratio of counselors to students also emerges as significant but, as before, has a substantially negative influence on mean ELA achievement for MLs (coef. = -0.478 , SE = 0.231, $t = -2.07$; Figure 10, p. 26).

Figure 9: Interaction of School Psychologist-to-Student Ratio and Percentage of Students with Disabilities and Multilingual Learners on Students' Mean ELA Achievement

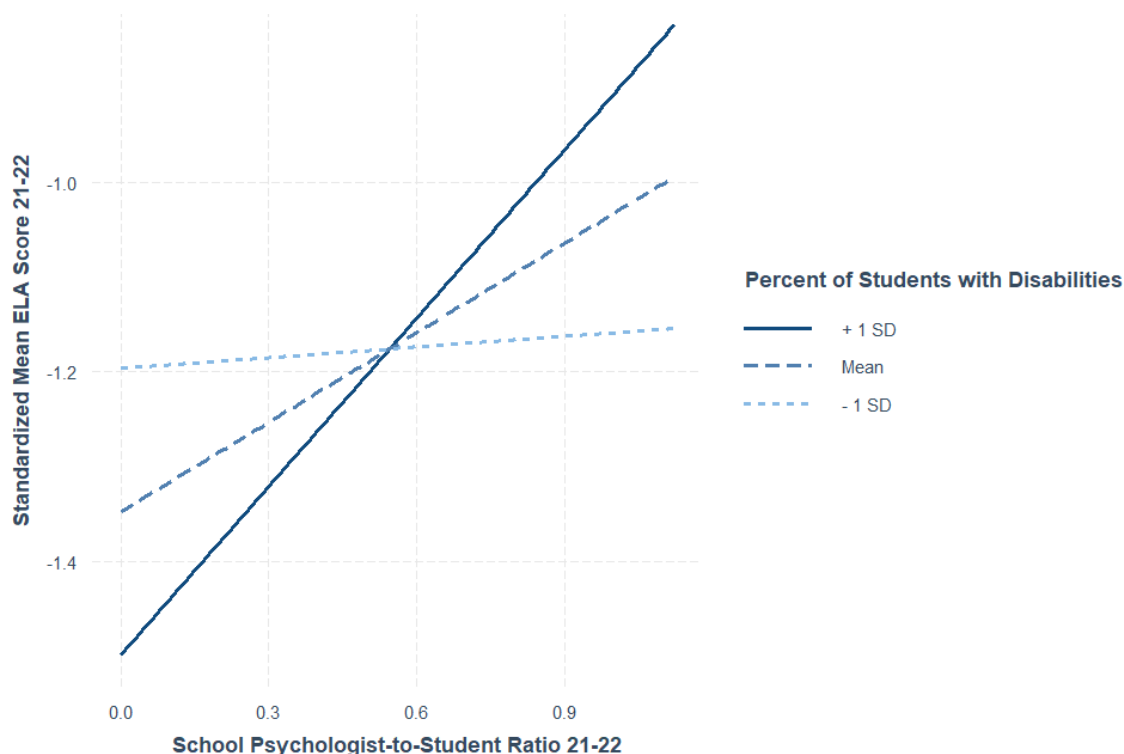
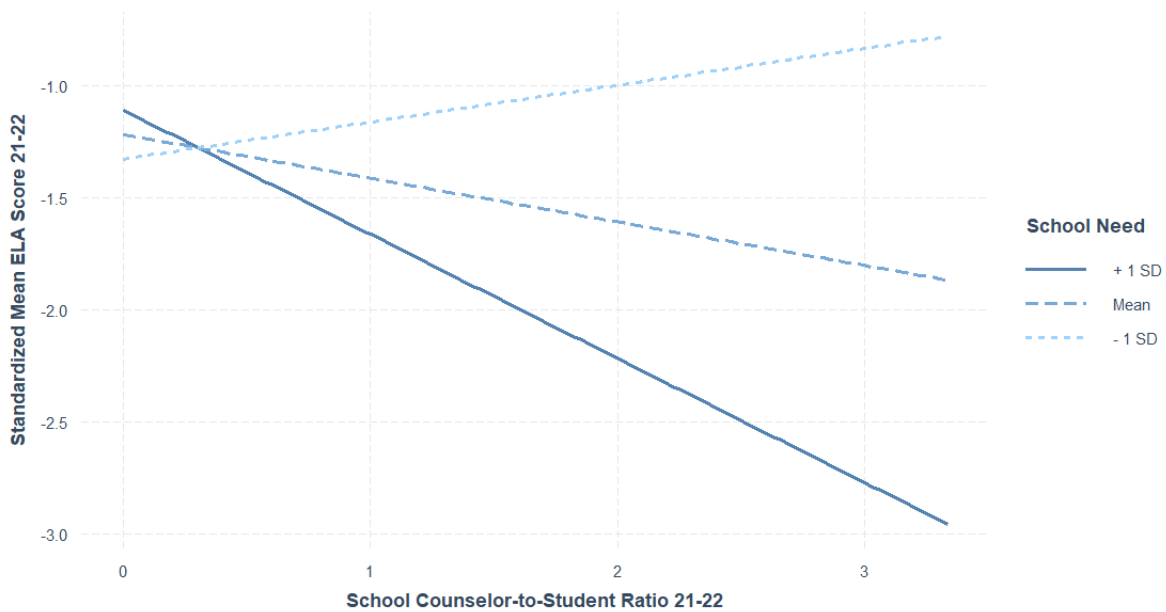


Figure 10: Interaction of School Counselor-to-Student Ratio and School Need on Multilingual Learner Students' Mean ELA Achievement

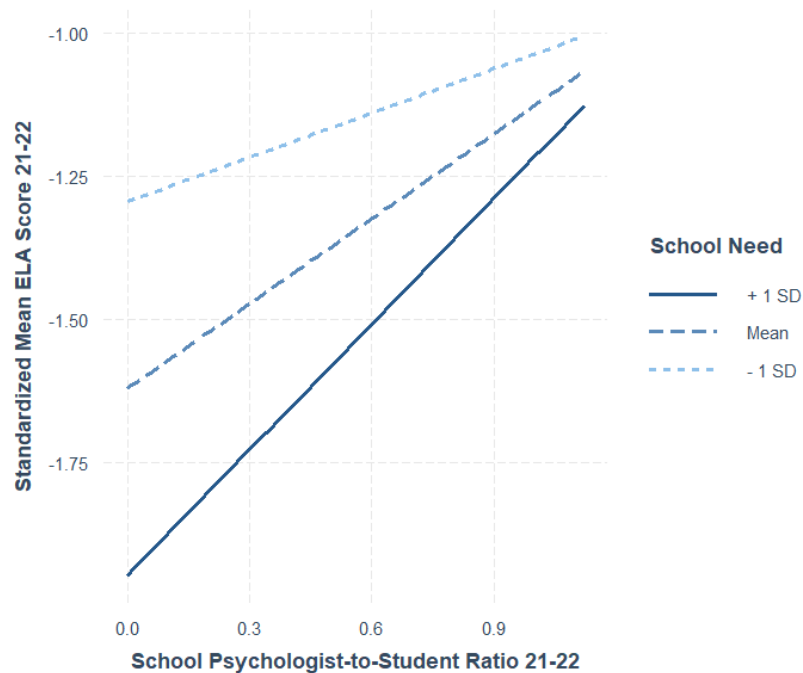


Students with Disabilities (SWDs)

Based on the results of Model 4, both school need and the psychologist-to-student ratio have a substantial influence on mean ELA achievement for students with disabilities (SWDs), but in opposite directions. SWDs are the only subgroup for which the school need index plays such a strong role (coef. = -0.258, SE = 0.033, t: -7.76). The psychologist-to-student ratio adds a substantial, positive association with mean achievement for SWDs (coef. = 0.385, SE = 0.148, t = 2.61). A similar pattern of decreasing achievement among SWDs as they reach higher grade levels is observed as with the model for multilingual students, but only the coefficient for Grade 5 was statistically significant (Grade 5: coef. = -0.127, SE = 0.053, t: -2.37). Proxy indicators of unsupportive school climate are also negatively associated with mean ELA achievement for SWDs but, here too, their influence is not substantial given other factors in the model.

In Model 5, where interactions between support staff and school context are controlled for, the positive influence of the psychologist-to-student ratio is now only present in its interaction with school need. The psychologist-to-student ratio is moderated by school need so that when both increase, mean ELA achievement for SWDs also increases (coef. = 0.243, SE = 0.127, t = 1.91; Figure 11, p.27). This finding, however, only approaches and does not reach statistical significance.

Figure 11: Interaction of School Psychologist-to-Student Ratio and School Need on Mean ELA Achievement Among Students with Disabilities



English Language Arts (ELA) Results Summary

The primary aim of this analysis was to identify school practices that may be leveraged to improve mean ELA achievement and mitigate the role of historical disadvantage. The analyses highlight the complex interplay between school demographics, staffing configurations, school climate, and contextual variables on mean ELA achievement schoolwide and for the five subgroups of interest.

Staffing-related variables tend to have the strongest association with mean ELA achievement. The psychologist-to-student ratio tends to positively influence achievement, but its influence is typically moderated by school need or by the percentage of students with disabilities enrolled. Among students schoolwide and for economically disadvantaged students, multilingual learners, and students with disabilities, this moderation still retains a positive influence on mean ELA achievement, but the opposite is true for Black students. For Hispanic students, it is the counselor-to-student ratio which has that positive role only when moderated; otherwise, the counselor-to-student ratio does not have a positive influence for any other group.

Similarly, the social worker-to-student ratio has a strong positive influence on mean achievement for economically disadvantaged students, but not for any other subgroup. Larger ratios of school administrators to students are also associated with lower ELA achievement for multilingual learners. Teachers' average years of experience also play a positive role in ELA achievement

for students schoolwide, Black students, Hispanic students, and economically disadvantaged students, with a nuanced U-shaped relationship showing slight gains associated with highly experienced teachers, but not from increases in teacher experience during their early years of service. These findings suggest a need to re-evaluate optimal staffing configurations in various school contexts and to understand the mechanisms behind psychologists', social workers', counselors', and administrators' influence on ELA outcomes.

Higher levels of school need are consistently associated with a substantial negative influence on mean ELA achievement, but such influence is only detectable in the models for students schoolwide and for students with disabilities. ELA achievement improves at higher grade levels for most groups, except for multilingual learners and students with disabilities, whose achievement declines in higher grades. Indicators of unsupportive school climate were also associated with lower ELA achievement; however, as measured, their role was weak compared to the key staffing and resource allocation variables.

Section 3: Studying Mean Achievement in Mathematics – HLM Results

Variability between Districts and Schools – A Cross-model Examination

Like the ELA model, 75% of the variation in mean math achievement schoolwide is attributable to district-level factors, rather than differences within schools. The subgroup models tended to show slightly more variability within schools compared to the schoolwide model. While both models include district-level factors, less of the variation in mean achievement is attributed to the influence of districts in the subgroup models. Nonetheless, across all subgroup models, more than half of the variability in mean math achievement could still be attributed to district factors. For Black students, Hispanic students, economically disadvantaged students, multilingual learners, and students with disabilities, the ICCs (i.e. the measures of variability between groups) were 65%, 66%, 53%, 64%, and 65% respectively.

Schoolwide

Like the schoolwide analysis on mean ELA achievement, several variables have a detectable relationship with mean schoolwide math achievement including demographic composition, grade level, school need, neighborhood socioeconomic status, school staffing and resource allocation, and proxy indicators of unsupportive school climate. Consistent with ELA findings, most variables do not have a substantial influence on mean math achievement. Largely, findings were consistent across early models in the stepwise regression, including Model 1 (controlling for student demographic composition, grade level, school need, and neighborhood socioeconomic status alone); Model 2 (adding school staffing and resource allocation to the base demographic model); and Model 3 (adding proxies for an unsupportive school climate to the base demographic model).

Model 5 (extending the cumulative Model 4 by adding interaction effects) revealed significant interaction effects between school staffing variables and school need. Among school support staff, the ratios of counselors to students (coef. = -0.355 , SE = 0.177 , $t = -2.01$) and teachers to students (coef. = -0.025 , SE = 0.007 , $t = -3.63$) were negatively associated with mean math achievement. School need (coef. = -0.110 , SE = 0.034 , $t = -3.22$) was also significantly negatively associated with mean math achievement. Notable interaction effects included the combination of school need and psychologist-to-student ratio (coef. = 0.658 , SE = 0.084 , $t = 7.84$; Figure 12, p. 30) and the combination of school need and counselor-to-student ratio (coef. = -0.381 , SE = 0.075 , $t = -5.07$).

These results suggest that while larger psychologist-to-student ratios help mitigate the negative effects of school need on mean math achievement in high-need schools, larger counselor-to-student ratios may indicate additional challenges, such as the need to address greater levels of student need. These findings highlight the importance of targeted resource allocation. Indeed, simply increasing staffing ratios may not yield significant math achievement unless paired with comprehensive policies and practices addressing students' needs.

Proxies for an unsupportive school climate (i.e., suspension and chronic absenteeism rates) showed significant associations with mean math achievement. Higher out-of-school suspension rates (coef. = -0.041, SE = 0.004, t = -9.61; Figure B3, p. 32) and chronic absenteeism rates (coef. = -0.025, SE = 0.003, t = -9.36; Figure B4, p. 33) were linked to lower mean math achievement, with schools reporting higher rates generally performing worse. These findings suggest that addressing absenteeism and reducing reliance on punitive discipline practices could be a pathway to improving academic outcomes.

In terms of school composition, grade-level indicators had the strongest associations with mean math achievement. Compared to the baseline of third-grade students, sixth- and seventh-grade students showed significantly higher achievement, with the largest gains observed in seventh grade (Grade 6: coef. = 0.151, SE = 0.031, t = 4.94; Grade 7: coef. = 0.201, SE = 0.037, t = 5.45). The eighth-grade to third-grade comparison was also positively correlated with mean math achievement; however, it did not reach statistical significance.

Figure 12: Interaction of School Psychologist-to-Student Ratio and School Need on Schoolwide Mean Math Achievement

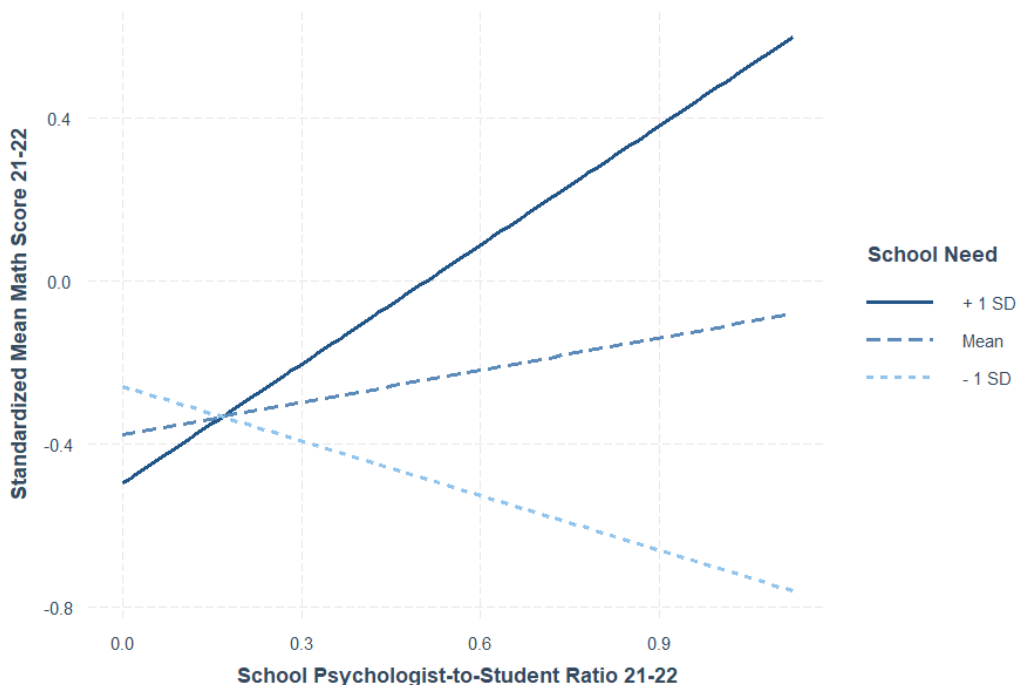
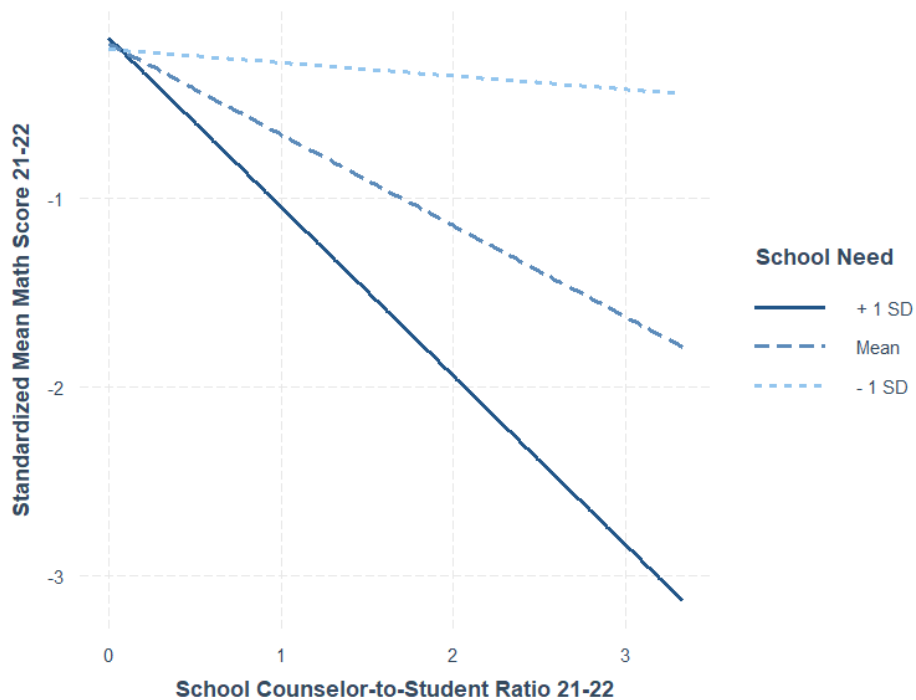
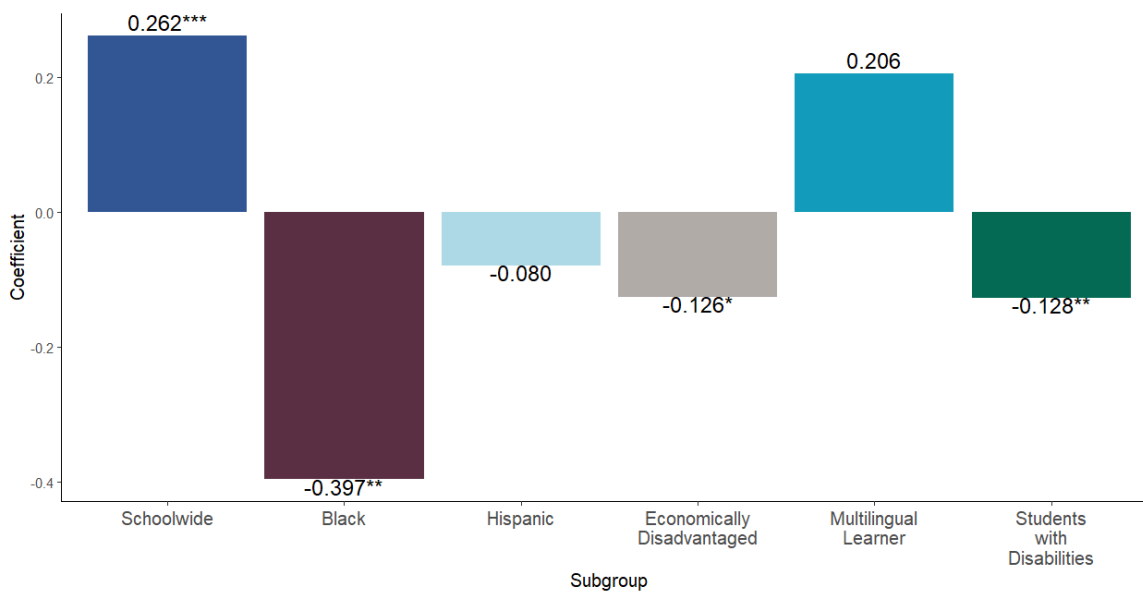


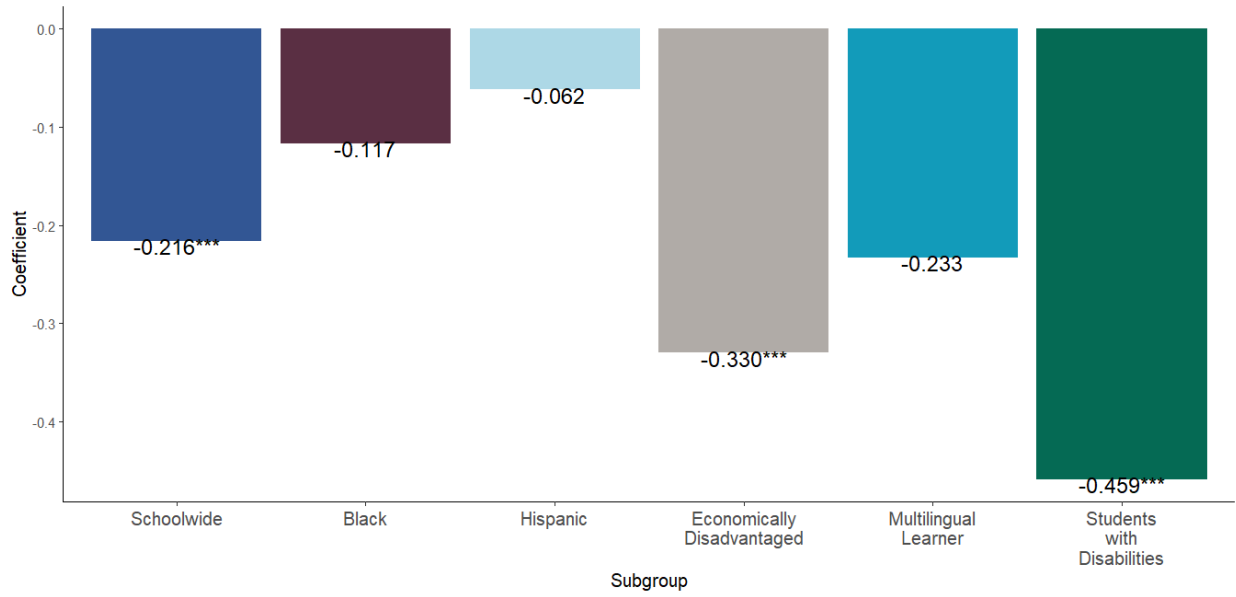
Figure 13: Interaction of School Counselor-to-Student Ratio and School Need on Schoolwide Mean Math Achievement



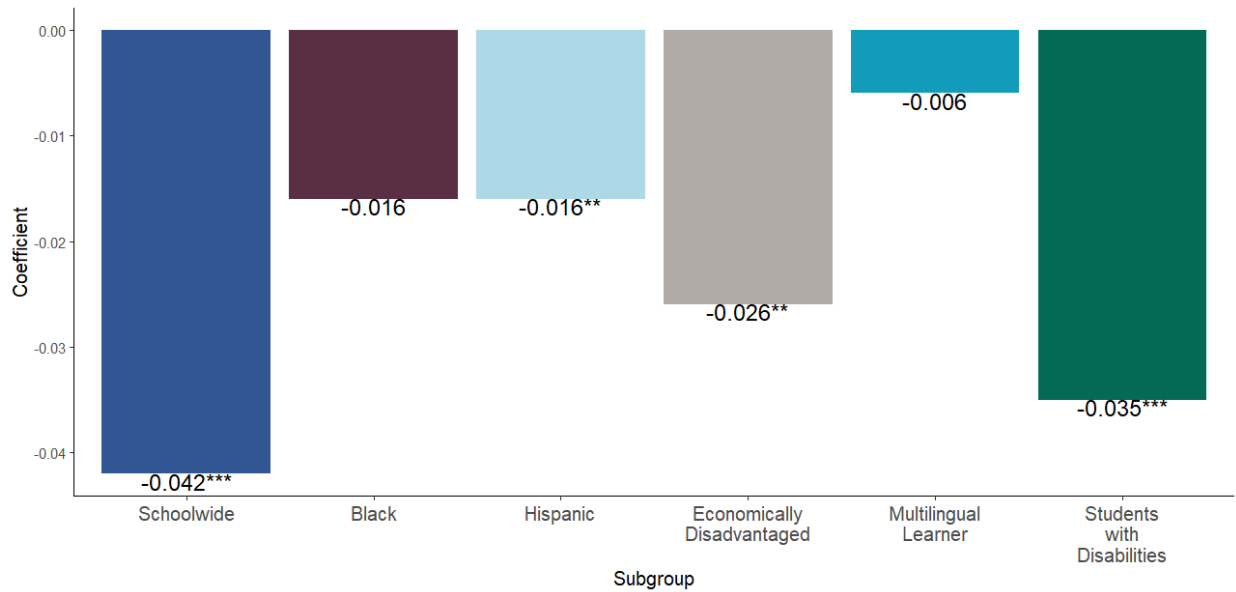
B1. Graph of Coefficients: Relationship between Psychologist-to-Student Ratio and Mean Math Achievement among Subgroups of Students



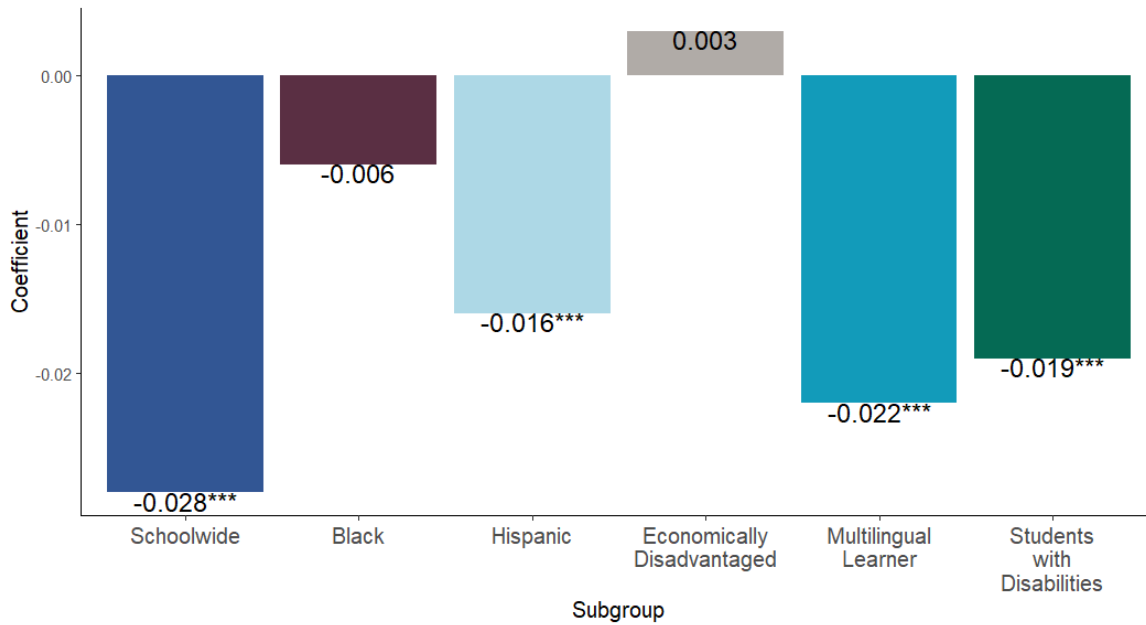
B2. Graph of Coefficients: Relationship between Counselor-to-Student Ratio and Mean Math Achievement among Subgroups of Students



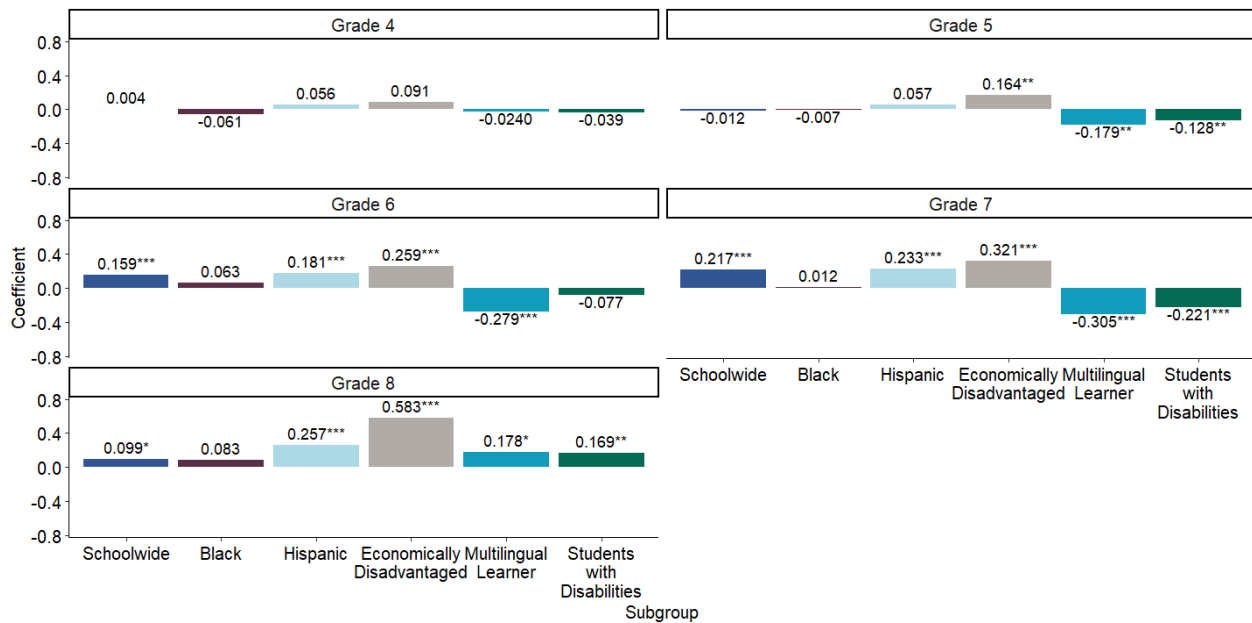
B3. Graph of Coefficients: Relationship between Schoolwide Out-of-School Suspension Rate and Mean Math Achievement among Subgroups of Students



B4. Graph of Coefficients: Relationship between Schoolwide Chronic Absenteeism Rates and Mean Math Achievement among Subgroups of Students



B5. Graph of Coefficients: Relationship between Grade Level and Mean Math Achievement



Student Subgroup Achievement

Black Students

Significant findings for the subgroup analysis on Black student math achievement highlighted the influence of student demographic composition, grade level, school need, neighborhood socioeconomic status, school staffing and resource allocation, and school climate.

According to Model 4, the psychologist-to-student ratio significantly and positively influences Black student math achievement (coef. = 0.457, SE = 0.189, $t = 2.41$). However, when accounting for interaction effects in Model 5, the direction of the relationship shifts, with the psychologist-to-student ratio now significantly and negatively influencing Black student math achievement. For every unit increase in the psychologist-to-student ratio (one more psychologist per 100 students), there is nearly a 1.5-point decrease in Black students' mean math achievement (coef. = -1.469, SE = 0.448, $t = -3.14$). The administrator-to-student ratio, too, is associated with a slight reduction in Black students' mean math achievement (coef. = -0.227, SE = 0.072, $t = -3$). Significant interaction effects add additional details to this finding. The psychologist-to-student ratio interacts positively with the percentage of students with disabilities (coef. = 0.087, SE = 0.020, $t = 4.38$; Figure 14, p. 35). Conversely, the psychologist-to-student ratio interacts negatively with school need (coef. = -0.498, SE = 0.183, $t = -2.72$; Figure 15, p. 35), indicating that adding psychologists may not be helpful to elevating Black student math achievement in high-need schools. The positive interaction between psychologist ratios and the percentage of students with disabilities suggests that targeted support for vulnerable subgroups may be more impactful than increasing psychologists broadly.

Differing from schoolwide findings related to proxies for an unsupportive school climate, schoolwide out-of-school suspension rates and schoolwide chronic absenteeism rates were not significantly associated with Black student math achievement. In this subgroup model, Black student absenteeism rates are significantly and negatively associated with mean math achievement (coef. = -0.011, SE = 0.001, $t = -7.39$), indicating that this subgroup-specific metric matters more for Black students than in schoolwide metrics (Figure B3, p. 32; Figure B4, p. 33).

Figure 14: Interaction of School Psychologist-to-Student Ratio and Percentage of Students with Disabilities on Black Students' Mean Math Achievement

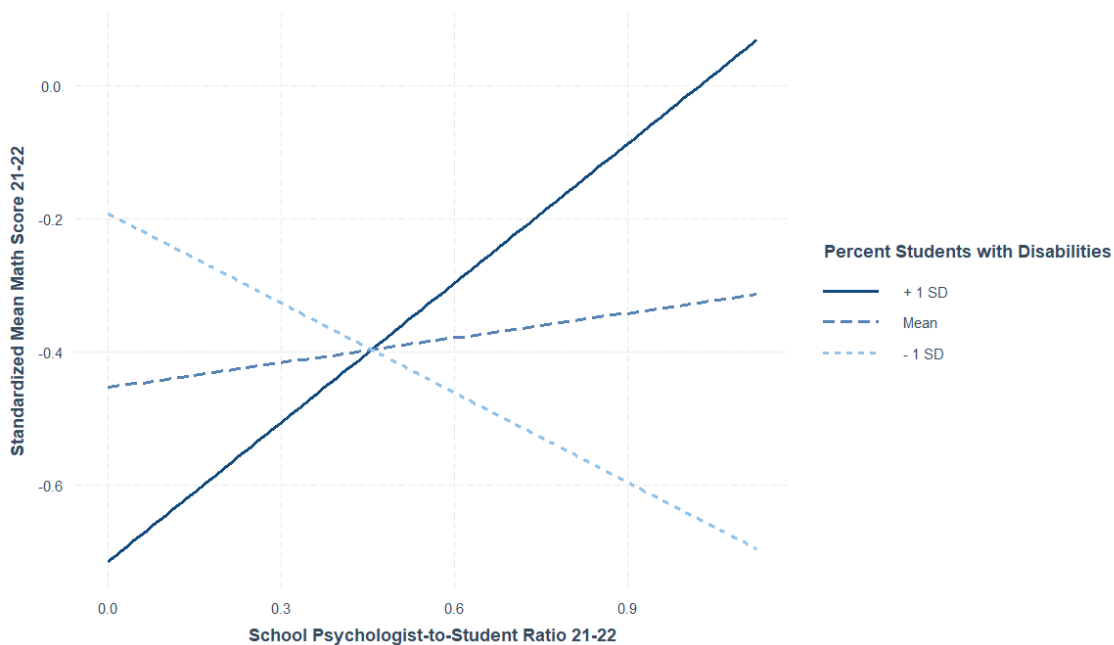
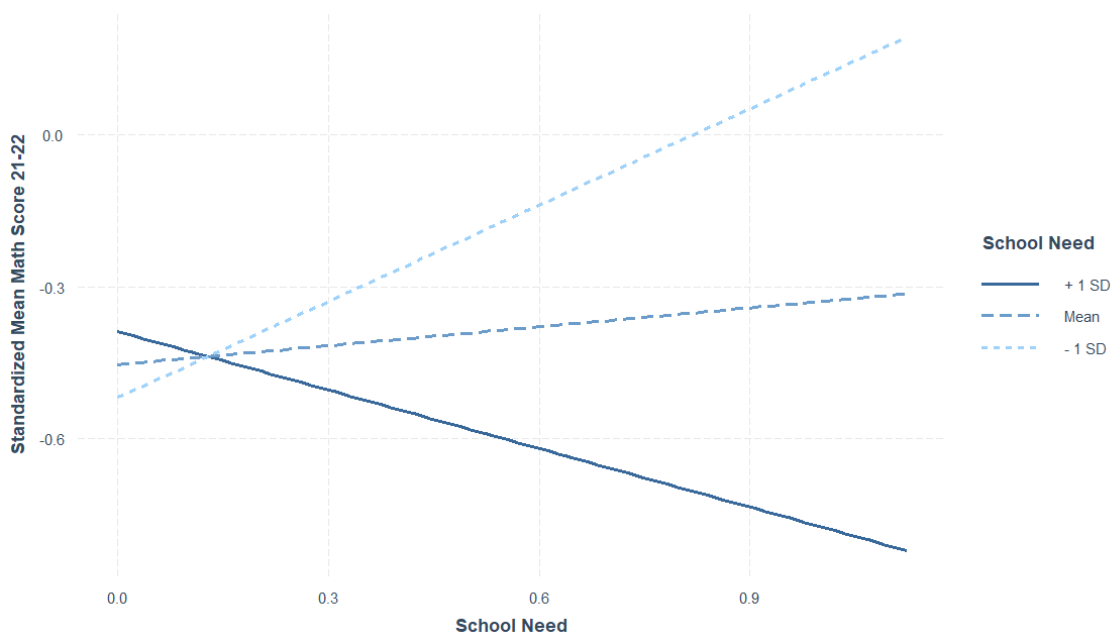


Figure 15: Interaction of School Psychologist-to-Student Ratio and School Need on Black Students' Mean Math Achievement



Hispanic Students

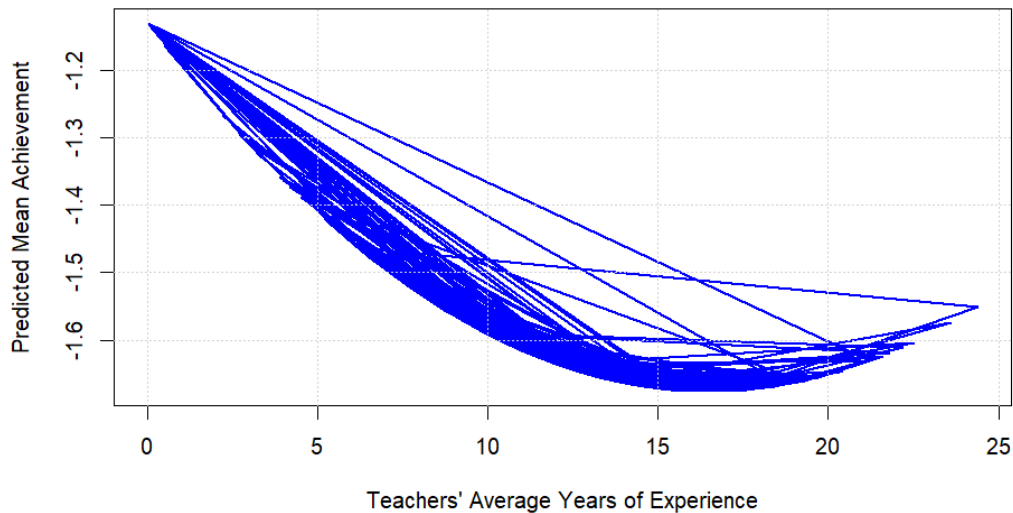
Significant findings for the subgroup analysis of Hispanic student math achievement highlighted the influence of student demographic composition, grade level, school staffing and resource allocation, and school climate. School need had a significant negative relationship with Hispanic math achievement in Model 4 (coef. = -0.081 , SE = 0.036 , $t = -2.24$) but not in Model 5 with interaction effects. That is, the impact of school need on Hispanic student math achievement is mitigated by the relationship between school need and school support staffing decisions.

The most pronounced Model 5 finding in the subgroup analysis of Hispanic students is the consistent year-after-year increase of sixth through eighth grade math scores. Compared with the baseline comparison group (third-grade Hispanic students), Hispanic students in higher school grades tend to have significantly higher average math achievement, and the improvement is larger as grade levels increase (Grade 6: coef. = 0.181 , SE = 0.055 , $t = 3.32$; Grade 7: coef. = 0.233 , SE = 0.060 , $t = 3.91$; and Grade 8: coef. = 0.257 , SE = 0.075 , $t = 3.44$).

There are unique school resource and staffing findings related to Hispanic student math achievement. Hispanic students' math achievement was higher for schools with higher per-pupil spending levels (coef. = 0.143 , SE = 0.060 , $t = 2.41$). The effect of teacher experience for Hispanic students follows the same non-linear pattern. On average, as a school's average years of teaching experience increases (coef. = -0.072 , SE = 0.035 , $t = -2.08$), math scores decrease (Figure 16, p. 37). The curvilinear relationship is present but less prominent: Mean math achievement is highest among mid- and later-career teachers (around 15–25 years of experience) and rises slightly for late-career teachers (around 25 years of experience) as indicated by the small, marginally significant, but positive quadratic term (coef. = 0.003 , SE = 0.001 , $t = 1.97$).

Schoolwide out-of-school suspension rates (coef. = -0.014 , SE = 0.007 , $t = -1.99$) and schoolwide chronic absenteeism rates (coef. = -0.015 , SE = 0.003 , $t = -4.35$) were negatively associated with Hispanic student math achievement.

Figure 16: Relationship between Mean Math Achievement and Teachers' Average Years of Experience for Hispanic Students

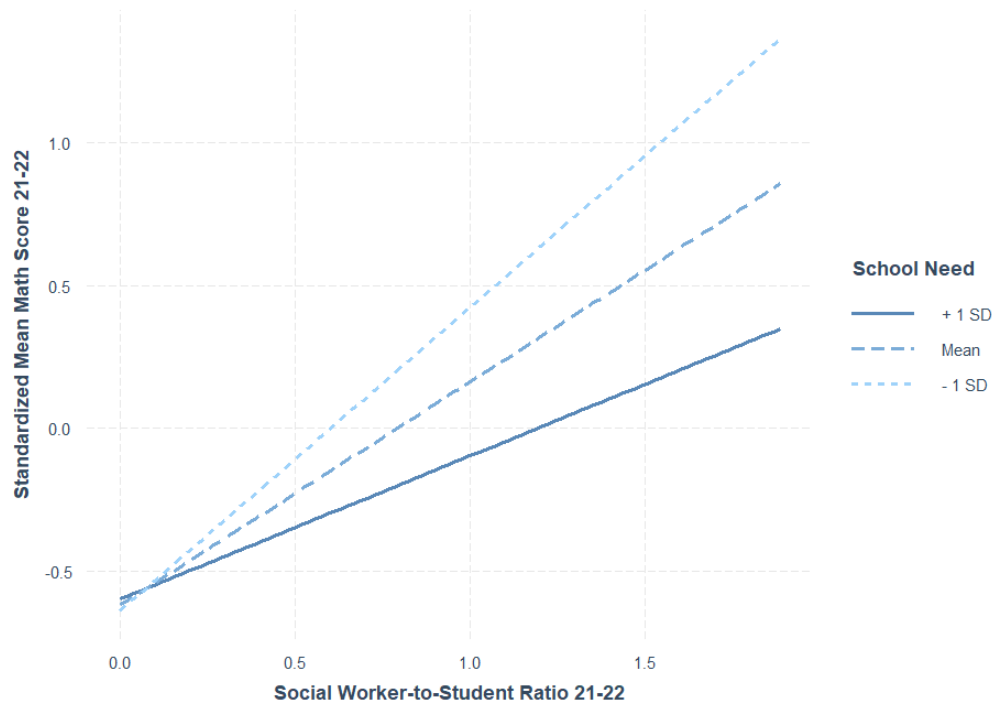


Economically Disadvantaged Students

Among economically disadvantaged students, grade-level effects represent the most prominent relationship with mean math achievement. Compared to the baseline of third-grade economically disadvantaged students, the fifth-, sixth-, seventh-, and eighth-grade students demonstrated significantly higher achievement, with gains increasing year after year (Grade 5: coef. = 0.168, SE = 0.073, $t = 2.31$; Grade 6: coef. = 0.262, SE = 0.077, $t = 3.42$; Grade 7: coef. = 0.323, SE = 0.090, $t = 3.58$; Grade 8: coef. = 0.592, SE = 0.088, $t = 6.71$). These effects were more pronounced than those observed in the schoolwide model, with eighth-grade economically disadvantaged students scoring more than half a point higher on math assessments than their third-grade peers.

Conversely, higher teacher-to-student ratios (coef. = -0.040 , SE = 0.013, $t = -3.19$) and the interaction term between school need and social worker-to-student ratios (coef. = -0.383 , SE = 0.150, $t = -2.55$; Figure 17, p. 38) were significantly associated with lower math achievement for economically disadvantaged students. The persistent negative association between level of school need and students' mean math achievement suggests that the systemic inequities that higher-need schools face continue to suppress academic outcomes.

Figure 17: Interaction of Social Worker-to-Student Ratio and School Need on Economically Disadvantaged Students’ Mean Math Achievement



Multilingual Learners (MLs)

One apparent difference in an analysis of multilingual learners (MLs) is the presence of “reversed” grade effects. Specifically, with third-grade MLs as a baseline comparison group, average math scores are significantly lower for MLs in fourth to seventh grade (Grade 5: coef. = -0.177 , SE = 0.085 , $t = -2.09$; Grade 6: coef. = -0.283 , SE = 0.098 , $t = -2.89$; Grade 7: coef. = -0.310 , SE = 0.099 , $t = -3.14$). With test scores being standardized within each grade, this might suggest that MLs are more likely to struggle in mathematics when they are promoted to higher school grades, until they reach eighth grade.

Consistent with broader trends, historically underserved students—including Black and Hispanic learners—show significantly lower average math achievement. School climate indicators also play a role in MLs’ academic outcomes. The schoolwide chronic absenteeism rate (coef. = -0.021 , SE = 0.006 , $t = -3.37$) and the absenteeism rate among MLs (coef. = -0.004 , SE = 0.002 , $t = -2.67$) both show a statistically significant negative association with math achievement. Note that the chronic absenteeism rate of Hispanic students (coef. = 0.010 , SE = 0.004 , $t = 2.38$) has a statistically significant but relatively small positive association with multilingual learning students’ average math achievement, which might partly be explained—mathematically—by the potential overlap between these two subgroups.

Students with Disabilities (SWDs)

In the subgroup analysis of students with disabilities (SWDs), a similar “reversed” grade effect as with multilingual learners has also been observed, with students in fifth to seventh grades scoring significantly lower in mathematics than baseline third-grade comparison groups, though the finding for sixth graders did not reach significance (Grade 5: coef. = -0.126 , SE = 0.052 , $t = -2.41$; Grade 6: coef. = -0.074 , SE = 0.064 , $t = -1.16$; Grade 7: coef. = -0.221 , SE = 0.073 , $t = -3.02$; Grade 8: coef. = 0.168 , SE = 0.076 , $t = 2.20$). However, by eighth grade, these students may benefit from greater familiarity with routines, targeted interventions, or specialized support systems that contribute to their improved performance as they progress through middle grades.

Related to enrollment composition, Black student achievement is the subgroup with the most compounded effect among the subgroups of SWDs, with Black American student enrollment negatively associated with mean math achievement (coef. = -0.015 , SE = 0.002 , $t = -9.49$). Hispanic student (coef. = -0.007 , SE = 0.002 , $t = -4.23$) and multilingual learner (coef. = -0.005 , SE = 0.002 , $t = -2.76$) enrollment rates are also significantly and negatively associated with math achievement. Consistent across subgroup analyses, these findings highlight the need for policies and practices that address the compounded barriers faced by SWDs in racially segregated schools.

A statistically significant negative association is observed between the ratios of teachers-to-students (coef. = -0.052 , SE = 0.011 , $t = -4.89$) and administrator-to-students (coef. = -0.134 , SE = 0.051 , $t = -2.61$), and average math achievement among SWDs. This counterintuitive finding points to concepts like targeted interventions, professional development, and inclusive instructional strategies over hiring additional staff alone to address the specific learning needs of SWDs more directly. This finding emphasizes the importance of ensuring that teaching staff are equipped with the necessary skills, training, and resources to support SWDs effectively.

Subgroup analysis for SWDs highlights the critical role of school counselors and psychologists in mitigating the negative relationship between the level of school need and students’ math achievement. While school need is significantly associated with lower math achievement (coef. = -0.383 , SE = 0.054 , $t = -2.85$), interaction terms reveal that increased support staff can help counteract this trend. Specifically, the interaction between school need and the counselor-to-student ratio (coef. = 0.312 , SE = 0.127 , $t = 2.46$; Figure 18, p. 40) and the interaction between school need and the psychologist-to-student ratio (coef. = 0.359 , SE = 0.124 , $t = 2.90$; Figure 19, p. 40) both show a positive association. These findings suggest that investing in mental health and counseling services is particularly impactful for addressing the challenges faced by SWDs in high-need school environments.

In terms of proxies for an unsupportive school climate, schoolwide out-of-school suspension rates (coef. = -0.036 , SE = 0.007 , $t = -5.10$) and chronic absenteeism rates (coef. = -0.018 , SE = 0.004 , $t = -4.52$) are negatively associated with math achievement for this subgroup. Consistent with trends

discussed earlier, chronic absenteeism may exacerbate existing challenges for SWDs. Addressing absenteeism through proactive engagement strategies, such as family outreach, wraparound services, and school-based supports, could play a pivotal role in improving outcomes.

Figure 18: Interaction of School Counselor-to-Student Ratio and School Need on Mean Math Achievement among Students with Disabilities

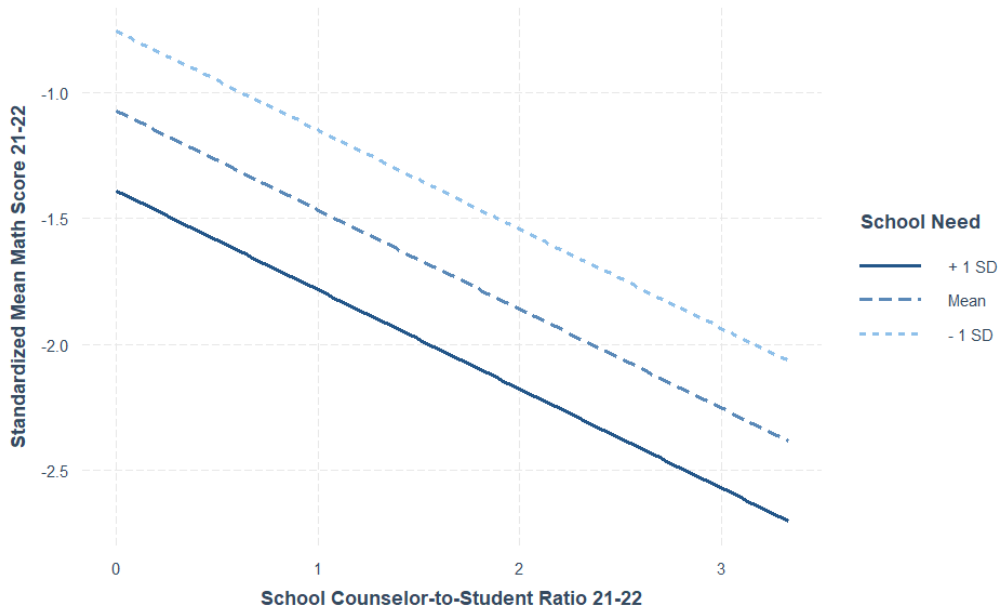
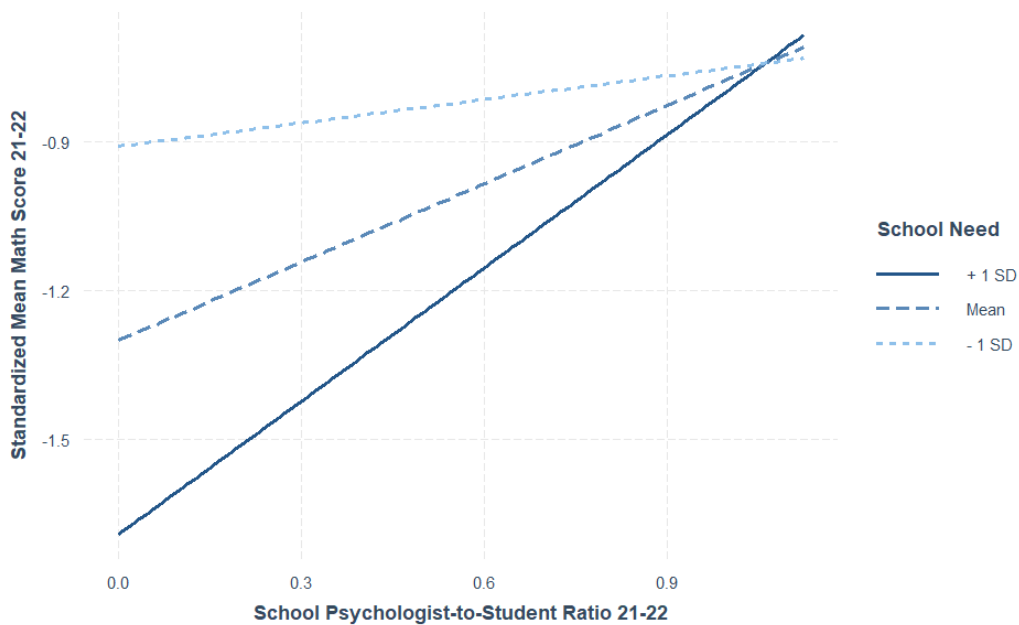


Figure 19: Interaction of School Psychologist-to-Student Ratio and School Need on Mean Math Achievement among Students with Disabilities



Mathematics Results Summary

Overall, mathematics results are consistent with the ELA results discussed in the previous section. There are mixed effects related to school staffing variables and mean math achievement. Schoolwide out-of-school suspension and chronic absenteeism rates have a significant, negative association with mean math achievement, and such associations are universally detected in schoolwide and subgroup samples. Additionally, grade indicators are significantly associated with math achievement among all students schoolwide and within each subgroup, except for Black students. However, for multilingual learners and students with disabilities, the effect was largely negative. The school need index is generally negatively associated with math achievement though, only significant in schoolwide and the subgroup models for students with disabilities.

Section 4: Studying the Likelihood of Being a "Positive Outlier" School – Ordinal Logistic Regression Results

Overview

Schools that exceeded expectations in supporting learning acceleration despite educational disruptions caused by the COVID-19 pandemic may hold valuable insights into effective practices and procedures. Complementing the qualitative study, understanding influential and replicable strategies could support improved performance across diverse school contexts.

This part of the analysis seeks to identify what distinguishes schools as "positive outliers"—those that exceeded academic performance expectations despite facing challenges. Specifically, this analysis addresses the research question: What school-level factors are associated with a school's likelihood of being a "positive outlier?" based on the residuals from the phase one quantitative analysis reported previously. This investigation focuses on the three broad areas of practice described earlier, consistent with the HLM analyses—school leadership and teacher experience, staffing and resource allocation, and school climate. By exploring the school-level practices contributing to these schools' success, this study aims to illuminate conditions that may be contributing to better-than-expected ELA and math NJSLA student performance.

Defining the Residual Classifications

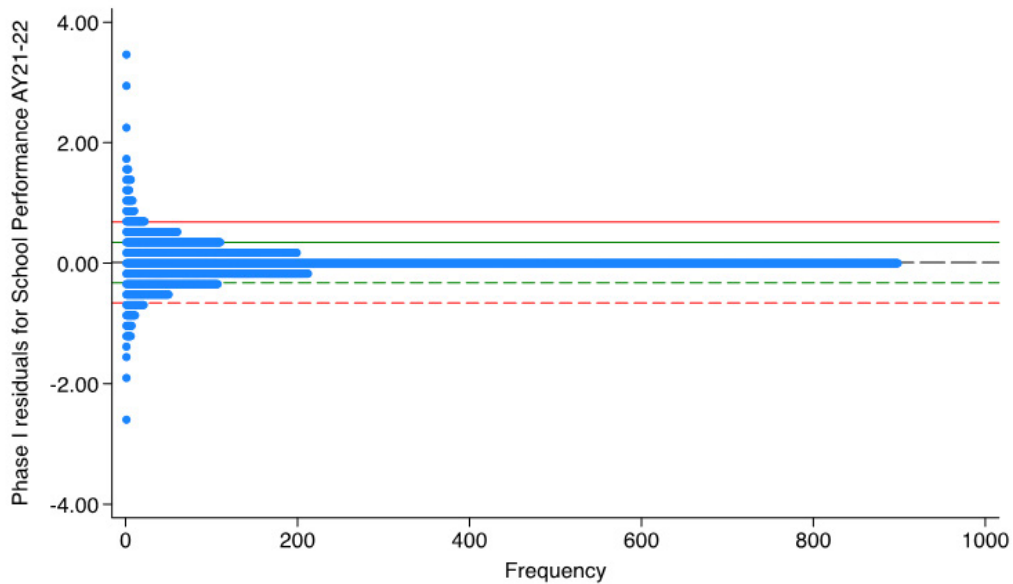
The residuals obtained from the phase one study indicate the extent to which schools' actual performance deviates from their predicted performance based on prior academic and demographic characteristics and district neighborhood contexts. Positive residuals identify schools which did better than expected. The residual variable follows an approximate normal distribution allowing for straightforward categorization of the variable for further analysis (Figure 20).

To facilitate the analysis, schools were categorized into five performance groups based on the relative position of their residuals in relation to the sample mean (the average of all residuals, the black dashed line in Figure 20, p. 44) and the standard deviations (SD) of all residuals. The variable with the five residual categories (Table 1, p. 44) is the outcome in the ordinal logistic regression analysis reported in this section, which tells the likelihood of being in positive residual categories versus negative residual categories.

Table 1. School Performance Categories Based on Phase I Residuals

Categories	Description	Range	In graph
Highly positive	Residual is more than 2 SDs above the mean	$[\text{mean}+2\text{SD}, +\infty)$, i.e., [.681, $+\infty$)	Red solid line and above
Moderately positive	Residual is between 1 and 2 SDs above the mean	$(\text{mean}+\text{SD}, \text{mean}+2\text{SD})$, i.e., (.345, .681)	Red solid line to green solid line
As expected	Residual is within 1 SD of the mean	$[\text{mean}-\text{SD}, \text{mean}+\text{SD}]$, i.e., [-.326, .345]	Within two green lines
Moderately negative	Residual is between 1 and 2 SDs below the mean	$(\text{mean}-\text{SD}, \text{mean}-2\text{SD})$, i.e., (-.661, -.326)	Green dashed line to red dash line
Highly negative	Residual is more than 2 SDs below the mean	$(-\infty, \text{mean}-2\text{SD}]$, i.e., $(-\infty, -.661]$	Red dashed line and below

Figure 20. Distribution of Phase I Residuals



Note: The values for the lines from top to bottom are as follows: the first line (red solid) is 0.681, the second line (green dashed) is 0.345, the third line (black long dashed) is 0.010, the fourth line (green dashed) is -0.326, and the fifth line (red dashed) is -0.661.

Using Ordinal Logistic Regression

This study employed a statistical method known as ‘ordinal logistic regression,’ which helps estimate the likelihood of schools falling into performance categories, such as “highly positive,” “moderately positive,” or “as expected.” This method permits the analysis of probabilities in a way that is both accurate and practical for decision-making. While these terms are conceptually similar, this study uses “likelihood” to refer to general chances, “probabilities” to indicate the specific chances of belonging to a performance category, and “odds” as defined in the statistics as follows.

The outcome variable is expressed as odds on the logit scale. In statistics, odds represent the ratio of the probability that a particular event will occur to the probability that it will not occur. Mathematically, if p is the probability of an event happening, then the odds of the event are defined as:

$$\text{Odds} = p/(1-p)$$

Where:

- p is the probability of the event occurring, and
- $1-p$ is the probability of the event not occurring.

Odds are often used in logistic regression to express the likelihood of outcomes in a way that can be transformed into probabilities. Odds greater than one indicate that the event is more likely to occur than not, while odds less than one to zero suggest the event is less likely. The event is just as likely to occur for the groups being compared when the odds are one. Notably, odds can range from zero to positive infinity.

The predictors (independent variables) include sets of variables reflecting school leadership and teacher experience, staffing and resource allocation, and school climate. The analysis assumes that the independent variables representing school resources and school climate each have similar effects on the estimated odds across all five performance groups. This assumption, known as the proportional odds assumption, implies that an increase in an independent variable affects the estimated log odds of school performance categories consistently, regardless of which groups they are in.

Analytic Results Summary

To illustrate the findings, this research modeled an “average school” where all independent variables were set to the sample mean. Table 2 (p. 46) shows descriptive statistics for the significant variables, which can be used as a reference for the averages. Using estimates from Model 3, the probabilities of this hypothetical school are calculated for each of the performance groups.¹

¹ The interpretation of the results primarily relies on estimates from a model incorporating all variables related to school practices (Model 3). To ensure rigor and provide nuanced insights into the influence of different variable categories, a series of models were also explored in a stepwise approach. These models, which tested distinct sets of variables, are detailed in Appendix 4.

Table 2. Descriptive Statistics of School Practice Variables

	N	Mean	Std. dev.	Minimum	Maximum
Staffing, Leadership, and Experience					
Per Pupil Spending	1,973	13,859.39	5,631.33	9.00	77,888.00
Logged Per Pupil Spending	1,973	9.45	0.49	2.20	11.26
Teacher-to-Student Ratio	1,983	9.70	2.42	0.40	33.33
Administrator-to-Student Ratio	1,983	0.56	0.48	0.11	5.26
Counselor-to-Student Ratio	1,983	0.33	0.34	0.00	12.50
Psychologist-to-Student Ratio	1,983	0.23	0.24	0.00	5.56
Social Worker-to-Student Ratio	1,983	0.25	0.24	0.00	3.57
Average Years of Teaching Experience	1,983	12.37	2.97	0.00	24.40
Squared Avg. Years of Teaching Experience	1,983	161.73	69.50	0.00	595.36
Admin. 4+ Years Retention Rate	1,947	77.86	19.49	0.00	100.00
Admin. 1 Year Retention Rate	1,983	87.81	13.45	0.00	100.00
Teacher 1 Year Retention Rate	1,983	90.80	7.68	0.00	100.00
School Climate					
In-School Suspension Rates	1,983	0.86	2.75	0.00	38.20
Out-of-School Suspension Rates	1,983	1.48	3.10	0.00	27.80
Chronic Absenteeism Rate, Schoolwide	1,909	16.80	11.61	0.30	100.00
Chronic Absenteeism Rate, White	1,879	16.01	15.70	0.00	100.00
Chronic Absenteeism Rate, Black	1,870	20.82	18.24	0.00	100.00
Chronic Absenteeism Rate, Hispanic	1,907	19.91	12.11	0.00	100.00
Chronic Absenteeism Rate, MLL	1,760	19.55	17.48	0.00	100.00
Chronic Absenteeism Rate, Economically Disadvantaged	1,846	24.83	14.40	0.00	100.00
Chronic Absenteeism Rate, Students with Disabilities	1,904	22.75	13.38	0.00	100.00

Note: All variables are measured as percentages, except for Per Pupil Spending, Logged Per Pupil Spending, Average Years of Teaching Experience, and Squared Avg. Years of Teaching Experience. To illustrate, the mean of Out-of-School Suspension Rates is listed as 1.48, meaning the average out-of-school suspension rates for all sampled schools is 1.48%, except for Per Pupil Spending, Logged Per Pupil Spending, Average Years of Teaching Experience, and Squared Avg. Years of Teaching Experience. For staff-to-student ratios, the percentages represent the number of staff members serving every 100 students.

For an average school, the probability of being categorized into an as-expected performance group (within one standard deviation of the mean) is 76.4%. The probability of being categorized in the moderately positive group (between one and two standard deviations above the mean) is 6.5%. The probability of having a much higher-than-expected performance (more than two standard deviations above the mean) is 9.0%. Conversely, the probability of being moderately negative (between one and two standard deviations below the mean) is 6.3%. Finally, the probability of being a highly negative outlier (more than two standard deviations below the mean) is 1.8%. The probabilities sum to one (100%), covering all possible categories.

Table 3. Predicted Probabilities of Performance Categories for an Average School

Categories	Predicted probabilities	Odds	Standard errors	Z-statistics	P-value	[95% conf. interval]	
Highly positive	0.090	0.007	12.850	0.000	0.076	0.104	0.090
Moderately positive	0.065	0.006	10.770	0.000	0.053	0.077	0.065
As expected	0.764	0.011	69.770	0.000	0.743	0.785	0.764
Moderately negative	0.063	0.006	10.710	0.000	0.051	0.074	0.063
Highly negative	0.018	0.003	5.930	0.000	0.012	0.025	0.018

Findings from the full model (Model 3) reveal that several independent variables significantly influence a school’s probabilities of being classified into specific performance categories. The details are discussed in separate subsections below. As an overview, student support staff, such as counselors, play a prominent role in raising the likelihood of schools being categorized in positive performance categories.

The average years of experience of all teachers at the school, along with its quadratic term, also emerges as a key factor, indicating potential nonlinear influences on the likelihood of schools’ performance categorization. Moreover, school climate variables demonstrate notable influences. For instance, an increase in schoolwide out-of-school suspension rates significantly raises the likelihood of schools falling into negative performance categories and lowers the likelihood of schools being in positive performance categories, highlighting the negative influence of extensive disciplinary practices on school performance.

A similar negative influence is observed for schoolwide chronic absenteeism. Contrary to the negative effects of schoolwide chronic absenteeism, subgroup-specific chronic absenteeism rates for Hispanic students and students with disabilities have positive but insubstantial influences on schools’ likelihood of being “positive outliers,” further indicating the importance of attendance-related issues and potential complexities in understanding the influences of school climate.

A detailed discussion of the implications and effects of these variables is provided in the following sections. Again, the term “likelihood” is used to refer to general chances across performance categories, and the term “probabilities” is used to indicate the specific chances of belonging to a performance category throughout the discussion sections.

School Leadership and Teacher Experience, Staffing, and Resource Allocation

Child Support Staff. Among staffing-related variables, increasing the counselor-to-student ratio (expressed as the number of counselors per 100 students) for an average school raises the likelihood of being in positive performance categories, while decreasing the likelihood of falling into negative performance categories, assuming all other school practices remain constant and at the average level of all sampled schools. Specifically, if a school initially has one counselor for every 100 students, hiring additional counselors (resulting in two counselors per 100 students) raises the probability of being in a moderately positive performance category from 9.0% to 17.2% (shown as +0.082 in Table 4). Similarly, the probability of the school being in a highly positive performance group increases from 6.5% to 11.4%, assuming all other school practices remain constant and at the average level of all sampled schools. This suggests that more access to counselors may support better student learning outcomes, potentially through enhanced support for social-emotional learning.

Table 4. Ordinal Logistics Regression Results – Counselor-to-Student Ratio

Categories	Changes in probabilities	Standard errors	Z-statistics	P-value	[95% conf. interval]	
Highly positive	+0.136	0.034	4.000	0.000	0.070	0.203
Moderately positive	+0.082	0.021	3.830	0.000	0.040	0.123
As expected	-0.093	0.027	-3.440	0.001	-0.146	-0.040
Moderately negative	-0.095	0.024	-3.920	0.000	-0.142	-0.047
Highly negative	-0.030	0.009	-3.450	0.001	-0.047	-0.013

The psychologist-to-student and social worker-to-student ratios are statistically significant in the analytic model that focuses solely on the effects of staffing, leadership, and experience on school performance categories (Model 1 in Appendix 4), but not in the full model (Model 3). The corresponding changes in probabilities are detailed in the Appendix.

Years of Teaching Experience. Among the school leadership and teacher experience variables, average years of teacher experience within schools is the only statistically significant predictor influencing the likelihood of schools being categorized into performance groups. A 1-year increase in the average years of teacher experience reduced the likelihood of being in a positive performance category and increased the likelihood of being in negative and as expected performance categories, assuming all other school practices remain constant and at the average level of all sampled schools. This counterintuitive finding may reflect challenges faced by schools with more experienced teachers, such as resource limitations or difficulties hiring new teachers. Notably, the quadratic term for teacher experience shows a slight increase in the probability of positive classification and a decrease in negative classification, indicating a potential non-linear effect, though this effect was insubstantial.

Table 5. Ordinal Logistics Regression Results – Teachers’ Average Years of Experience

Categories	Changes in probabilities	Standard Errors	Z-statistics	P-value	[95% conf. interval]	
Years of experience						
Highly positive	-0.024	0.010	-2.530	0.012	-0.043	-0.005
Moderately positive	-0.015	0.006	-2.480	0.013	-0.026	-0.003
As expected	+0.017	0.007	2.380	0.018	0.003	0.030
Moderately negative	+0.017	0.007	2.500	0.013	0.004	0.030
Highly negative	+0.005	0.002	2.370	0.018	0.001	0.010
Years of experience (squared)						
Highly positive	+0.001	0.000	1.980	0.047	0.000	0.001
Moderately positive	0.000	0.000	1.960	0.050	0.000	0.001
As expected	-0.001	0.000	-1.910	0.056	-0.001	0.000
Moderately negative	-0.001	0.000	-1.970	0.049	-0.001	0.000
Highly negative	0.000	0.000	-1.900	0.057	0.000	0.000

School Climate

Out-of-School Suspension Rate. Increases in out-of-school suspension rates by 1% (e.g., from 1.5% to 2.5%) decrease the likelihood of an average school being categorized into positive performance categories and raise the likelihood of falling into negative performance categories. This highlights the negative influences of higher suspension rates, considered an exclusionary discipline response, on overall school performance. Specifically, the probability of being in a highly positive performance category decreases from 9.0% to 8.3%, and that of being in a moderately positive performance category decreases from 6.5% to 6.1%. Correspondingly, the probability of being in a moderately negative performance category increases from 6.3% to 6.8%, and that of being in a highly negative performance category rises from 1.8% to 2.0%. Meanwhile, the probability of being in an as-expected performance category slightly raises from 76.4% to 76.9%, assuming all other school practices remain constant and at the average level of all sampled schools.

Table 6. Ordinal Logistics Regression Results – Out-of-School Suspension

Categories	Changes in probabilities	Standard Errors	Z-statistics	P-value	[95% conf. interval]	
Highly positive	-0.007	-3.830	0.000	-0.011	-0.003	-0.007
Moderately positive	-0.004	-3.700	0.000	-0.006	-0.002	-0.004
As expected	+0.005	3.300	0.001	0.002	0.008	0.005
Moderately negative	+0.005	3.810	0.000	0.002	0.007	0.005
Highly negative	+0.002	3.400	0.001	0.001	0.002	0.002

Schoolwide Chronic Absenteeism. Consistent with suspension rates, increases in schoolwide chronic absenteeism rates similarly reduce the likelihood of an average school being categorized in positive performance categories, and increase the likelihood of falling into negative and as-expected performance categories. Specifically, an increase in schoolwide absenteeism rates by 1% (e.g., from 16.8% to 17.8%) reduces the probability of being in a highly positive performance category from 9.0% to 8.3%, and from being in a moderately positive performance category from 6.5% to 6.1%. Meanwhile, the probability of falling into moderately negative performance category increases from 6.3% to 6.8%, and that of falling into a highly negative classification rises from 1.8% to 2.0%.

Table 7. Ordinal Logit Regression Results – Schoolwide Chronic Absenteeism

Categories	Changes in probabilities	Standard errors	Z-statistics	P-value	[95% conf. interval]	
Highly positive	+0.136	0.034	4.000	0.000	0.070	0.203
Moderately positive	+0.082	0.021	3.830	0.000	0.040	0.123
As expected	-0.093	0.027	-3.440	0.001	-0.146	-0.040
Moderately negative	-0.095	0.024	-3.920	0.000	-0.142	-0.047
Highly negative	-0.030	0.009	-3.450	0.001	-0.047	-0.013

Chronic Absenteeism for Student Subgroups. Regression results showed nuanced but counterintuitive influences of chronic absenteeism among subgroups, particularly for Hispanic students and students with disabilities. Unlike the trend observed with schoolwide chronic absenteeism rates, higher absenteeism rates for Hispanic students slightly increase the likelihood of being in positive performance categories and decrease the likelihood of being in negative performance categories. This counterintuitive finding suggests that schools with higher absenteeism rates for Hispanic students were more likely to perform better than expected, assuming other school practices remain constant. A similar trend is observed for chronic absenteeism rates among students with disabilities. However, the influences of subgroup absenteeism rates on school performance categories are insubstantial, despite reaching statistical significance.

Table 8. Ordinal Logistics Regression Results – Subgroup Chronic Absenteeism

Categories	Changes in probabilities	Standard errors	Z-statistics	P-value	[95% conf. interval]	
Chronic Absenteeism for Hispanic students						
Highly positive	+0.003	3.350	0.001	0.001	0.005	0.003
Moderately positive	+0.002	3.240	0.001	0.001	0.003	0.002
As expected	-0.002	-3.010	0.003	-0.004	-0.001	-0.002
Moderately negative	-0.002	-3.290	0.001	-0.004	-0.001	-0.002
Highly negative	-0.001	-2.990	0.003	-0.001	0.000	-0.001
Chronic Absenteeism for Students with Disabilities						
Highly positive	+0.003	4.010	0.000	0.002	0.005	0.003
Moderately positive	+0.002	3.850	0.000	0.001	0.003	0.002
As expected	-0.002	-3.490	0.000	-0.003	-0.001	-0.002
Moderately negative	-0.002	-3.870	0.000	-0.003	-0.001	-0.002
Highly negative	-0.001	-3.470	0.001	-0.001	0.000	-0.001

Summary

The main goal of the ordinal logistic analysis was to identify which school practices influence the likelihood of a school being a “positive outlier” (i.e., one that exceeded academic performance expectations given its student populations and despite facing challenges of the COVID-19 pandemic). By investigating how these school-level practices influence the probabilities of a school being in various performance categories, the analyses shed light on the conditions that may be contributing to better-than-expected school performance on ELA and math NJSLA.

The analytic results emphasized the critical role that school climate plays in influencing students’ academic performance. Schools with higher out-of-school suspension rates and chronic absenteeism rates are significantly less likely to be classified as “positive outliers” (i.e., with better-than-expected performance) and are more likely to fall into negative (worse-than-expected) performance categories. In addition, student support staff and overall teacher experience emerge as important factors. Among child support staff, increases in the counselor-to-student ratio raise the likelihood of a school being in positive performance categories, and reduce the likelihood of a school being in negative performance categories. Teacher experience also plays a role, with findings indicating a nonlinear relationship.

This evidence highlights the importance of investing in school climate improvements, student support services, and strategic teacher staffing to foster exceptional academic outcomes.

Discussion and Conclusion

The quantitative analyses reported here respond to two research questions. The first research question sought to understand the factors contributing to mean NJSLA scaled scores in ELA and math. The second research question studied the sample from a different angle, with an aim to understand the factors explaining schools' likelihood of being a "positive outlier," defined as schools which exceeded statistically-based expectations for mean NJSLA scaled scores in ELA and math.

For both research questions, three central sets of variables were investigated—school leadership and teaching experience, staffing and resource allocation, and school climate. Variables were selected out of the available data to identify malleable factors that could be levers for improving learning and recovery. Most of the selected variables were at the school level, consistent with the requested scope of the project. This study considers these potential levers in the context of school and neighborhood composition and prior performance.

As context for interpreting results, this study reports on the between-district and between-school variability in average student performance. If more of the variation is between districts then, ideally, efforts for improvement would pay close attention to district factors. If more of the variation is between schools, then efforts for improvement would pay slightly more attention to levers in schools.

Across all models, most of the variability can be attributed to differences between districts. This finding resonates with research demonstrating the influence of district practices on school outcomes. Where poor socioeconomic conditions of the district are related to depressed student outcomes, concerted districtwide efforts have been found to mitigate them (Bottoms & Schmidt-Davis, 2010; Darling-Hammond, 2004; Darling-Hammond, 2005; Datnow, 2005; Waters & Marzano, 2007; Snipes et al., 2002).

The literature points to the critical importance of strong district vision and school leadership's ability to execute that vision in ways that work for the school's population (Bottoms & Schmidt-Davis, 2010). Still, districts and their schools do not automatically align, and well-intended district efforts can fall short if poorly implemented in schools (Datnow, 2005; Oldac & Kondakci, 2019).

School Leadership and Teaching Experience

Variables representing school leadership and teaching experience included indicators of administrator retention in the district and teachers' years of experience in the school, along with a quadratic term to study a possible non-linear relationship. This study's findings indicate that teachers with more experience—approximately mid-career and beyond—consistently contribute

to a slight increase in achievement in ELA and math, and increase the likelihood that schools will achieve "better than expected" performance categories. Earlier increases in teachers' years of experience—consider an early career teacher—were associated with decreased mean achievement and decreased likelihood of being in the "better than expected" performance categories. From the subgroup analyses, this finding was true for Black, Hispanic, and economically disadvantaged students. Evidence from the schoolwide models also indicates that administrator retention in the district for at least 1 year plays a role in boosting ELA and math student achievement.

Research consistently shows that increased teacher experience is positively associated with student achievement (Kini & Podolsky, 2016; Ladd & Sorensen, 2017; Podolsky et al., 2019), and some evidence from value-added models indicates that grade-level experience is a driver of teacher experience effects (Huang & Moon, 2009). An oft-cited finding is that teacher effectiveness typically increases dramatically in the first 2 to 3 years of teaching and flattens thereafter (Boyd et al., 2009; Henry et al., 2011; Staiger & Rockoff, 2010).

This study's analyses do not identify a positive effect of the first 5 years of teaching, but corroborate the part of the research which finds learning gains with greater years of teaching experience. As teachers gain experience, they can refine classroom management skills, instructional strategies, and the ability to adapt to diverse student needs, which contributes to improved academic performance (Kini & Podolsky, 2016).

School administrator retention is similarly impactful, as consistent leadership fosters a stable school environment and provides continuity in implementing policies and educational practices. High administrator turnover disrupts school culture, undermines teacher morale, and interrupts the implementation of long-term improvement plans. Conversely, administrators who stay longer can build trust with teachers, students, and parents, leading to sustained improvements in student learning outcomes (Grissom et al., 2021).

Staffing and Resource Allocation

Staffing and resource allocation variables included teacher-to-students ratios, administrator-to-student ratios, support staff-to-student ratios (i.e., social worker, counselor, and psychologist), and per-pupil spending. Per-pupil spending did not emerge as the most central predictor among all the other variables; but, in general, it was either clearly or marginally associated with increased ELA and math achievement schoolwide and for most subgroups of students. Per-pupil spending was one of the more substantial predictors for Hispanic students' math achievement.

Ratios of support staff-to-students were interacted with two school demographic variables—percent of students with disabilities and school need—to study the hypothesis that the influence of support staff may vary with these aspects of school context given the needs these staff are typically hired to address. The ordinal logistic regression analysis finds that all three support staff

roles—counselors, social workers, and psychologists—were associated with increased likelihood of schools being in the “better than expected” performance categories. When predicting mean achievement, however, the findings were mixed.

Considering schoolwide mean achievement, the psychologist-to-student ratio was associated with sizeable increases in both ELA and math achievement as school need increased. In other words, the psychologist-to-student ratio appears to have the potential to offset the negative effects of concentrated need in schools. Concurrently, however, once the moderating role of school need is controlled for along with the other variables, the counselor-to-student and/or social worker-to-student ratios tend to be negatively associated with both ELA and math achievement.

Some additional variability in the influence of support staff ratios on subgroup ELA and math achievement is observed. The psychologist-to-student ratio boosts ELA and/or math performance for all subgroups and appears to be moderated by either school need and/or percent of students with disabilities, so that the positive influence of the psychologist-to-student ratio is seen when contextual characteristics increase. One exception is for Black students’ mean ELA achievement, where the psychologist-to-student ratio’s influence is negative as school need increases. The counselor-to-student ratio appears positive for Hispanic students and students with disabilities, particularly when either school need or percent of students with disabilities increases. For other subgroups, the counselor-to-student ratio plays a negative or null role after accounting for all the other modeled variables. The social worker-to-student ratio does not emerge as a prominent influence on ELA or math mean achievement for most subgroups except for economically disadvantaged student achievement where it is generally positive, but not as the percentage of students with disabilities increases.

These findings may merely be signaling the complexity of the relationship between support staff allocation and academic performance when needs specific to school context are considered. With this in mind, readers are cautioned against using these findings without further qualitative inquiry. Ideally, it would be important to understand the mechanism through which each of these support staff roles could directly impact student learning, the timeframe within which any impact would be detectable (the study only covers 1 year), and the relative weight of each staff role relative to the other. Note, for example, that the effect of the psychologist-to-student ratio mostly remains positive with increasing enrollment of students with disabilities or school need. For Hispanic students, there is a positive influence of the counselor-to-student ratio when the percentage of students with disabilities also increases.

It is clear, though, that schools should be thinking carefully about where they can invest in support staff roles because, for all subgroups and schoolwide, at least one support staff is beneficial for average achievement. The mixed findings around staffing and resource allocation suggest a need to reevaluate optimal staffing configurations within school context.

Established literature explores possible mechanisms in the relationship between support staff and academic achievement. Research has identified positive effects of increased psychologist-to-student ratios, particularly in high-need schools (López et al., 2021). Noted mechanisms include

improvement of social-emotional learning, working with teachers to implement academic and behavioral interventions, and promoting problem-solving skills (National Association of School Psychologists, 2021).

School psychologists are often associated with the special education identification process, but according to the National Association of School Psychologists (NASP), that role may be broader and is directly connected to student learning. Indeed, their role is designed to impact both general and special education (NASP, 2021). "School psychologists help schools and families address some of our biggest challenges in education: improving and individualizing instruction to close the achievement gap; increasing graduation rates and preventing dropouts; creating safe, positive school climates and preventing violence; providing meaningful accountability; and strengthening family-school partnerships" (NASP, 2020).

The sometimes negative association between school social workers and reading achievement does not necessarily mean that social workers harm literacy achievement directly. Instead, it could reflect contextual factors. For example, schools with higher ratios of social workers might be responding to more significant social or behavioral challenges, or severe systemic or socioeconomic challenges (e.g., poverty, chronic absenteeism), which could indirectly impact literacy outcomes.

While social workers may not directly influence literacy achievement, their role in addressing social-emotional and behavioral needs can indirectly support academic environments over time. Recent research unfortunately has not explicitly studied the link between school social workers and reading performance. Some research finds positive impacts of integrated social services on reading achievement (Chen et al., 2023; Wegmann et al., 2017); however, a social worker-to-student ratio will not necessarily capture integrated social services. More investigation is needed here.

The literature generally links better counselor-to-student ratios with improved academic performance and highlights mechanisms (Carey & Dimmitt, 2018), but the research does not have a strong base of causal evidence (Brown & Trusty, 2005; Carey & Dimmitt, 2018; Sink & Stroh, 2003). Though more often linked to improved behavioral outcomes (Carey & Dimmitt, 2018), school counseling programs might enhance academic achievement through direct interventions, such as personalized academic planning, goal setting, and teaching study skills through classroom lessons and small group sessions to address specific academic challenges (Sink & Stroh, 2003; Whiston & Quinby, 2009). Counselors might play a role in creating a supportive environment that enables better focus on academics by addressing emotional and behavioral barriers to learning through short-term counseling and by connecting students to external resources (American School Counselor Association, 2019). According to the American School Counselor Association (ASCA), counselors can also advocate for equitable access to resources for underserved populations. Comprehensive school counseling programs (CSCPs), aligned with the ASCA National Model, emphasize reducing systemic barriers to student success and collaborating with teachers and

parents to identify and address student needs, aligning strategies to improve academic outcomes (Brown & Trusty, 2005). However, like any intervention, outcomes of counseling programs will most likely depend on the quality of implementation, consistency between counseling and broader school goals and priorities, and alignment between the counseling approach and the student needs and family preferences. Counseling can also be stigmatized or deemed irrelevant, which could impact prioritization of the resource (ASCA, 2019).

School Climate

School climate emerges as an important factor in the analytic results of both research questions. Specifically, out-of-school suspension rates and chronic absenteeism, both at the schoolwide level and for specific student subgroups, are consistently associated with reduced mean achievement in ELA and math and reduced likelihood of schools being in “better than expected” performance categories. The results highlight the critical need for policies and interventions aimed at improving the overall school climate, such as reducing out-of-school suspensions through restorative practices (Darling-Hammond, 2023) and tackling chronic absenteeism through targeted outreach (Allensworth et al., 2021).

Notably, the contrasting effects of subgroup-specific chronic absenteeism compared to schoolwide chronic absenteeism point to the importance of addressing vulnerable student populations' unique challenges and needs. Attendance issues like absenteeism became particularly concerning during the COVID-19 pandemic, as educational disruptions disproportionately impacted students from vulnerable populations more severely, which can exacerbate existing inequities in academic outcomes. Therefore, it is essential to design targeted, evidence-based strategies that address the needs of these student subgroups to promote equitable academic opportunities and outcomes. Addressing absenteeism through proactive engagement strategies, such as family outreach, wraparound services, and school-based supports, could play a pivotal role in improving outcomes for all groups of students.

Varying Achievement with Grade Progression

Grade-level indicators were included in the models to understand achievement in each grade separately. Grade level is consistently associated with higher mean achievement in both subjects, with substantial increases observed as students advance from fifth through eighth grades as compared with third grade. However, for multilingual learners and students with disabilities, a “reversed” grade effect shows achievement declines in higher grades. This highlights the importance of an equitable approach to grade-level progression to support academic outcomes for all students.

It is important to note that as some students achieve language proficiency, they are no longer included among multilingual learners. The same may be true for students who test out of special education services. In general, these results could raise questions about curriculum alignment, developmental shifts, or instructional practices at specific grade levels. Educators might consider evaluating instructional quality and curricular coherence across grade spans to ensure continuity, building on the observed improvements in middle grades.

Conclusion and Future Research

The findings from the quantitative analyses provide valuable insights into the factors driving school performance, challenging simplistic views of academic performance by uncovering the significant roles of student support staff and school climate. The findings that various support staff positively influence achievement schoolwide and for subgroups suggest that investing in mental health, support services, and academic interventions remains particularly impactful for addressing the challenges students face—especially in high-need school environments. The importance of supportive staffing and school climate reforms to improve outcomes for all students offers policy and practice implications.

These results suggest important directions for future research. Qualitative studies are needed to explore the unique challenges faced by various student subgroups and better understand their unique struggles within New Jersey’s diverse educational settings, during and after the COVID-19 pandemic. Meanwhile, quantitatively examining differential effects for specific student populations can inform both qualitative research and policy design, helping to develop tailored interventions that address subgroup-specific needs and promote equitable academic outcomes.

Furthermore, future research should investigate the causal mechanisms underlying the significant associations and complex relationships identified in this study. One example would be exploring how student support staff contribute to improved outcomes, whether through providing additional social-emotional support, academic guidance, or facilitating family engagement.

References

- Allensworth, E., Balfanz, R., Rogers, T., & Demarzi, J. (2021). *Absent from school: Understanding and addressing student absenteeism*. Harvard Education Press.
- Alvarez, M. E., Bye, L., Bryant, R., & Mumm, A. M. (2013). School social workers and educational outcomes. *Children & Schools*, 35(4), 235–243. https://www.researchgate.net/publication/274170962_School_Social_Workers_and_Educational_Outcomes
- American School Counselor Association. (2019). The ASCA National Model: A framework for school counseling programs. <https://www.schoolcounselor.org/About-School-Counseling/ASCA-National-Model-for-School-Counseling-Programs>
- Baker, B. D. (2018). Educational inequality and school finance. Why money matters for America’s students. Harvard Education Press.
- Bottoms, G. & Schmidt-Davis, J. (2010). *The three essentials: Improving schools requires district vision, district and state support, and principal leadership*. Southern Regional Education Board. <https://doi.org/10.59656/EL-LS7338.001>
- Boyd D., Grossman P., Lankford H., Loeb S., & Wyckoff J. (2009). Teacher preparation and student achievement. *Educational Evaluation and Policy Analysis*, 31, 416–440.
- Brown, D., & Trusty, J. (2005). School counselors, comprehensive school counseling programs, and academic achievement: Are school counselors promising more than they can deliver? *Professional School Counseling*, 9(1), 1-10.
- Burroughs, N., Gardner, J., Lee, Y., Guo, S., Touitou, I., Jansen, K., & Schmidt, W. (2019). A review of the literature on teacher effectiveness and student outcomes. In *teaching for excellence and equity*, 7–17. https://doi.org/10.1007/978-3-030-16151-4_2
- Campbell, V. A. (2022). The NJ school need index for monitoring equity. Rutgers Joseph C. Cornwall Center for Metropolitan Studies.
- Carey, J., & Dimmitt, C. (2018). School counseling and student outcomes: Summary of six statewide studies. *Professional School Counseling*, 16(2), 146–156. <https://doi.org/10.1177/2156759X0001600204>
- Chen, I. C., Kuo, N. C., & Smith, B. (2023). Exploring the Impacts of Community Services on Student Reading Achievement in a Title I School. *School Community Journal*, 33(2), 115-132.
- Darling-Hammond, S. Fostering Belonging, Transforming schools: The impact of restorative Practices. Learning Policy Institute, 2023. <https://doi.org/10.54300/169.703>.

- Darling-Hammond, L. (2004). Standards, accountability, and school reform. *Teachers College Record*, 106(6), 1047-1085. <https://doi.org/10.1111/j.1467-9620.2004.00372.x>
- Darling-Hammond, L. (2005). New standards and old inequalities: School reform and the education of African American students. In J. E. King (Ed.), *Black/African American Education. A Transformative Research and Action Agenda for the New Century* (pp. 197–223). Routledge.
- Datnow, A. (2005). The sustainability of comprehensive school reform models in changing district and state contexts. *Educational Administration Quarterly*, 41(1), 121–153. <https://doi.org/10.1177/0013161X04269578>
- Dee, T. S. (2024, Jan 16). Higher chronic absenteeism threatens academic recovery from the COVID-19 pandemic. *Proc Natl Acad Sci*, 121(3), e2312249121. <https://doi.org/10.1073/pnas.2312249121>.
- Ding, X., Lightfoot, E., Berkowitz, R., Guz, S., Franklin, C., & DiNitto, D. M. (2023). Characteristics and outcomes of school social work services: A scoping review of published evidence 2000–June 2022. *School Mental Health*, 15(3), 787–811.
- Education Trust. (2019). School counselors matter. Education Trust. <https://edtrust.org/wp-content/uploads/2014/09/School-Counselors-Matter.pdf>
- Graham, L. J., White, S. L., Cologon, K., & Pianta, R. C. (2020). Do teachers' years of experience make a difference in the quality of teaching?. *Teaching and Teacher Education*, 96, 103190.
- Grissom, J. A., Egalite, A. J., & Lindsay, C. A. (2021). How principals affect students and schools. *Wallace Foundation*, 2(1), 30–41.
- Henry, G. T., Bastian, K. C., & Fortner, C. K. (2011). Stayers and leavers: Early-career teacher effectiveness and attrition. *Educational Researcher*, 40(6), 271–280. <https://doi.org/10.3102/0013189X11419042>
- Huang, F. L., & Moon, T. R. (2009). Is experience the best teacher? A multilevel analysis of teacher characteristics and student achievement in low performing schools. *Educational Assessment, Evaluation and Accountability*, 21, 209–234.
- Kraft, M. A. (2020). Interpreting effect sizes of education interventions. *Educational Researcher*, 49(4), 241–253. <https://doi.org/10.3102/0013189X20912798>
- Kini, T. & Podolsky, A. (2016). Does teaching experience increase teacher effectiveness? A review of the research (research brief). Palo Alto, CA: Learning Policy Institute.
- Podolsky, A., Kini, T. & Darling-Hammond, L. (2019). Does teaching experience increase teacher effectiveness? A review of US research. *Journal of Professional Capital and Community*. 4(4), 286–308.

López, V., Cárdenas, K. & González, L. (2021, Feb 23). The effect of school psychologists and social workers on school achievement and failure: A national multilevel study in Chile. *Front Psychol.*, 12, 639089. <https://doi.org/10.3389/fpsyg.2021.639089>

National Association of School Psychologists. (2021). School psychologists: Improving student and school outcomes [Research summary]. National Association of School Psychologists.

National Association of School Psychologists. (2020a). The Professional Standards of the National Association of School Psychologists. <https://www.nasponline.org/x55315.xml>

National Association of Social Workers (2024). School social workers. National Association of Social Workers. <https://www.socialworkers.org/Practice/School-Social-Work>

NJ Department of Education. (2022). 2021-2022 New Jersey school performance reports: Reference guide. <https://rc.doe.state.nj.us/additional>

Oldac, Y. I., & Kondakci, Y. (2020). Multilevel analysis of the relationship between school-level variables and student achievement. *Educational Management Administration & Leadership*, 48(4), 762-780. <https://doi.org/10.1177/1741143219827303>

Rafa, A. (2017). Chronic absenteeism: A key indicator of student success. Policy analysis. Education Commission of the States.

Schmid, R. (2018). Pockets of excellence: Teacher beliefs and behaviors that lead to high student achievement at low achieving schools. *Sage Open*, 8(3). <https://doi.org/10.1177/2158244018797238>

Sink, C. A., & Stroh, H. R. (2003). Raising achievement test scores of early elementary school students through comprehensive school counseling programs. *Professional School Counseling*, 6(5), 350-364.

Snipes, J., Doolittle, F. & Herlihy, C. (2002). Foundations for success: Case studies of how urban school systems improve student achievement [and] abstract. MDRC and Council of the Great City Schools. https://www.mdrc.org/sites/default/files/foundations_for_success_summary.pdf

Solheim, O. J., & Opheim, V. (2019). Beyond class size reduction: Towards more flexible ways of implementing a reduced pupil-teacher ratio. *International Journal of Educational Research*, 96, 146-153.

Staiger, D. O., & Rockoff, J. E. (2010). Searching for effective teachers with imperfect information. *Journal of Economic Perspectives*, 24(3), 97-118.

Theobald, N. D., & Gritz, R. M. (1996). The effects of school district spending priorities on the exit paths of beginning teachers leaving the district. *Economics of education review*, 15(1), 11-22.

Trawick-Smith, J. (Feb. 25, 2024). The strategic small school: supporting equity and sustainability in schools of every size. *Education Resource Strategies*.

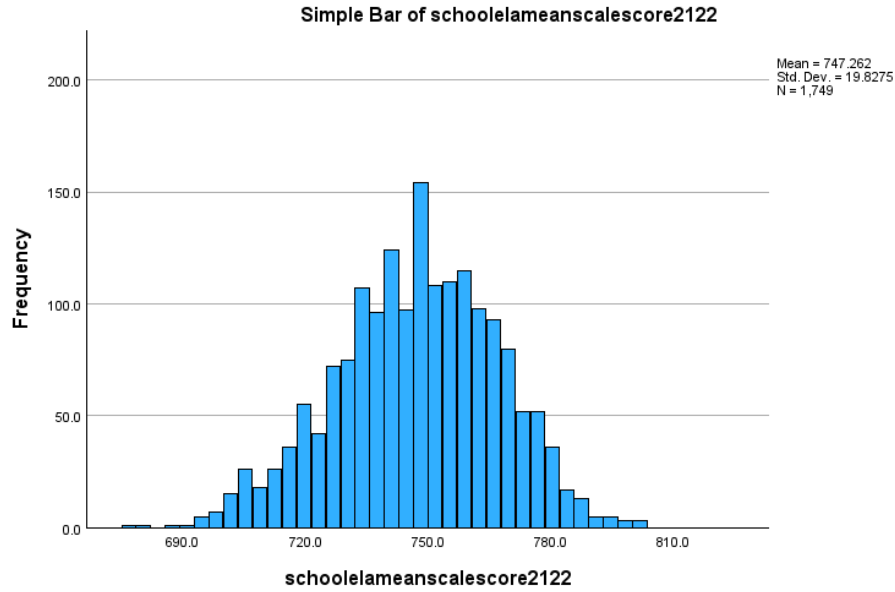
- Waters, J. T., & Marzano, R. J. (2007). School district leadership that works: The effect of superintendent leadership on student achievement. *Education Research Service Spectrum*, 25
- Wegmann, K. M., Powers, J. D., Swick, D. C., & Watkins, C. S. (2017). Supporting academic achievement through school-based mental health services: A multisite evaluation of reading outcomes across one academic year. *School Social Work Journal*, 41(2), 1–22.
- Whiston, S. C., & Quinby, R. F. (2009). Review of school counseling outcome research. *Psychology in the Schools*, 46(3), 267–278. <https://doi.org/10.1002/pits.20372>
- Zabek, F., Lyons, M. D., Alwani, N., Taylor, J. V., Brown-Meredith, E., Cruz, M. A., & Southall, V. H. (2023). Roles and functions of school mental health professionals within comprehensive school mental health systems. *School Mental Health*, 15(1), 1–18.

Appendix

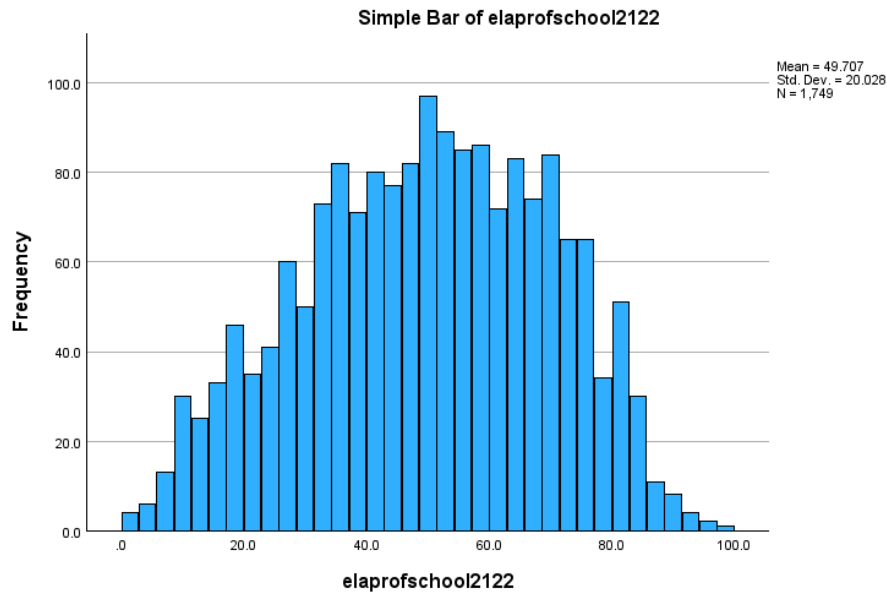
(Appendices begin on the following page.)

Appendix 1. Descriptive Statistics

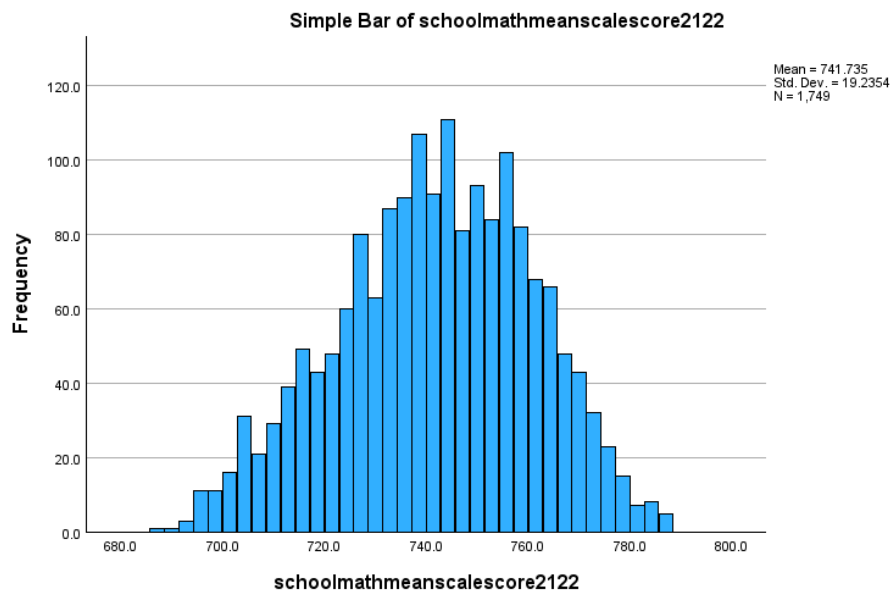
ELA Mean Scale Score



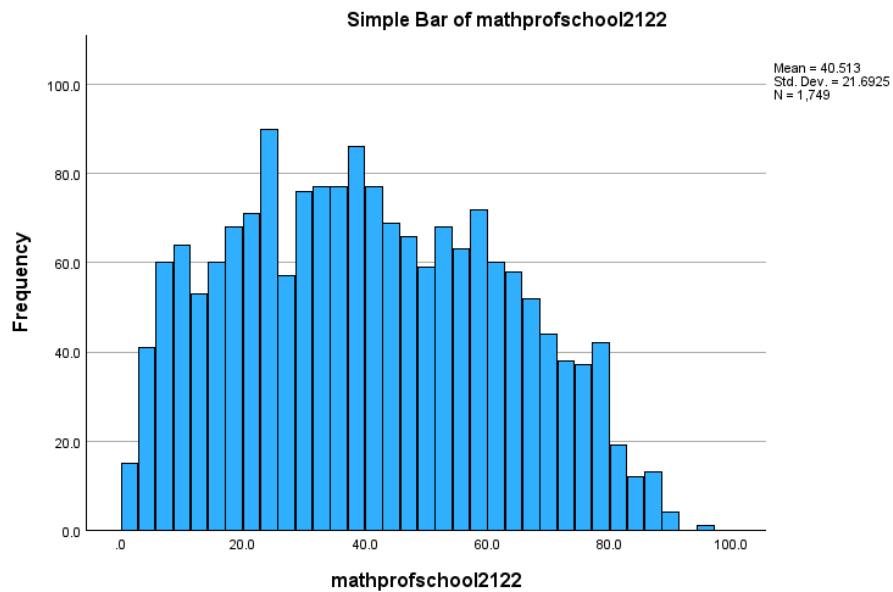
ELA Proficiency Rate



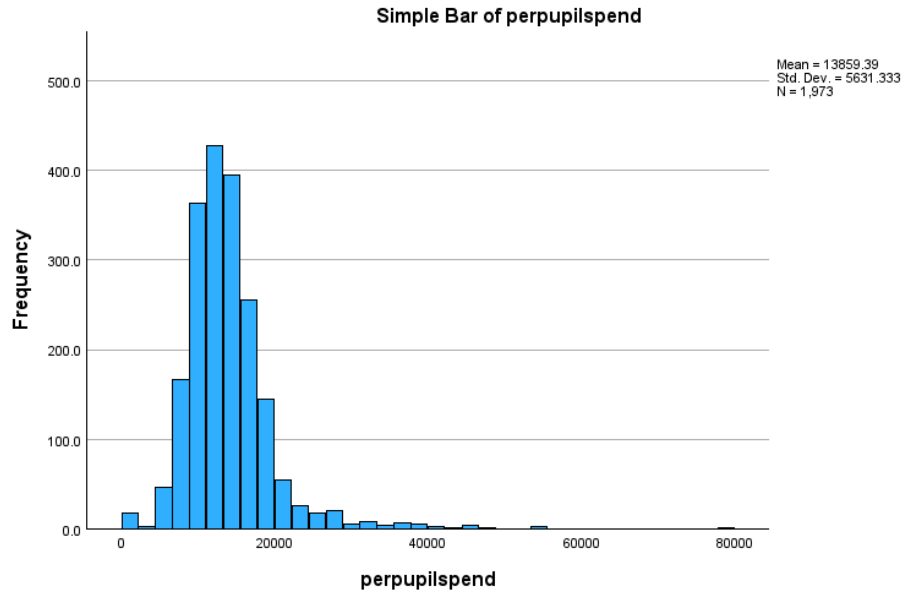
Math Mean Scale Score



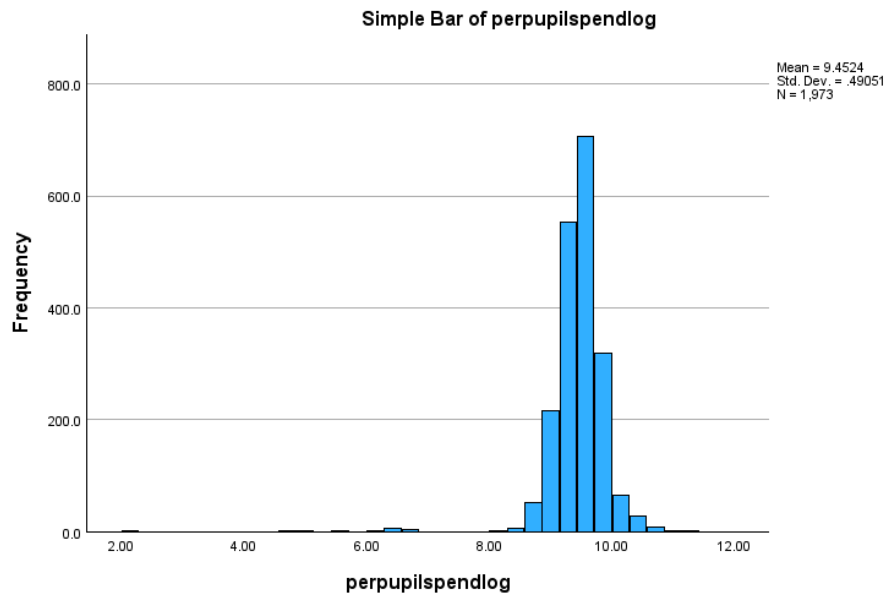
Math Proficiency Rate



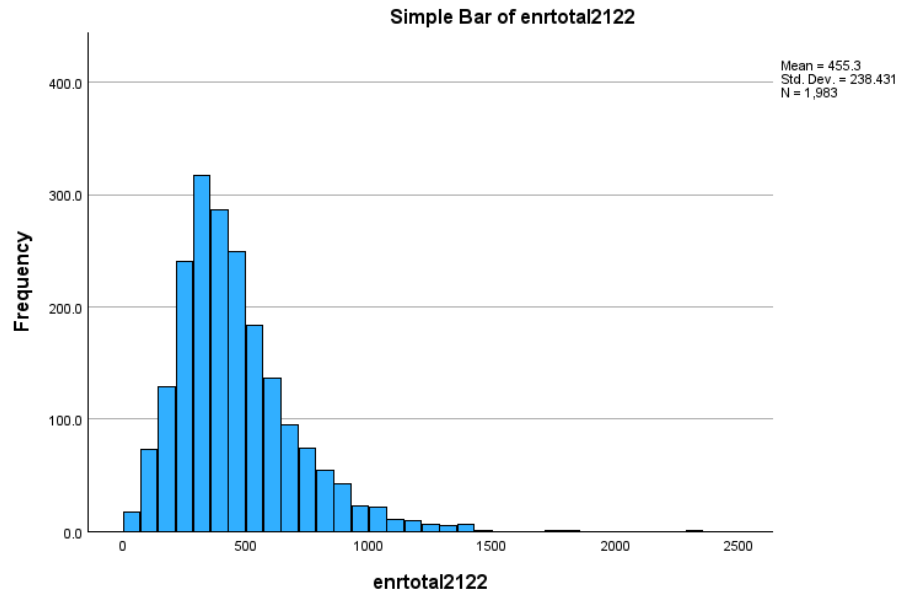
Per-Pupil Expenses



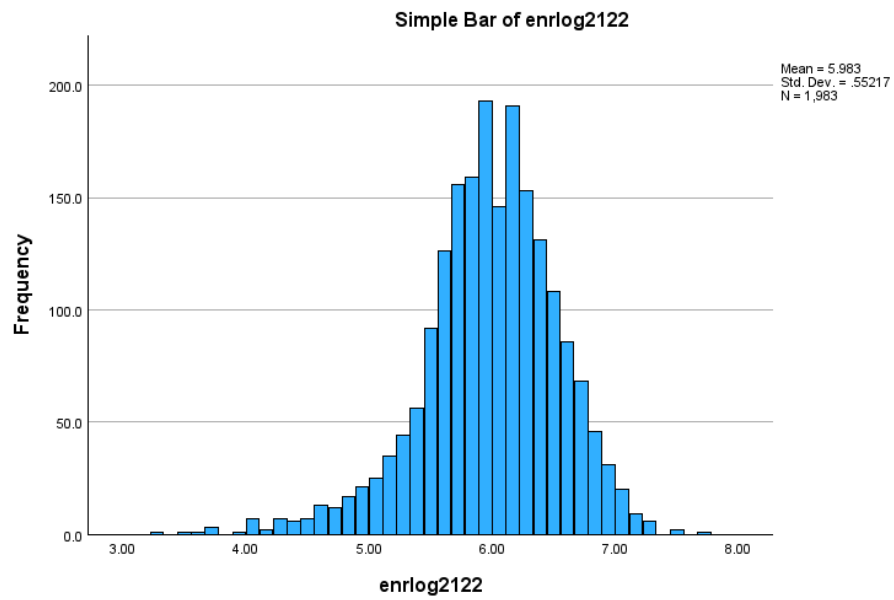
Per-Pupil Expenses (log)



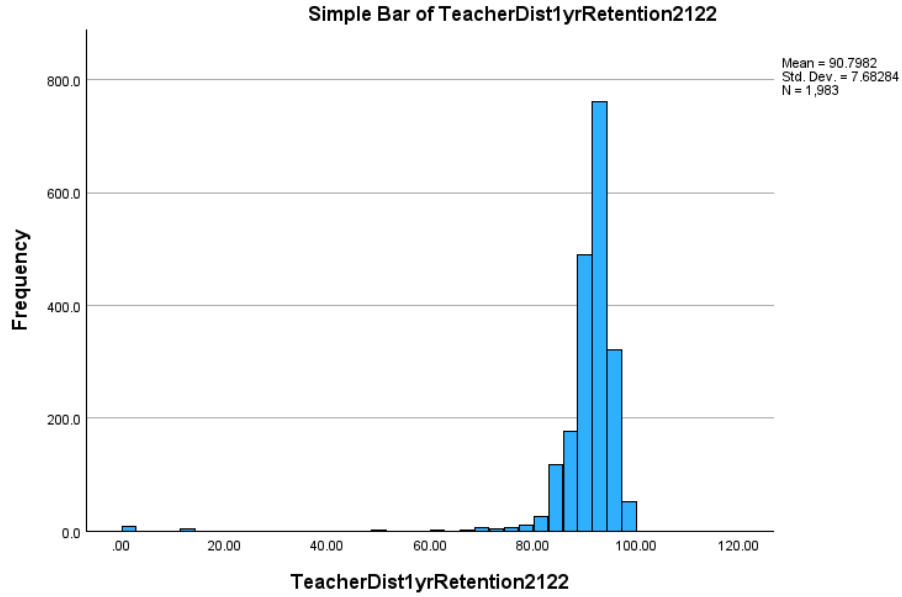
Enrollment Total



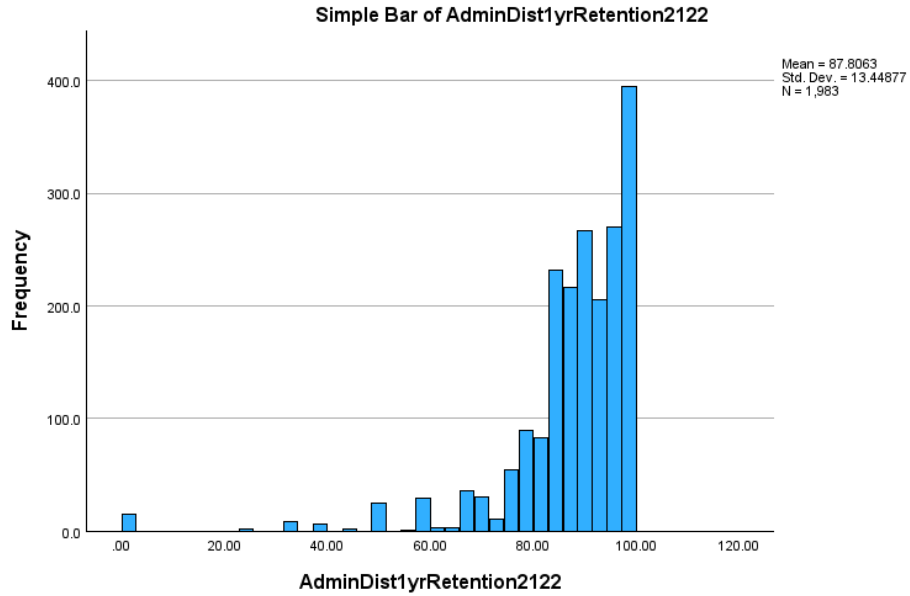
Enrollment Total (log)



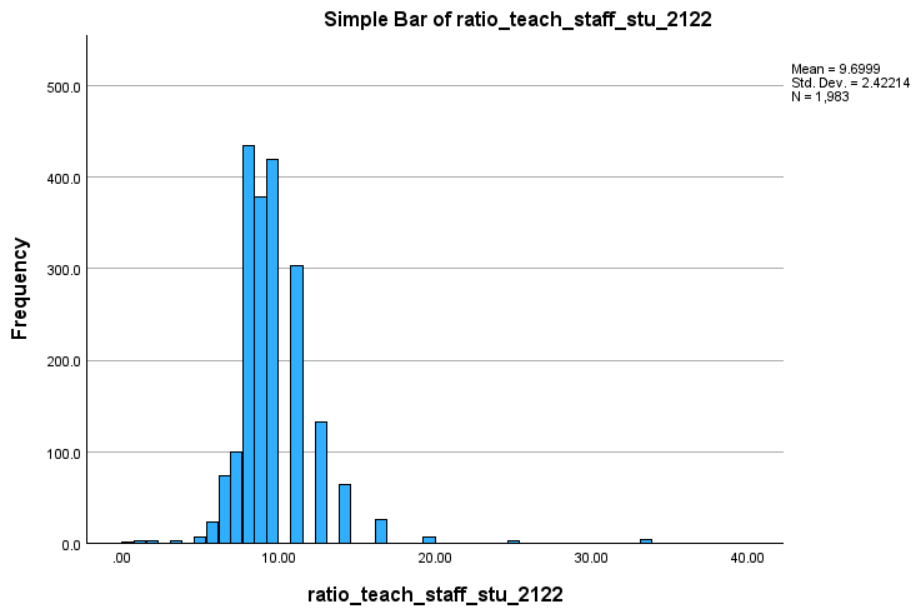
Percent Teacher 1yr Retained (District)



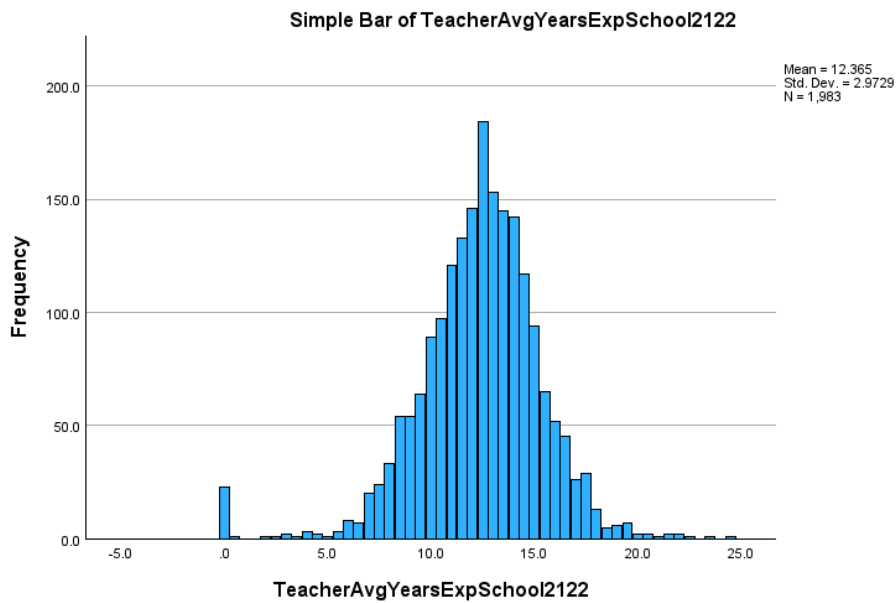
Percent Admin 1yr Retained (District)



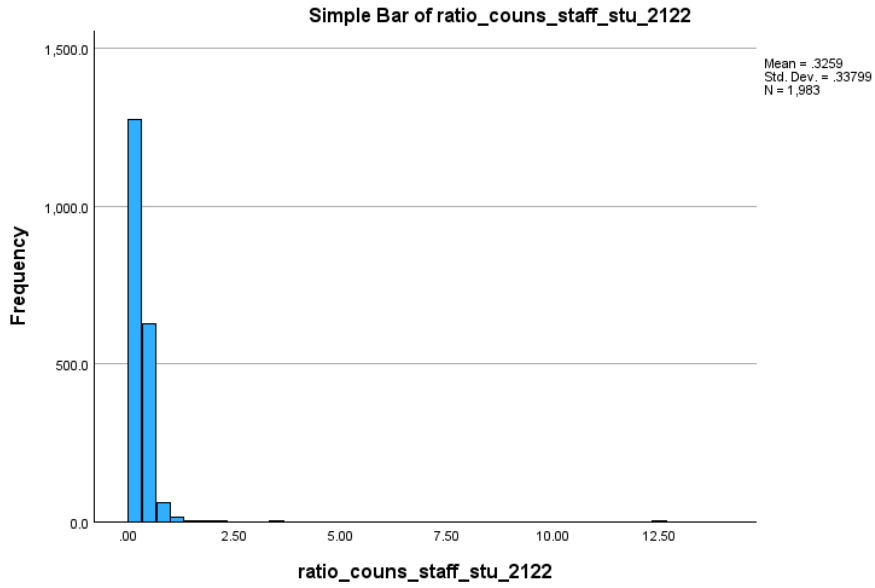
Teacher-to-Student Ratio



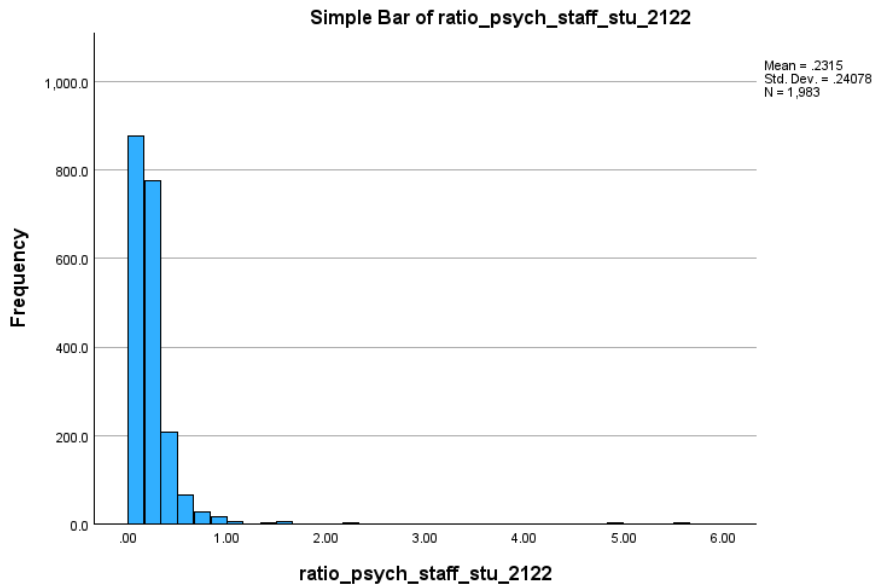
Teacher Average Years of Experience



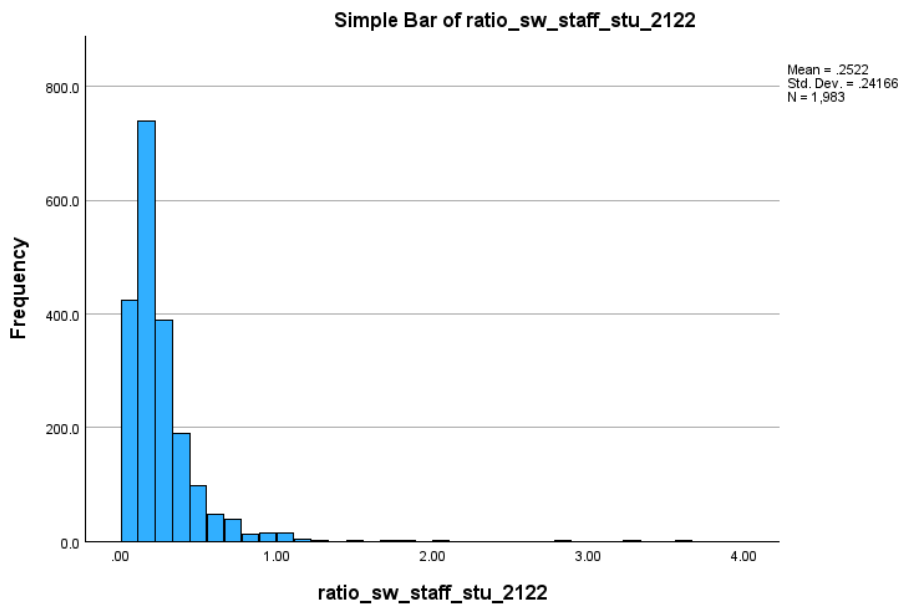
Counselor-to-Student Ratio



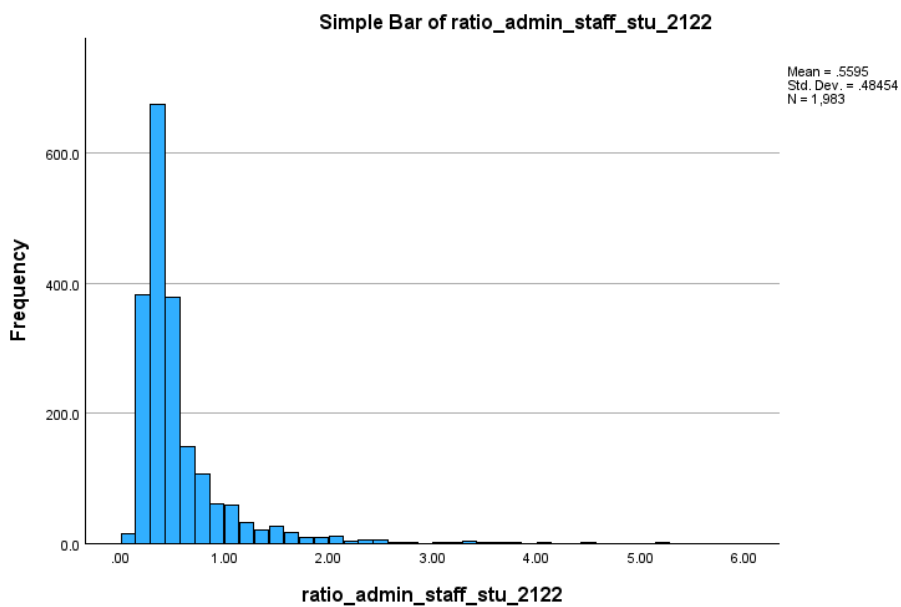
Psychologist-to-Student Ratio



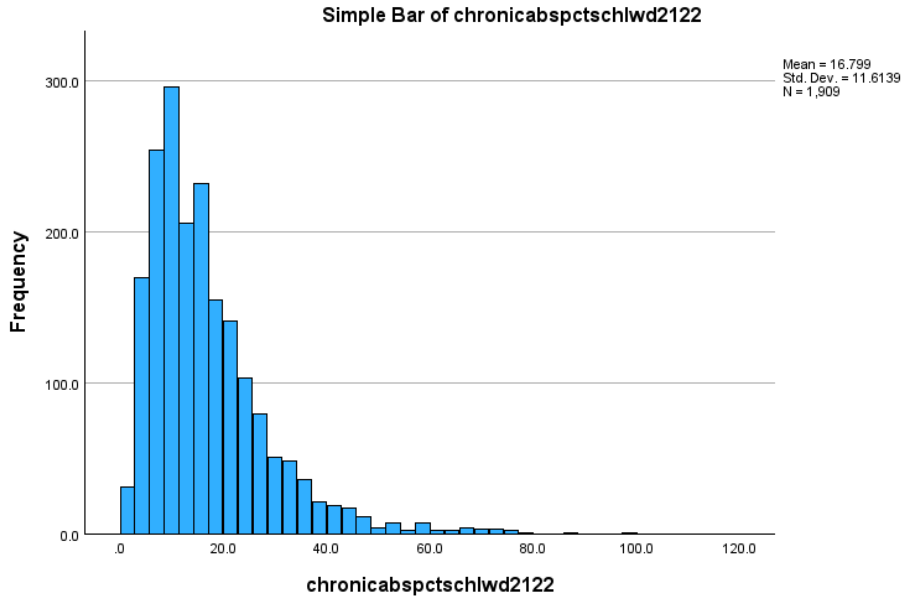
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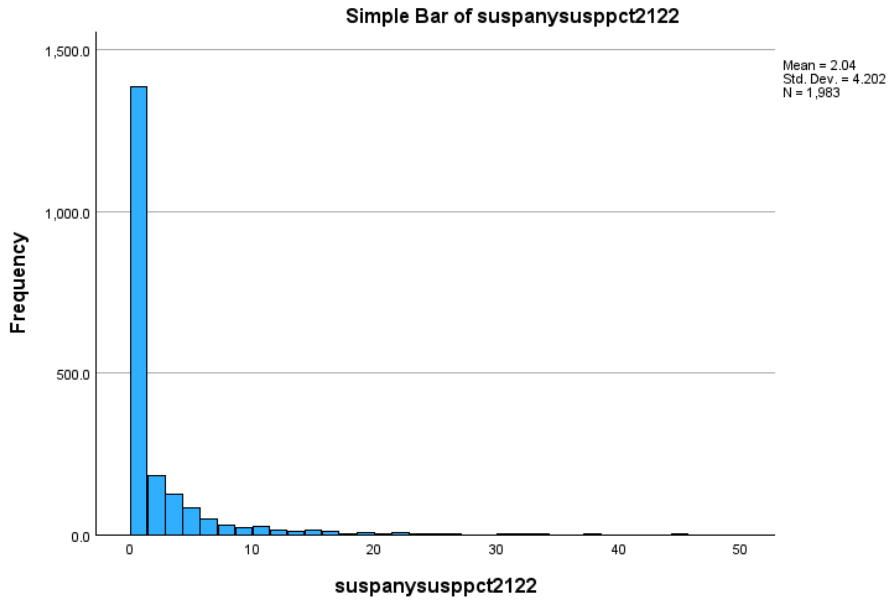
Administrator-to-Student Ratio



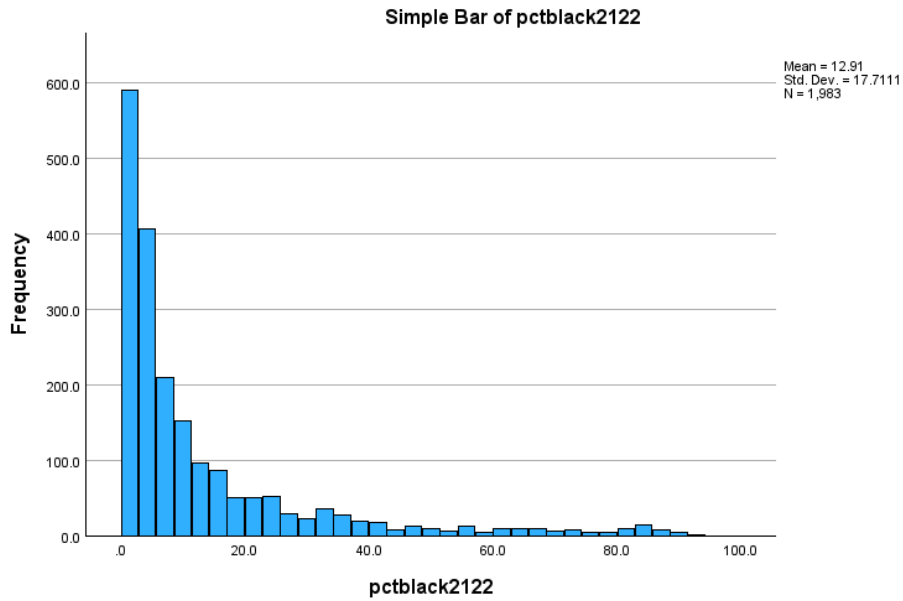
Chronic Absenteeism Rate 21–22 Schoolwide



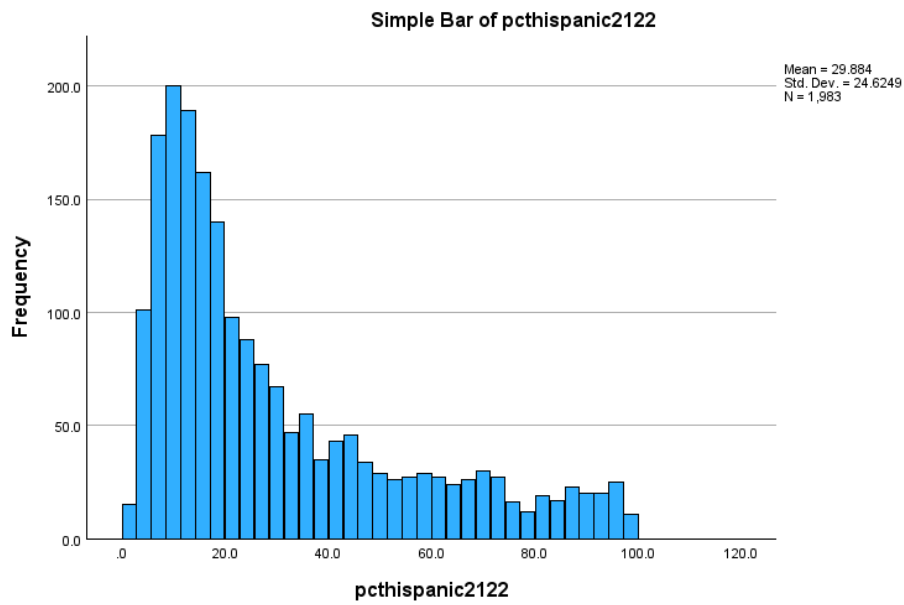
Any Suspension Rate 21–22



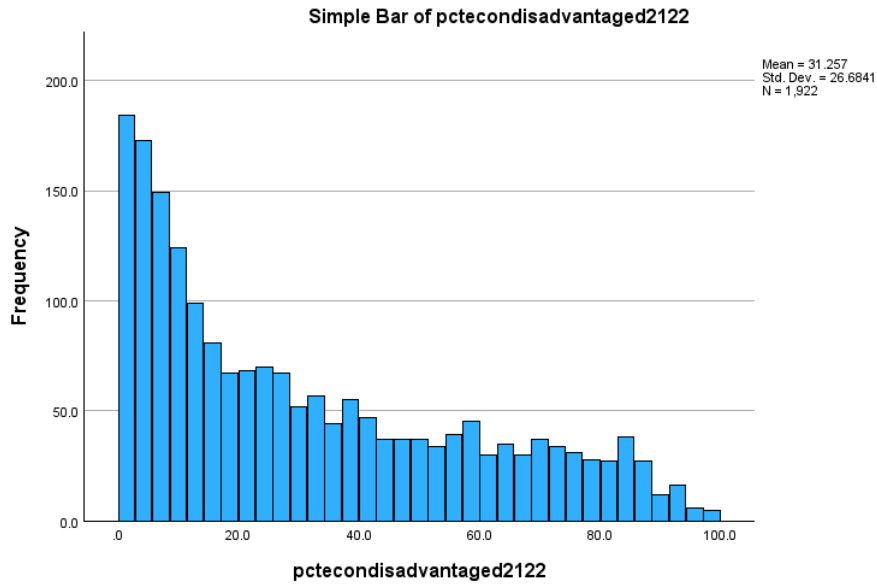
Percent Black



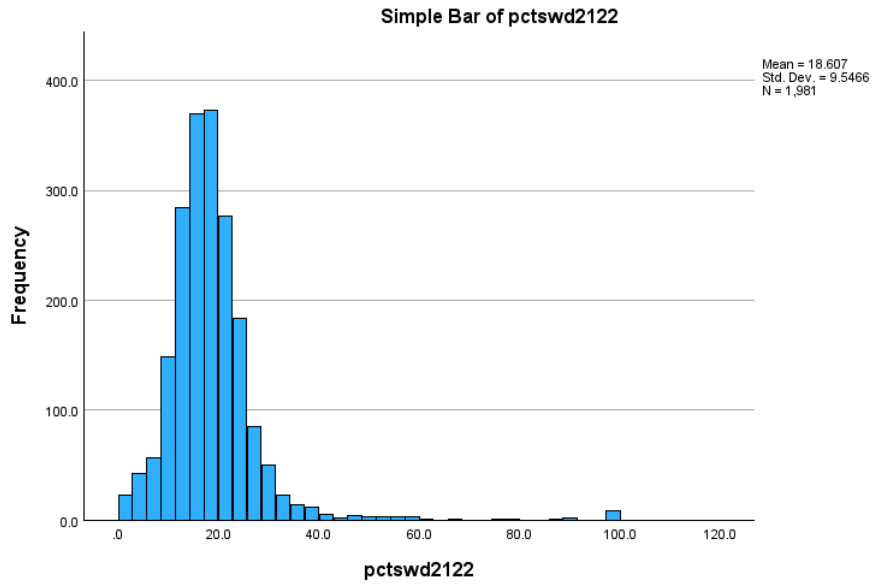
Percent Hispanic



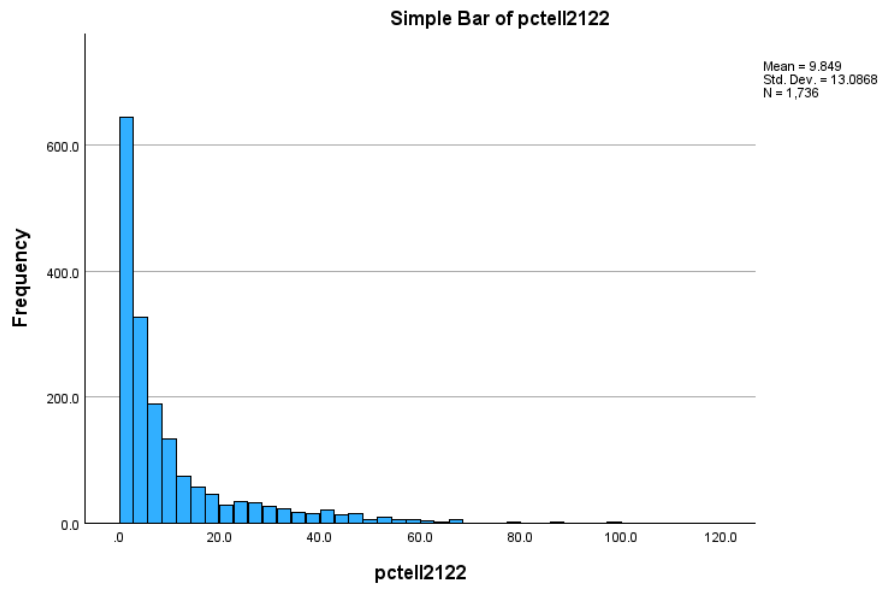
Percent Economically Disadvantaged



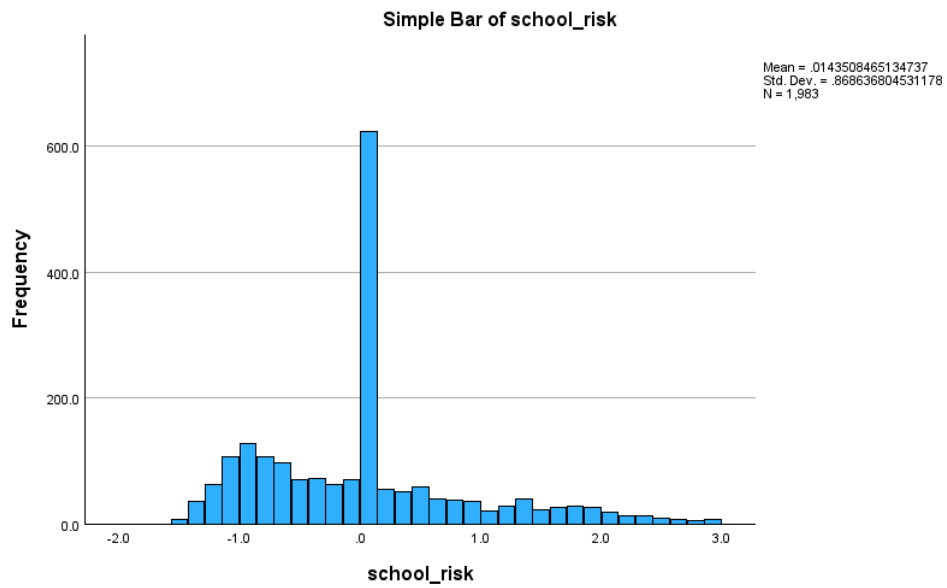
Percent Students with Disabilities



Percent Multilingual Learner



School Risk



Appendix 2. Studying Mean Achievement in English Language Arts – HLM Results

Schoolwide ELA 21-22 ELA Achievement (Standardized Mean Scale Score)						
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Black	-0.024***	-0.023***	-0.012***	-0.011***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Hispanic	-0.011***	-0.011***	-0.003***	-0.003***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Economically Disadvantaged	-0.009***	-0.006***	-0.007***	-0.006***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Students with Disabilities	-0.011***	-0.010***	-0.009***	-0.008***	-0.018***	-0.005
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.007)
Percent Multilingual Learner	-0.022***	-0.014***	-0.016***	-0.016***	-0.016***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
School Risk	-0.005	-0.117***	-0.044**	-0.083***	-0.116***	-0.231***
	(0.019)	(0.023)	(0.020)	(0.022)	(0.036)	(0.068)
Enrollment Total Log-Centered within Clusters	-0.015	-0.009	-0.033***	-0.027**	-0.030**	-0.034***
	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Percent of Parents with BA or Higher (Grand Mean Centered)	0.013***	0.013***	0.012***	0.011***	0.012***	0.011***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Median Income (Grand Mean Centered)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent Unemployed (Grand Mean Centered)	0.001	0.003	0.006	0.006	0.005	0.004
	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Percent of Children in Poverty (Grand Mean Centered)	0.018***	0.017***	0.014***	0.015***	0.015***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Percent of Households led by Single Mothers (Grand Mean Centered)	0.002	0.003	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Percent of Households Participating in SNAP (Grand Mean Centered)	-0.005	-0.006	-0.003	-0.004	-0.004	-0.005
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Per Pupil Expenses (Log)		0.067		0.072	0.062	0.053
		(0.050)		(0.045)	(0.045)	(0.045)
Teacher-to-Student Ratio		-0.028***		-0.022***	-0.022***	-0.029***
		(0.007)		(0.007)	(0.007)	(0.007)
Administrator-to-Student Ratio		-0.011		-0.030	-0.023	-0.046
		(0.037)		(0.035)	(0.035)	(0.035)
Counselor-to-Student Ratio		-0.133***		-0.204***	-0.460***	
		(0.044)		(0.042)	(0.170)	
Social Worker-to-Student Ratio		0.025		-0.044	-0.369*	
		(0.074)		(0.070)	(0.194)	
Psychologist-to-Student Ratio		0.363***		0.296***	0.143	
		(0.102)		(0.096)	(0.220)	

Teacher Average Years of Experience		-0.075***		-0.054**	-0.053**	0.022
		(0.026)		(0.024)	(0.025)	(0.020)
Teacher Average Years of Experience (Quad.)		0.003***		0.002**	0.002**	-0.001
		(0.001)		(0.001)	(0.001)	(0.001)
Percent of Administrators with 4yrs or More (District)		0.002		0.001	0.002	0.002*
		(0.001)		(0.001)	(0.001)	(0.001)
Percent Admin 1yr Retained (District)		0.005**		0.003*	0.003*	0.002
		(0.002)		(0.002)	(0.002)	(0.002)
Percent Teacher 1yr Retained (District)		-0.001		-0.001	-0.001	-0.006
		(0.004)		(0.003)	(0.003)	(0.004)
In-School Suspension Rate 21-22			-0.018***	-0.018***	-0.017***	-0.020***
			(0.006)	(0.006)	(0.006)	(0.006)
Out of School Suspension Rate 21-22			-0.025***	-0.024***	-0.023***	-0.023***
			(0.004)	(0.004)	(0.004)	(0.004)
Chronic Absenteeism Rate 21-22 Schoolwide			-0.043***	-0.045***	-0.043***	-0.042***
			(0.003)	(0.003)	(0.003)	(0.003)
Chronic Absenteeism Rate 21-22 Black Students			0.001	0.001	0.001	0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 Hispanic Students			0.010***	0.011***	0.011***	0.010***
			(0.002)	(0.002)	(0.002)	(0.002)
Chronic Absenteeism Rate 21-22 Economically Disadvantaged Students			-0.0001	-0.0003	-0.0005	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 Students with Disabilities			0.009***	0.010***	0.010***	0.009***
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 English Language Learners			0.001	-0.0003	-0.0004	0.0001
			(0.001)	(0.001)	(0.001)	(0.001)
Grade 4	-0.001	-0.001	-0.008	-0.010	-0.007	-0.006
	(0.023)	(0.023)	(0.020)	(0.020)	(0.020)	(0.020)
Grade 5	-0.016	-0.013	-0.016	-0.017	-0.016	-0.017
	(0.028)	(0.028)	(0.026)	(0.026)	(0.026)	(0.026)
Grade 6	0.075***	0.111***	0.118***	0.131***	0.133***	0.127***
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
Grade 7	0.094**	0.135***	0.200***	0.210***	0.213***	0.203***
	(0.037)	(0.037)	(0.034)	(0.034)	(0.034)	(0.034)
Grade 8	0.077*	0.115***	0.176***	0.195***	0.196***	0.184***
	(0.041)	(0.041)	(0.038)	(0.038)	(0.038)	(0.038)
School Psychologist Ratio and Percent Special Education Interaction					0.009	
					(0.009)	
School Psychologist Ratio and School Risk Interaction					0.385***	
					(0.087)	
School Social Worker Ratio and Percent Special Education Interaction					0.015*	
					(0.008)	
School Social Worker Ratio and School Risk Interaction					-0.196***	
					(0.069)	

School Counselor Ratio and Percent Special Education Interaction					0.014	
					(0.008)	
School Counselor Ratio and School Risk Interaction					0.033	
					(0.084)	
Counselor-to-Student Ratio (District)						-0.609*
						(0.361)
Social Worker-to-Student Ratio (District)						0.155
						(0.353)
Psychologist-to-Student Ratio (District)						2.660***
						(0.522)
School Psychologist Ratio and Percent Special Education Interaction (District)						-0.087***
						(0.019)
School Psychologist Ratio and School Risk Interaction (District)						0.870***
						(0.222)
School Social Worker Ratio and Percent Special Education Interaction (District)						-0.010
						(0.015)
School Social Worker Ratio and School Risk Interaction (District)						-0.089
						(0.165)
School Counselor Ratio and Percent Special Education Interaction (District)						0.036**
						(0.015)
School Counselor Ratio and School Risk Interaction (District)						0.239*
						(0.141)
Constant	1.376***	0.699	1.237***	0.711	0.973*	0.790
	(0.084)	(0.569)	(0.080)	(0.505)	(0.509)	(0.536)
Missing Variables Included	Yes	Yes	Yes	Yes	Yes	Yes
Imputation Variables Included	Yes	Yes	Yes	Yes	Yes	Yes
Level 1 Residuals	4.004	0.004	0.004	0.004	0.004	0.004
Level 2 Residuals	0.210	0.189	0.122	0.121	0.124	0.138
Number of Clusters	417	415	414	412	412	412
Observations	5,042	4,985	4,978	4,933	4,933	4,933

Note: p*** p<0.01, ** p<0.05, * p<0.1; standard errors are in parentheses. Observations are by school and grade

Appendix 3. Studying Mean Achievement in Mathematics – HLM Results

Schoolwide 21–22 Math Achievement (Standardized Mean Scale Score)						
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Black	–0.023***	–0.022***	–0.014***	–0.013***	–0.014***	–0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Hispanic	–0.009***	–0.009***	–0.006***	–0.005***	–0.006***	–0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Economically Disadvantaged	–0.008***	–0.006***	–0.006***	–0.005***	–0.005***	–0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Students with Disabilities	–0.003*	–0.001	0.0004	0.0004	–0.009**	–0.0001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)	(0.007)
Percent Multilingual Learner	–0.012***	–0.010***	–0.010***	–0.010***	–0.012***	–0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
School Risk	–0.057***	–0.121***	–0.050**	–0.093***	–0.110***	–0.308***
	(0.020)	(0.025)	(0.022)	(0.023)	(0.034)	(0.068)
Enrollment Total Log-Centered within Clusters	–0.010	0.009	–0.028**	–0.021	–0.022*	–0.029**
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Percent of Parents with BA or Higher (Grand Mean Centered)	0.012***	0.012***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Median Income (Grand Mean Centered)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent Unemployed (Grand Mean Centered)	0.003	0.002	0.008	0.005	0.005	0.004
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Percent of Children in Poverty (Grand Mean Centered)	0.014***	0.014***	0.011***	0.013***	0.013***	0.013***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Percent of Households led by Single Mothers (Grand Mean Centered)	–0.003	–0.002	–0.002	–0.001	–0.001	–0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Percent of Households Participating in SNAP (Grand Mean Centered)	–0.002	–0.003	–0.0005	–0.001	–0.001	–0.0004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Per Pupil Expenses (Log)		–0.038		–0.033	–0.020	–0.036
		(0.046)		(0.043)	(0.043)	(0.043)
Teacher-to-Student Ratio		–0.045***		–0.035***	–0.025***	–0.038***
		(0.007)		(0.007)	(0.007)	(0.007)
Administrator-to-Student Ratio		0.064*		0.039	0.050	0.040
		(0.037)		(0.035)	(0.035)	(0.036)
Counselor-to-Student Ratio		–0.225***		–0.216***	–0.355**	
		(0.045)		(0.043)	(0.177)	
Social Worker-to-Student Ratio		0.360***		0.259***	–0.257	
		(0.072)		(0.068)	(0.200)	
Psychologist-to-Student Ratio		0.402***		0.268***	0.045	
		(0.102)		(0.096)	(0.225)	
Teacher Average Years of Experience		0.005		0.025	0.024	0.100***
		(0.026)		(0.025)	(0.024)	(0.020)

Teacher Average Years of Experience (Quad.)		-0.0002		-0.001	-0.001	-0.004***
		(0.001)		(0.001)	(0.001)	(0.001)
Percent of Administrators with 4yrs or More (District)		0.0005		-0.0001	0.00004	0.0005
		(0.001)		(0.001)	(0.001)	(0.001)
Percent Admin 1yr Retained (District)		0.004***		0.003**	0.003*	0.004***
		(0.002)		(0.002)	(0.002)	(0.002)
Percent Teacher 1yr Retained (District)		-0.004		-0.004	-0.003	-0.008**
		(0.003)		(0.003)	(0.003)	(0.003)
In-School Suspension Rate 21-22			0.001	0.003	0.003	0.003
			(0.006)	(0.006)	(0.006)	(0.006)
Out of School Suspension Rate 21-22			-0.042***	-0.042***	-0.041***	-0.044***
			(0.004)	(0.004)	(0.004)	(0.004)
Chronic Absenteeism Rate 21-22 Schoolwide			-0.024***	-0.028***	-0.025***	-0.025***
			(0.003)	(0.003)	(0.003)	(0.003)
Chronic Absenteeism Rate 21-22 Black Students			0.003***	0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 Hispanic Students			0.001	0.005**	0.003	0.003
			(0.002)	(0.002)	(0.002)	(0.002)
Chronic Absenteeism Rate 21-22 Economically Disadvantaged Students			-0.002	-0.001	-0.002**	-0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 Students with Disabilities			-0.001	0.002	0.002	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)
Chronic Absenteeism Rate 21-22 English Language Learners			0.003***	0.001**	0.002***	0.002***
			(0.001)	(0.001)	(0.001)	(0.001)
Grade 4	0.013	0.007	0.012	0.004	0.006	0.007
	(0.023)	(0.023)	(0.022)	(0.021)	(0.021)	(0.021)
Grade 5	-0.014	-0.019	-0.006	-0.012	-0.013	-0.011
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.028)
Grade 6	0.124***	0.140***	0.158***	0.159***	0.151***	0.158***
	(0.033)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)
Grade 7	0.102**	0.117***	0.221***	0.217***	0.201***	0.218***
	(0.041)	(0.041)	(0.037)	(0.037)	(0.037)	(0.037)
Grade 8	-0.053	-0.033	0.094*	0.099*	0.075	0.094*
	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)	(0.054)
School Psychologist Ratio and Percent Special Education Interaction					0.007	
					(0.010)	
School Psychologist Ratio and School Risk Interaction					0.658***	
					(0.084)	
School Social Worker Ratio and Percent Special Education Interaction					0.013	
					(0.009)	
School Social Worker Ratio and School Risk Interaction					0.048	
					(0.063)	

School Counselor Ratio and Percent Special Education Interaction					0.008	
					(0.009)	
School Counselor Ratio and School Risk Interaction					-0.381***	
					(0.075)	
Counselor-to-Student Ratio (District)						0.245
						(0.358)
Social Worker-to-Student Ratio (District)						-0.734**
						(0.348)
Psychologist-to-Student Ratio (District)						0.959*
						(0.494)
School Psychologist Ratio and Percent Special Education Interaction (District)						-0.040**
						(0.019)
School Psychologist Ratio and School Risk Interaction (District)						0.560***
						(0.207)
School Social Worker Ratio and Percent Special Education Interaction (District)						0.041***
						(0.016)
School Social Worker Ratio and School Risk Interaction (District)						0.048
						(0.163)
School Counselor Ratio and Percent Special Education Interaction (District)						0.003
						(0.016)
School Counselor Ratio and School Risk Interaction (District)						0.450***
						(0.142)
Constant	1.053***	1.328***	1.133***	1.504***	1.572***	1.342***
	(0.084)	(0.515)	(0.082)	(0.477)	(0.477)	(0.502)
Missing Variables Included	Yes	Yes	Yes	Yes	Yes	Yes
Imputation Variables Included	Yes	Yes	Yes	Yes	Yes	Yes
Level 1 Residuals	0.005	0.005	0.004	0.004	0.004	0.004
Level 2 Residuals	0.123	0.115	0.098	0.098	0.101	0.103
Number of Clusters	417	415	414	412	412	412
Observations	5,007	4,951	4,943	4,899	4,899	4,899

Note: p*** p<0.01, ** p<0.05, * p<0.1; standard errors are in parentheses

Appendix 4: Studying the Likelihood of Being a “Positive Outlier” School – Ordinal Logistic Regression Results

Ordinal Logistic Regression (Residual-Based School Performance Categories)			
VARIABLES	Model 1	Model 2	Model 3
Per Pupil Expenses (Log)	0.984		1.089
	(0.116)		(0.155)
Teacher-to-Student Ratio	0.969		0.949
	(0.0271)		(0.0340)
Administrator-to-Student Ratio	1.017		1.106
	(0.126)		(0.185)
Counselor-to-Student Ratio	3.525***		5.301***
	(1.111)		(2.179)
Psychologist-to-Student Ratio	3.954***		2.025
	(1.429)		(1.036)
Social Worker-to-Student Ratio	2.581***		1.186
	(0.801)		(0.532)
Teacher Average Years of Experience	0.629***		0.742**
	(0.0590)		(0.0871)
Teacher Average Years of Experience (Quad.)	1.016***		1.009**
	(0.00377)		(0.00467)
Percent of Administrators with 4 yrs or More (District)	1.002		1.003
	(0.00309)		(0.00393)
Percent Admin 1yr Retained (District)	0.999		0.991
	(0.00487)		(0.00593)
Percent Teacher 1yr Retained (District)	1.014		1.002
	(0.00914)		(0.0105)
ratio_stu_counselor_imputed	1.635***		1.015
	(0.227)		(0.162)
ratio_stu_social_worker_imputed	1.380**		1.173
	(0.180)		(0.171)
ratio_stu_psychologist_imputed	1.399**		1.282*
	(0.184)		(0.185)
In-School Suspension Rate 21–22		1.001	1.001
		(0.0225)	(0.0220)
Out of School Suspension Rate 21–22		0.931***	0.918***
		(0.0200)	(0.0202)
Chronic Absenteeism Rate 21–22 Schoolwide		0.923***	0.914***
		(0.0156)	(0.0157)
Chronic Absenteeism Rate 21–22 Economically Disadvantaged Students		0.996	0.995
		(0.00589)	(0.00595)
Chronic Absenteeism Rate 21–22 Black Students		1.005	1.005
		(0.00446)	(0.00446)

Chronic Absenteeism Rate 21–22 Hispanic Students		1.033***	1.039***
		(0.0118)	(0.0119)
Chronic Absenteeism Rate 21–22 White Students		0.997	0.997
		(0.00534)	(0.00546)
Chronic Absenteeism Rate 21–22 Multi-Language Learners		1.008**	1.006
		(0.00387)	(0.00390)
Chronic Absenteeism Rate 21–22 Students with Disabilities		1.033***	1.039***
		(0.00991)	(0.00980)
Missing indicators Included	Yes	Yes	Yes
Imputation Variables Included	Yes	Yes	Yes
1st Threshold	0.00578***	0.0215***	0.00487***
	(0.00739)	(0.00462)	(0.00738)
2nd Threshold	0.0266***	0.0979***	0.0229**
	(0.0337)	(0.0151)	(0.0346)
3rd Threshold	1.521	5.570***	1.414
	(1.929)	(0.784)	(2.131)
4th Threshold	2.528	10.07***	2.620
	(3.207)	(1.516)	(3.948)
Observations	1,939	1,675	1,658

Note: p*** p<0.01, ** p<0.05, * p<0.1; standard errors are in parentheses; coefficients are in the scale of odds ratios

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