Analyzing Mathematics Assessment Data in Florida: A Multilevel Approach

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Abstract

Understanding mathematics achievement data requires analyzing if and how factors at the school and county levels can influence student outcomes. This research applies multilevel modeling to explore the relationships between school characteristics, which include economically disadvantaged student percentages, English Language Learner (ELL) rates, Students with Disabilities (SWD) rates, funding per student, and chronic absenteeism, alongside county-level factors of poverty and crime rates. A total of 492 high schools across all 67 Florida counties were analyzed using a two-level hierarchical linear model. The findings reveal that while school-level factors significantly predict mathematics achievement, county-level variables exhibit limited direct effects. Notably, cross-level interactions suggest that increased school funding in high-poverty counties can mitigate disparities and enhance educational outcomes. These results emphasize the critical role of equitable resource distribution and targeted strategies to address systemic inequities.

Keywords: mathematics achievement, educational policy, Florida, equity, multilevel modeling, assessment

Introduction

Educational achievement can be shaped by numerous, complex, and interrelated factors across different individual, school, and community levels, with different styles of interpretation varying by district. While individual characteristics such as socioeconomic background and English language proficiency are well-established influences on performance (Hanushek, 2011; Sirin, 2005), research increasingly emphasizes the impact of broader contexts like school resources, neighborhood conditions, and county-level policies on student outcomes (Raudenbush & Bryk, 2002; Sampson, Morenoff, & Gannon-Rowley, 2002). Mathematics achievement, in particular, is sensitive to these multilevel influences, with students' success in this subject often reflecting both personal and environmental factors outside of the classroom that vary widely across regions and school settings (Darling-Hammond, 2010; Owens et al., 2016).

In diverse states like Florida, inconsistencies in county-level resources, school demographics, and local socioeconomic conditions create distinct educational experiences and achievement levels (Rumberger & Lim, 2008; Sharkey & Elwert, 2011). Understanding these effects on mathematics achievement is crucial for identifying structural inequalities and guiding policies that promote educational equity. These concerns can be addressed by examining how county- and school-level factors influence student mathematics achievement across Florida high schools.

In Florida, each of the 67 counties operates its own public school district, making the county a meaningful unit of analysis when examining structural conditions such as funding, poverty, and crime. This county-based governance system contributes to geographic variation in school funding, staffing, and resources, which influence students' access to high-quality learning environments. This study supports the need for regionally focused research by analyzing how student performance in mathematics is shaped by school and county-level factors within the Florida context, where district-level decisions are made at the county level.

Purpose and Research Questions

The purpose of this study is to examine how school and county-level factors influence mathematics achievement among Florida high school students. By focusing on these multilevel interactions, this research aims to illuminate how educational contexts meet or challenge student needs and to reveal intervention points to improve academic outcomes statewide.

This study is guided by ecological systems theory (Bronfenbrenner, 1994) and equity-focused educational frameworks (Ladson-Billings, 2006; Milner, 2012), which emphasize how student outcomes are shaped by interconnected influences across multiple levels of their environment. These theoretical perspectives inform our focus on how both school-level and county-level conditions contribute to mathematics achievement, particularly in settings characterized by social and structural inequalities.

This research addresses a critical need for localized analysis in Florida, where governance at the county level creates considerable variation in educational conditions. The study is intended to provide insight for educators, district leaders, and policymakers who are working to understand how regional contexts shape student outcomes and where targeted supports can be most impactful. By grounding the analysis in Florida's structure, the study also contributes to broader conversations about educational equity by examining how place-based characteristics influence mathematics achievement.

Using a multilevel model framework, this analysis explores and seeks to address the following research questions:

1. How do school- and county-level factors influence mathematics achievement across Florida high schools?
2. What are the cross-level interactions between school-level factors and county characteristics in predicting mathematics achievement?
3. What role do county-level educational resources and external factors play in mediating or moderating the impact of school-level covariates on mathematics achievement?

Literature Review

Understanding the influences on student mathematics achievement requires examining a web of factors at multiple levels—individual, school, and county. Research has shown that individual characteristics, such as English Language Learner (ELL) status and disability, have substantial impacts on student performance, particularly in mathematics. However, these impacts do not occur in isolation; rather, they interact with the broader contexts in which students learn (Hanushek, 2011; Coleman et al., 1966). Recent studies have emphasized the importance of examining cross-level interactions to understand how both school and county-level factors influence individual achievement, especially within economically and demographically diverse populations (Raudenbush & Bryk, 2002; Sirin, 2005).

In Florida, mathematics achievement at the high school level is measured using the Florida Standards Assessments (FSA) End-of-Course (EOC) exams in Algebra I and Geometry. These exams are scored on a five-level scale, with Level 1 indicating inadequate performance and Level 5 indicating mastery. The Florida Department of Education defines proficiency as scoring at Level 3 or higher, which represents satisfactory performance. In this study, mathematics achievement is operationalized as the percentage of students in each school scoring at Level 3 or above on the Algebra I and Geometry EOC exams, consistent with the state's accountability and reporting standards (Florida Department of Education, 2021).

County-Level Factors and Student Achievement

County-level factors such as crime rates, poverty levels, and general economic conditions play a significant role in shaping educational outcomes (Sampson et al., 2002). High poverty rates in a county, for example, are often associated with resource limitations and elevated stress levels in both students and staff, which can impede learning and decrease academic achievement (Duncan & Murnane, 2011). Crime rates are another critical factor, as neighborhoods with high crime tend to experience higher levels of instability and student absenteeism, which negatively impact performance (Rumberger & Lim, 2008). In Florida, where socioeconomic diversity is pronounced across counties, examining economic and crime rates at the county level offers insight into systemic issues that individual schools may not be able to address independently.

Chronic Absenteeism and Its Impact on Mathematics Achievement

Chronic absenteeism, defined as missing 10% or more of school days in an academic year, has been widely recognized as a critical barrier to student success. Research consistently shows that students who are chronically absent are at a higher risk of academic underperformance, particularly in mathematics, where continuous practice and skill-building are essential (Balfanz & Byrnes, 2012; Gottfried, 2014). Absenteeism disrupts learning continuity and weakens the connection between students and school environments, compounding challenges for students in underserved or high-poverty areas. Studies also highlight the disproportionate impact of absenteeism on students from economically disadvantaged backgrounds, where external factors such as health issues, unstable housing, and family responsibilities exacerbate the problem (Ready, 2010). Florida's public schools face varying rates of absenteeism across counties, making it an important factor to explore within the broader framework of school-level influences on mathematics achievement.

While the effects of chronic absenteeism are generally negative, research suggests that its impact may vary across student populations. Ready (2010) found that absenteeism had a more pronounced effect on students from low-income households compared to their more affluent peers, which reinforces the idea that missed instructional time can deepen existing achievement gaps. Gottfried (2014) also reported variation in how absenteeism influences performance across subject areas, with mathematics being particularly sensitive to lost instructional time. Other studies have suggested that absenteeism may not operate independently, but instead reflects broader social vulnerabilities such as unstable housing, food insecurity, or limited access to healthcare. These perspectives highlight the importance of interpreting absenteeism within a wider social and demographic context, rather than as an isolated variable.

Funding per Student and Resource Equity

Funding per student is another significant factor influencing educational outcomes, as it reflects the resources available to support student learning and engagement. Increased funding is linked to improved student performance, particularly in schools serving economically disadvantaged populations (Jackson et al., 2016). Adequate funding enables smaller class sizes, access to advanced coursework, higher teacher salaries, and additional support services, all of which contribute to better educational outcomes (Lafortune et al., 2018). However, disparities in funding across Florida's counties create inequities that may influence mathematics achievement differently based on geographic location. Studies indicate that counties with higher per-student funding often outperform those with lower funding levels, suggesting that resource allocation plays a key role in mitigating the effects of poverty and other systemic challenges (Baker et al., 2018). Examining funding per student as a moderating factor can provide insights into its role in mediating the relationship between school and county-level influences on student outcomes.

Cross-Level Interactions Between School- and County-Level Factors

Studies increasingly focus on the interactions between school-level conditions, such as the proportion of economically disadvantaged students, school funding, and student demographics. Economically disadvantaged schools often face greater challenges, including larger class sizes, lower teacher retention, and limited access to advanced coursework, which disproportionately affect students who are already at risk, such as ELLs and Students with Disabilities (SWD) (Darling-Hammond, 2010; Owens et al., 2016). Cross-level interactions suggest that students' challenges may be compounded in resource-limited school environments, leading to disparities in achievement. Investigating these interactions is particularly pertinent in diverse educational settings like Florida's, where school demographics vary widely across the state. This focus on interactions directly informs us how school-level factors and student demographics jointly influence mathematics achievement.

County-Level Educational Resources and External Factors as Mediators or Moderators

In addition to direct impacts, county-level resources and external conditions, such as per-student funding and local crime rates, may play mediating or moderating roles in student achievement. Educational resources at the county level, including funding allocation per student and available support services, are critical to supporting effective teaching and addressing diverse student needs (Ladd & Fiske, 2011). Studies show that higher funding levels correlate with improved outcomes, especially in underfunded schools serving at-risk populations (Jackson et al., 2016). Meanwhile, external factors like local crime rates not only directly influence students but also indirectly affect school climates, potentially moderating the impact of school and student characteristics on achievement (Sharkey & Elwert, 2011). These factors suggest that a multilevel framework is essential to understanding the full scope of influences on mathematics achievement. This insight supports an examination of the role that county-level educational resources and external factors take in shaping student outcomes in Florida high schools.

This study is conceptually informed by ecological systems theory, which emphasizes that students are shaped by multiple nested environments. These environments range from proximal settings such as the classroom to broader systems like neighborhoods and regional policy contexts (Bronfenbrenner, 1994). In this framework, school-level factors such as absenteeism or economic disadvantage are understood in relation to larger community and structural influences, including county-level poverty and crime. Applying this ecological perspective supports the use of multilevel modeling to examine how factors at different levels interact to influence mathematics achievement. Additionally, equity-focused research traditions emphasize that social and educational disparities are often tied to geographic and structural inequalities (Ladson-Billings, 2006; Milner, 2012). These perspectives frame place-based variables such as school funding and county-level conditions not just as contextual factors, but as central mechanisms in understanding how systemic inequality impacts educational outcomes.

Multilevel Modeling in Educational Data

Multilevel modeling (MLM) is a critical methodological approach for analyzing hierarchical data structures in educational research, where students are nested within schools, and schools are nested within counties or districts. Unlike traditional regression methods, MLM accounts for the dependence of observations within clusters, allowing for more precise estimates by separating variance attributable to individual, school, and county levels (Raudenbush & Bryk, 2002). By doing so, MLM offers a nuanced understanding of the factors impacting student outcomes at each level (Hox, 2010).

Research utilizing MLM has illustrated how school-level characteristics, such as teacher quality, funding, and instructional resources, interact with individual student factors, such as socioeconomic status and prior achievement, to shape academic performance (Snijders & Bosker, 2012; Goldstein, 2011). Studies from other states and countries using multilevel modeling reveal similar patterns of inequality in educational outcomes, particularly in regions with significant socioeconomic diversity (Gelman & Hill, 2007; Snijders & Bosker, 2012). For example, research from urban U.S. districts highlights the critical role of localized funding allocation, while international studies underscore the importance of community support systems (Ladd & Fiske, 2011). This study extends such applications to Florida, offering localized insights with broader implications for addressing achievement gaps.

The flexibility of MLM enables researchers to investigate cross-level interactions, making it particularly relevant for exploring how broader contextual factors like county-level poverty and crime rates influence individual students' learning outcomes (Huang, 2018). Moreover, MLM provides a means to address the issue of statistical bias when using large datasets by controlling for variations across nested levels, which is crucial for accurately estimating the impact of covariates on student performance (Gelman & Hill, 2007). This approach of analyzing educational data enables the exploration of direct effects and interactions simultaneously, offering a comprehensive framework for understanding the complexities of educational achievement.

Method

Research Design

This quantitative study employs a multilevel modeling approach to examine the impact of school and county-level factors on mathematics achievement among high school students in Florida. Using a two-level hierarchical linear model (HLM), with schools nested within counties, allows us to account for variations across these levels, aligning with best practices in educational research for handling nested data structures (Raudenbush & Bryk, 2002; Hox, 2010). As stated earlier in the literature review, this approach supports our focus on both direct effects and cross-level interactions.

Variables

Variables for the multilevel model analysis include both school-level and county-level factors to explore their impact on mathematics achievement. The dependent variable is school-level mathematics achievement, measured by the combined rate of students scoring proficient (three or higher) on the Algebra 1 and Geometry End-of-Course (EOC) assessments. At the school level (Level 1), variables include the percentage of economically disadvantaged students, English language learners (ELL), Students with Disabilities (SWD), chronic absenteeism counts, and total costs per pupil (combined expenses incurred at both the school and district levels for each student). For the county level (Level 2), variables encompass the county family poverty rates and overall crime rates, both per 100,000 people within the population.

Data Source and Structure

School-level data, including ELL status, SWD status, and socioeconomic indicators, were obtained from the Florida Department of Education's Student Database Reports (2023b). Mathematics achievement was measured by scores on the Florida Standards Assessments (FSA) or EOC exams in mathematics in Algebra 1 and Geometry courses, standardized for comparability across schools and counties (Florida Department of Education, 2023b). The Florida School Accountability Report Card provided data on school grades, assessment performance, and accountability metrics (Florida Department of Education, 2023a).

County-level crime rates, specifically violent crimes that include murder, rape, robbery, and aggravated assault, were obtained from the Florida Department of Law Enforcement (FDLE) through the Florida Incident-Based Reporting System (FIBRS) (Florida Department of Law Enforcement, 2023). County-level poverty rates were sourced from the U.S. Census Bureau and the American Community Survey, specifically the 2018–2022 five-year estimates (Census Bureau, 2023; American Community Survey, 2023).

High school mathematics achievement data were obtained from the Florida Department of Education, encompassing all available public high schools across the state's 67 counties. This dataset includes school-level observations nested within county-level contexts and represents a full dataset rather than a traditional sample. This analysis draws on data from every public high school in Florida across all 67 counties for the 2022–2023 academic year, providing complete statewide coverage of the target population. Although no statistical sampling procedures were used, the multilevel structure of the data, with schools nested within counties, supports the use of hierarchical modeling.

The nesting of schools within counties reflects natural administrative and geographic boundaries. Counties serve as level-2 units to model contextual effects such as poverty, crime, and funding, while schools represent level-1 units that contribute to variation in student outcomes. This design aligns with best practices in multilevel educational research, where hierarchical structures are explicitly modeled to capture contextual dependencies and reduce aggregation bias (Raudenbush & Bryk, 2002; Hox, 2010; Snijders & Bosker, 2012).

Table 1. *Descriptive Statistics*

			Level 1		
Variable	*N*	Mean	*SD*	Minimum	Maximum
Math Achievement	492	41.82	18.56	9.3	100.0
Cost per Pupil	492	9905.21	3625.30	4064.0	48390.0
Chronic Absenteeism	492	630.05	421.68	0.0	2276.0
SWD	492	12.57	5.05	0.0	40.8
ELL	492	6.28	6.78	0.0	45.4
Economically Dis.	492	48.68	17.62	0.0	100.0
			Level 2		
Variable	*N*	Mean	*SD*	Minimum	Maximum
Poverty	67	18.45	10.82	3.1	45.6
Crime Rate	67	152.30	75.65	50.2	320.1

Analytic Approach

A two-level hierarchical linear model (HLM) was used to examine the relationship of both school and county factors on mathematics achievement (i.e., dependent variable). Level 1 represents school-level variables, while Level 2 represents county-level variables. As part of the data preparation process, all continuous predictors were centered to enhance interpretability and reduce multicollinearity in the hierarchical models (Raudenbush & Bryk, 2002; Hox, 2010). At the county level and school level, variables were grand mean-centered to reflect deviations from the statewide averages. These centering decisions align with best practices in multilevel modeling, ensuring that interaction terms are meaningfully interpretable in the context of nested data structures (Snijders & Bosker, 2012; Gelman & Hill, 2007).

The analysis begins with constructing a null model, or unconditional model, to partition the variance in mathematics achievement between school and county levels. This initial model provides a baseline understanding of how much variation in student achievement is attributable to each level, serving as a foundation for adding predictors and examining interactions (Raudenbush & Bryk, 2002). We then introduce a random intercept model by adding school-level covariates, while treating county-level variables as random intercepts, allowing us to observe how variations in school characteristics contribute to differences in mathematics achievement across Florida high schools (Hox, 2010). Following, a full model was built that includes both school and county-level predictors. Finally, cross-level interaction terms were added to the full model.

Model fit was evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are widely used measures for comparing the quality of statistical models by balancing goodness-of-fit with model complexity (Burnham & Anderson, 2002). Lower AIC and BIC values indicate better-fitting models, providing a robust basis for model selection. Additionally, the Intraclass Correlation Coefficient (ICC) was calculated for each model to estimate the proportion of variance in mathematics achievement attributable to differences between counties, aligning with best practices for multilevel modeling (Raudenbush & Bryk, 2002). Improvements in model fit were assessed by comparing the AIC and BIC values across models, with reductions indicating enhanced explanatory power through the inclusion of additional predictors or interactions.

While random slopes were considered for selected school-level predictors, such as chronic absenteeism, SWD rates, and economically disadvantaged student rates, the chi-square statistics required to test their significance could not be computed for the majority of counties due to insufficient data. At most, only half of the counties had adequate data for these computations, rendering random slope estimates unreliable. As a result, fixed slopes were used for all predictors to ensure stable and interpretable results across the full dataset (Raudenbush & Bryk, 2002; Snijders & Bosker, 2012). This decision aligns with the need to prioritize robust estimation over added model complexity when data limitations are present (Hox, 2010).

Assumptions

The assumptions of hierarchical linear modeling were analyzed to ensure the validity and robustness of findings, as detailed in Appendix A. The linearity assumption was assessed using scatterplots of residuals versus fitted values (Figures A5 and A6), which showed a random distribution around zero with no systematic patterns, indicating that the relationship between predictors and the outcome variable, mathematics achievement, was linear for both levels (Raudenbush & Bryk, 2002).

The normality of residuals at Level 1 was evaluated through histograms, Q-Q plots, and the Shapiro-Wilk test (Table A1), which revealed slight deviations, such as positive skewness, but approximate normality overall. The large sample size of 492 schools mitigates concerns about minor deviations due to the central limit theorem (Snijders & Bosker, 2012). The histogram and Q-Q plot of Level 2 residuals (Figures A2 & A4) revealed more noticeable deviations from normality. The Shapiro-Wilk test for Level 2 residuals indicated significant non-normality. Despite this, the use of fixed slopes ensured the robustness of fixed effect estimates, reducing reliance on the normality assumption for Level 2 residuals. Furthermore, with 67 counties included, the sample size was deemed sufficient for reliable estimation of fixed effects (Hox et al., 2017).

Homoscedasticity, or constant variance of residuals, was examined at both levels. At Level 1, residuals displayed consistent variance across fitted values (Figure A5), and at Level 2, scatterplots of residuals versus fitted values (Figure A6) showed minimal variability or patterns, supporting this assumption.

Independence of errors was assumed at both levels, supported by the intraclass correlation coefficients (ICCs), which justified partitioning variance across schools and counties (Snijders & Bosker, 2012). Collectively, these diagnostics confirmed that the assumptions of the hierarchical linear model were adequately met.

Software

The analyses were conducted using HLM version 8.2.2.1, which is specifically designed for hierarchical linear modeling. HLM offers robust estimation methods for complex, nested data structures (Raudenbush et al., 2019). This software enables precise estimation of cross-level interactions and random effects at both the school and county levels. Data preparation and visualization are completed using supplementary tools, ensuring data integrity and clarity in results presentation.

Results

Null Model

The null model (Table 2), which included no predictors at either the school or county level, estimated an average mathematics achievement score (intercept) of 41.56 ($SE = 1.29$, $p < 0.001$) across Florida high schools, representing the grand mean of the observed outcome variable (percentage of students scoring at Level 3 or above on the Algebra I and Geometry EOC exams). This estimate can be interpreted as approximately 41.56% of students meeting the state-defined benchmark for mathematics proficiency. The intraclass correlation coefficient (ICC) indicated that approximately 11.4% of the variance in mathematics achievement was attributable to differences between counties, underscoring the importance of multilevel modeling to account for the nested structure of the data.

Model 1: School-Level Predictors

Adding school-level predictors significantly improved model fit compared to the null model. Chronic absenteeism ($\gamma = –0.0099$, $SE = 0.0015$, $p < 0.001$), the percentage of Students with Disabilities (SWD) ($\gamma = –1.07$, SE = 0.13, $p < 0.001$), English Language Learners (ELL) ($\gamma = –0.45$, $SE = 0.09$, $p < 0.001$), and the percentage of economically disadvantaged students ($\gamma = –0.48$, $SE = 0.04$, $p < 0.001$) were all significantly negatively associated with mathematics achievement. School funding per student ($\gamma = –0.00007$, $SE = 0.00016$, $p = 0.670$) was not a significant predictor. See Table 2.

Model 2: Adding County-Level Predictors

Model 2 (Table 2) incorporated county-level predictors, including poverty rates and crime rates. Neither poverty ($\gamma = –0.17$, $SE = 0.39$, $p = 0.669$) nor crime rates ($\gamma = –0.012$, $SE = 0.018$, $p = 0.500$) were significant predictors of mathematics achievement. However, school-level factors retained their significance, indicating that within-county variability in school-level characteristics has a stronger influence on achievement than county-level factors.

Table 2. *Multilevel Model Fixed Effects and Model Fit*

	Null Model		Model 1		Model 2	
Variable	β	*SE*	β	*SE*	β	*SE*
Intercept	41.562*	1.303	40.747*	1.046	40.467222*	1.080409
Cost Per Pupil			–0.00007	0.000157	–0.00007	0.000157
Chronic Absenteeism			–0.010*	0.002	–0.010*	0.002
SWD			–1.067*	0.126	–1.068*	0.126
ELL			–0.446*	0.088	–0.456*	0.088
Economically Dis.			–0.489*	0.035	–0.481*	0.036
Poverty					–0.169	0.348
Crime Rate					–0.0121	0.021
Model Fit						
ICC	0.114		0.245		0.226	
AIC	4269.1		4114.5		4099.3	
BIC	4275.3		4120.7		4105.5	

*$p < 0.05$

Model 3: Adding County-Level Predictors Cross-Interactions

Table 3 presents results from the final multilevel model, including fixed effects, random effects, and cross-level interactions. A significant cross-level interaction was found between school-level funding per student and county-level poverty (γ_{11} = 0.000323, *SE* = 0.000147, *p* = 0.028). This indicates that the relationship between per-pupil funding and mathematics achievement differs depending on the poverty level of the county. Figure 1 presents predicted values of mathematics achievement across a range of funding levels, plotted at three representative county poverty values: one standard deviation below the mean (low), the mean (average), and one standard deviation above the mean (high). Although all variables were modeled as continuous, this visualization technique is commonly used to clarify interactions involving continuous variables (Aiken & West, 1991; Raudenbush & Bryk, 2002). As shown in Figure 1, the effect of funding is most pronounced in high-poverty counties, where increases in per-pupil funding are associated with greater predicted achievement. In contrast, funding has a weaker association with achievement in low-poverty counties. This pattern suggests that the benefits of increased funding are more substantial in areas facing greater economic challenges.

A similar pattern was found for the interaction between the percentage of economically disadvantaged students and county poverty (γ_{51} = 0.046380, *SE* = 0.021746, *p* = 0.034). Figure 2 illustrates that in counties with lower poverty levels, economic disadvantage is more strongly associated with lower achievement. However, in higher poverty counties, this relationship is less pronounced. These results suggest that the broader socioeconomic context can amplify or buffer the effects of school-level disadvantage.

The interaction between school-level funding per student and county-level crime rates was not statistically significant. Additionally, cross-level interactions for chronic absenteeism, ELL rates, and the percentage of economically disadvantaged students with county-level variables were generally non-significant. These non-significant findings imply that some contextual factors may exert limited moderating influence, or that their effects depend on additional unmeasured variables.

Table 3. *Linear Multilevel Model Cross-Level Interaction Results*

Fixed Effect	Coefficient	Standard Error	t	Approx. df	p
Math Achievement, β_0					
Math achievement, γ_{00}	39.135139	1.196002	32.722	64	<0.001
Poverty, γ_{01}	–0.680075	0.457176	–1.488	64	0.142
Crime rate, γ_{02}	0.007521	0.024051	0.313	64	0.756
Cost Per Pupil slope, β_1					
Slope, γ_{10}	0.000142	0.000169	0.837	410	0.403
Poverty, γ_{11}	0.000323	0.000126	2.553	410	0.011
Crime Rate, γ_{12}	–0.000013	0.000006	–2.013	410	0.045
For Chronic Absenteeism slope, β_2					
Slope, γ_{20}	–0.008865	0.001708	–5.191	410	<0.001
Poverty, γ_{21}	0.001448	0.000944	1.535	410	0.126
Crime Rate, γ_{22}	–0.000012	0.000048	–0.246	410	0.806
For SWD slope, β_3					
Slope, γ_{30}	–1.071056	0.133646	–8.014	410	<0.001
Poverty, γ_{31}	–0.060268	0.063469	–0.950	410	0.343
Crime Rate, γ_{32}	0.001409	0.003941	0.358	410	0.721
For ELL slope, β_4					
Slope, γ_{40}	–0.490931	0.091202	–5.383	410	<0.001
Poverty, γ_{41}	–0.137199	0.072701	–1.887	410	0.060
Crime Rate, γ_{42}	0.005533	0.003241	1.707	410	0.089
For Economically Disadvantaged slope, β_5					
Slope, γ_{50}	–0.444978	0.037803	–11.771	410	<0.001
Poverty, γ_{51}	0.046380	0.021746	2.133	410	0.034
Crime Rate, γ_{52}	–0.000389	0.001068	–0.364	410	0.716
ICC	0.235				
AIC	4089.0				
BIC	4095.2				

Figure 1. *Moderation of County-Level Poverty on the Relationship between School Funding per Pupil and Mathematics Achievement*

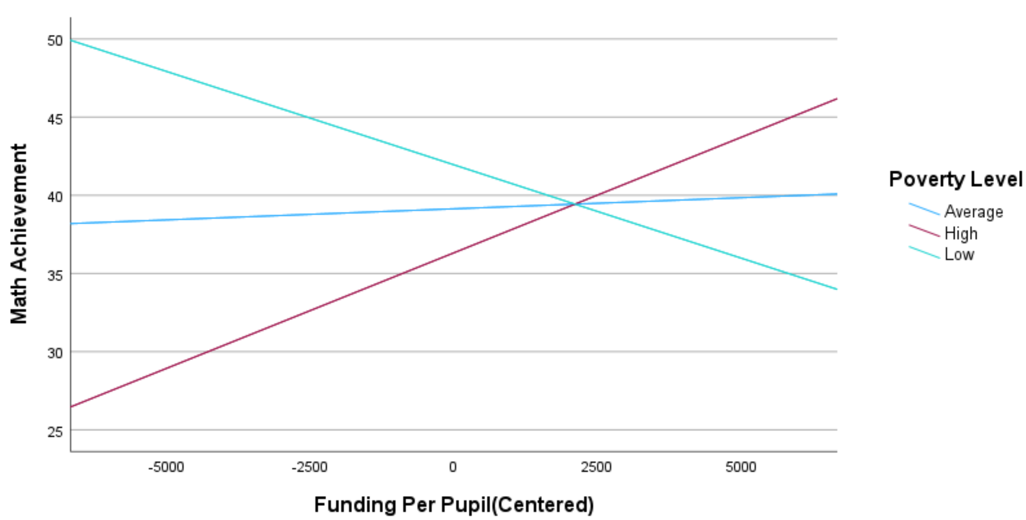
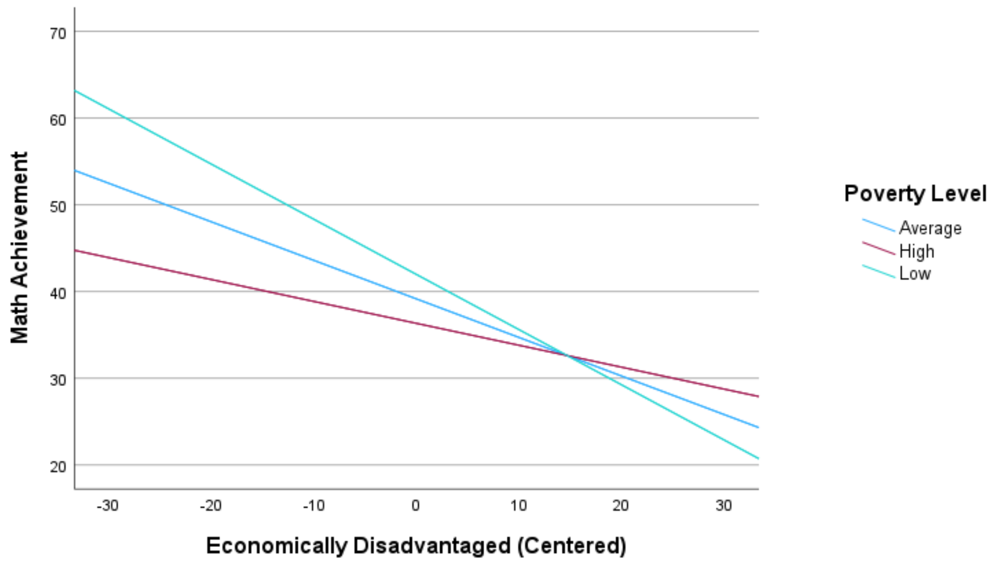


Figure 2. *Moderation of County-Level Poverty on the Relationship between the Proportion of Economically Disadvantaged Students and Mathematics Achievement*



Model Fit

The null model serves as a baseline for comparing each model by partitioning the variance in mathematics achievement between school-level and county-level predictors. The null model had an AIC of 4269.1, BIC of 4275.3, and ICC of 0.114. Model 1 with the addition of school-level predictors significantly improved model fit, with an AIC of 4114.5, BIC of 4120.7, and ICC of 0.245. Model 2 expanded upon Model 1 by including county-level predictors. The inclusion of these broader contextual variables further improved model fit, with an AIC of 4105.5, BIC of 4112.0, and ICC of 0.226. The final model, including the cross-level interactions, achieved the best fit, with an AIC of 4089.0, BIC of 4095.2, and ICC of 0.235.

Discussion

Key Findings and Interpretation

This study found that several school-level factors were statistically significant predictors of mathematics achievement across Florida high schools. Chronic absenteeism, the percentage of students with disabilities, English language learner (ELL) populations, and economic disadvantage were all significantly and negatively associated with proficiency rates on the Algebra 1 and Geometry End-of-Course (EOC) assessments. These findings align with previous research that emphasizes the importance of continuous engagement, adequate instructional support, and equitable access for historically underserved student populations (Balfanz & Byrnes, 2012; Gottfried, 2014; Owens et al., 2016; Ready, 2010).

In contrast, school-level per-pupil funding did not emerge as a statistically significant predictor when considered in isolation. Similarly, county-level poverty and crime rates were not significant direct predictors of mathematics achievement. These results suggest that broader contextual factors may not directly influence academic outcomes but instead exert their influence through interactions with more proximal school-level conditions. This interpretation is supported by ecological systems theory (Bronfenbrenner, 1979), which posits that outcomes are shaped by dynamic interactions between individuals and their nested environments. The absence of significant main effects at the county level underscores the importance of examining cross-level interactions to better understand how community contexts shape school performance.

From a policy and school-level perspective, these findings indicate that mathematics achievement tends to be lower in schools with higher rates of absenteeism, economic disadvantage, English language learners, and students with disabilities. However, in counties facing greater economic hardship, increased school funding appears to have a stronger positive effect on achievement. This underscores the importance of viewing school-level challenges within the broader context of community conditions and supports the case for funding policies that are responsive to local needs.

Emphasizing Key Moderators

Although county-level predictors did not show significant direct effects, several important cross-level interactions emerged. For instance, the interaction between school funding per student and county-level poverty was statistically significant. This result indicates that additional school funding is more strongly associated with improved mathematics achievement in higher-poverty counties. These findings are consistent with studies showing that increased investment in under-resourced schools yields measurable academic gains (Jackson et al., 2016; Lafortune et al., 2018). Similarly, the interaction between economic disadvantage and county poverty suggests that structural inequities in academic performance can be mitigated when schools receive adequate support in the form of targeted resources. Taken together, these findings highlight the importance of funding models that respond to local context and are designed to promote equitable educational opportunities.

The significant cross-level interactions reinforce the importance of modeling school outcomes within their broader socioeconomic context. The stronger association between school funding and achievement in high-poverty counties suggests that increased investment has a greater potential impact where baseline conditions are more constrained. Similarly, the reduced negative effect of economic disadvantage in high-poverty contexts may reflect systemic responses or support structures tailored to these communities. These patterns demonstrate how county-level poverty can either amplify or buffer school-level influences, emphasizing the value of multilevel frameworks in educational policy research. Visualizing these interactions helped clarify these dynamics, revealing relationships that would be overlooked in models that examine only main effects.

However, not all cross-level interactions reached statistical significance. Interactions involving county-level poverty or crime rates with school-level variables, such as chronic absenteeism, the proportion of English language learners, and the percentage of students with disabilities, did not yield meaningful moderation effects. These non-significant results suggest that some broader contextual factors may exert limited or indirect influence on achievement, or that their effects may depend on unmeasured variables such as district leadership or instructional practices. This highlights the importance of refining how community-level conditions are measured and modeled when studying their relationship to student outcomes.

Limitations

The findings from this study may have limited generalizability beyond Florida or similarly structured states with diverse socioeconomic and demographic characteristics. Educational systems with different governance models or funding structures may not exhibit the same patterns. In addition, the analysis is based on cross-sectional data and school-level aggregates, which limits causal inference. Unmeasured variables such as instructional quality, teacher effectiveness, or community engagement may also have influenced mathematics outcomes. While these limitations identify areas for refinement in future studies, the practical relevance of the findings remains strong and offers valuable insights for guiding policy and practice.

Implications for Practice and Policy

The results carry important implications for educators, district leaders, and policymakers. First, reducing chronic absenteeism should be a central focus of school improvement efforts, given its demonstrated impact on mathematics achievement. Schools serving economically disadvantaged populations may benefit from expanded access to wraparound services and other supports to address barriers to attendance (Balfanz & Byrnes, 2012; Ready, 2010). Furthermore, increasing school funding in high-poverty counties appears to produce greater gains in student achievement, highlighting the importance of resource equity. Policymakers should consider funding formulas that respond to contextual need, ensuring that investments in instruction and student supports are aligned with the challenges schools face (Jackson et al., 2016).

Future Research

Future research should expand the scope of county-level predictors to include variables such as governance structures, teacher labor markets, and indicators of civic or parental engagement. These factors may offer a more comprehensive understanding of how local context shapes students' educational experiences beyond the effects of poverty and crime. Additional predictors like teacher turnover, certification levels, and access to mental health or community-based support services could provide more nuanced explanations for achievement disparities across regions.

While this study intentionally examined a broad set of predictors to capture multilevel effects, future research may also benefit from narrowing the focus to specific student populations, such as English language learners or students with disabilities. Targeted analyses could yield more actionable insights and inform policies tailored to these groups' unique needs. Researchers should also test a broader range of cross-level interactions, such as how the effectiveness of magnet programs or teacher qualifications may vary depending on county-level resource availability. Longitudinal designs would further strengthen this line of inquiry by allowing researchers to track how changes in policy or community conditions affect achievement over time. Additionally, qualitative or mixed-method studies could explore how school and district leaders interpret and respond to structural constraints within their local environments.

Although this study focuses on Florida, the findings may be applicable to other states with similar socioeconomic and governance diversity. Prior research has shown that the organization of school districts, particularly when aligned to county or geographic boundaries, contributes to disparities in funding, staffing, and academic outcomes (Owens et al., 2016; Lubienski & Lubienski, 2006). States such as California, Texas, and Pennsylvania exhibit comparable patterns of educational inequality (Berliner, 2006; Bischoff, 2008). Replicating this multilevel model in other settings could help assess the consistency of the findings and provide a broader foundation for advancing educational equity.

Conclusion

Multilevel modeling helps to highlight the critical role of school-level factors in driving mathematics achievement and demonstrates the nuanced interplay between funding and county-level poverty. While county-level characteristics such as poverty and crime rates did not show significant direct effects, the interaction between funding and poverty underscores the importance of targeting resources to economically disadvantaged areas. Addressing absenteeism and increasing funding across counties represent key strategies for reducing achievement gaps and improving outcomes statewide for student equity. By incorporating a broader range of contextual variables and adopting longitudinal approaches, this research can build on the outcomes to inform more effective educational policies and practices.

References

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Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

American Community Survey. (2023). About the American Community Survey: 2018–2022 5-year estimates. U.S. Census Bureau. Retrieved from http://www.census.gov/acs/www/

Balfanz, R., & Byrnes, V. (2012). Chronic absenteeism: Summarizing what we know from nationally available data. *Johns Hopkins University Center for Social Organization of Schools*.

Baker, B. D., Farrie, D., & Sciarra, D. G. (2018). Is school funding fair? A national report card. *Education Law Center*.

Berliner, D. C. (2006). Our impoverished view of educational reform. *Teachers College Record, 108*(6), 949–995.

Bischoff, K. (2008). School district fragmentation and racial residential segregation: How do boundaries matter? *Urban Affairs Review, 44*(2), 182–217. https://doi.org/10.1177/1078087408320654

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design*. Harvard University Press.

Bronfenbrenner, U. (1994). *Ecological models of human development*. In T. Husén & T. N. Postlethwaite (Eds.), *International encyclopedia of education* (2nd ed., Vol. 3, pp. 1643–1647). Pergamon Press.

Burnham, K. P., & Anderson, D. R. (2002). *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach* (2nd ed.). Springer.

Census Bureau. (2023). Explore Census data: 2018–2022 American Community Survey 5-year estimates. U.S. Census Bureau. Retrieved from http://www.census.gov/

Coleman, J. S., Campbell, E. Q., Hobson, C. J., McPartland, J., Mood, A. M., Weinfeld, F. D., & York, R. L. (1966). *Equality of educational opportunity.* U.S. Department of Health, Education, and Welfare, Office of Education.

Darling-Hammond, L. (2010). *The flat world and education: How America's commitment to equity will determine our future.* Teachers College Press.

Duncan, G. J., & Murnane, R. J. (Eds.). (2011). *Whither opportunity? Rising inequality, schools, and children's life chances.* Russell Sage Foundation.

Florida Department of Education. (2021). *Achievement level descriptions*. Office of Assessment. https://www.fldoe.org/core/fileparse.php/5663/urlt/FSA-AchieveLevelDescription.pdf

Florida Department of Education. (2023a). *Florida school accountability report card.* Retrieved from https://edudata.fldoe.org/index.html

Florida Department of Education. (2023b). *Student Database Reports.* Retrieved from https://edudata.fldoe.org/AdvancedReports.html

Florida Department of Law Enforcement. (2023). *Florida Incident-Based Reporting System (FIBRS).* Retrieved from https://www.fdle.state.fl.us/CJAB/FIBRS

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models.* Cambridge University Press.

Goldstein, H. (2011). *Multilevel statistical models* (4th ed.). Wiley.

Gottfried, M. A. (2014). Chronic absenteeism and its effects on students' academic and socioemotional outcomes. *Journal of Education for Students Placed at Risk (JESPAR), 19*(2), 53–75. https://doi.org/10.1080/10824669.2014.962696

Hanushek, E. A. (2011). The economic value of higher teacher quality. *Economics of Education Review, 30*(3), 466–479. https://doi.org/10.1016/j.econedurev.2010.12.006

Hox, J. J. (2010). *Multilevel analysis: Techniques and applications* (2nd ed.). Routledge.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2017). *Multilevel analysis: Techniques and applications* (3rd ed.). Routledge. https://doi.org/10.4324/9781315650982

Huang, F. L. (2018). Multilevel modeling and ordinary least squares regression: How comparable are they? *Journal of Experimental Education, 86*(2), 265–281. https://doi.org/10.1080/00220973.2016.1277339

Jackson, C. K., Johnson, R. C., & Persico, C. (2016). The effects of school spending on educational and economic outcomes: Evidence from school finance reforms. *The Quarterly Journal of Economics, 131*(1), 157–218. https://doi.org/10.1093/qje/qjv036

Ladd, H. F., & Fiske, E. B. (2011). Weighted student funding in the Netherlands: A model for the U.S.? *Journal of Policy Analysis and Management, 30*(3), 584–605. https://doi.org/10.1002/pam.20589

Ladson-Billings, G. (2006). From the achievement gap to the education debt: Understanding achievement in U.S. schools. *Educational Researcher*, 35(7), 3–12. https://doi.org/10.3102/0013189X035007003

Lafortune, J., Rothstein, J., & Schanzenbach, D. W. (2018). School finance reform and the distribution of student achievement. *American Economic Journal: Applied Economics, 10*(2), 1–26. https://doi.org/10.1257/app.20160567

Lubienski, C., & Lubienski, S. T. (2006). Charter, private, public schools and academic achievement: New evidence from NAEP mathematics data. *National Center for Education Statistics*.

Maas, C. J. M., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 1*(3), 86–92. https://doi.org/10.1027/1614-2241.1.3.86

Milner, H. R. (2012). But what is urban education? *Urban Education*, 47(3), 556–561. https://doi.org/10.1177/0042085912447516

Owens, A., Reardon, S. F., & Jencks, C. (2016). Income segregation between schools and school districts. *American Educational Research Journal, 53*(4), 1159–1197. https://doi.org/10.3102/0002831216652722

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Sage Publications.

Raudenbush, S. W., Bryk, A. S., & Congdon, R. (2019). *HLM 8.2.2.1 for Windows* [Computer software]. Scientific Software International, Inc.

Ready, D. D. (2010). Socioeconomic disadvantage, school attendance, and early cognitive development: The differential effects of school exposure. *Sociology of Education, 83*(4), 271–286. https://doi.org/10.1177/0038040710383520

Rumberger, R. W., & Lim, S. A. (2008). *Why students drop out of school: A review of 25 years of research.* California Dropout Research Project Report No. 15. University of California, Santa Barbara.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "neighborhood effects": Social processes and new directions in research. *Annual Review of Sociology, 28*, 443–478. https://doi.org/10.1146/annurev.soc.28.110601.141114

Sharkey, P., & Elwert, F. (2011). The legacy of disadvantage: Multigenerational neighborhood effects on cognitive ability. *American Journal of Sociology, 116*(6), 1934–1981. https://doi.org/10.1086/660009

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417–453. https://doi.org/10.3102/00346543075003417

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Sage Publications.

Appendix A

Assumptions for Hierarchical Linear Model

This appendix outlines the diagnostics and methods used to evaluate the assumptions of the hierarchical linear models presented in this study. These checks ensure the validity and robustness of the results.

Figure A1. *Histogram of the Level-1 Residuals*

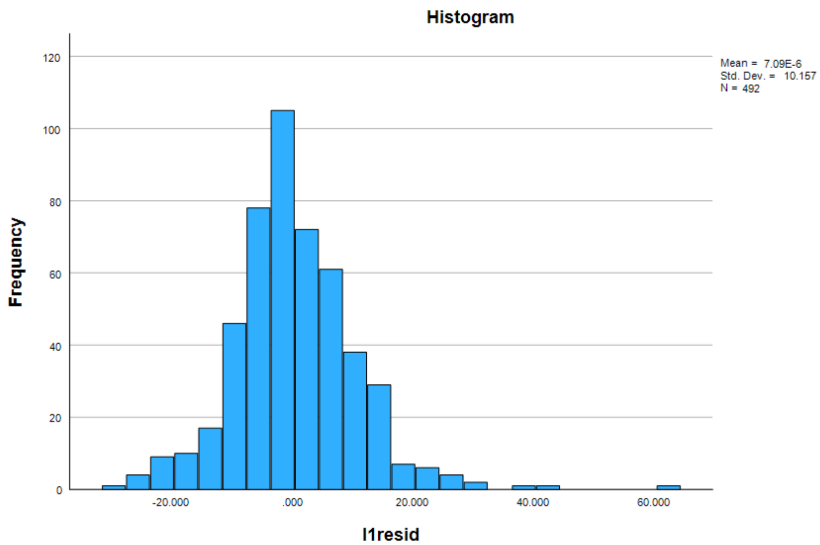


Figure A2. *Histogram of the Level-2 Residuals*

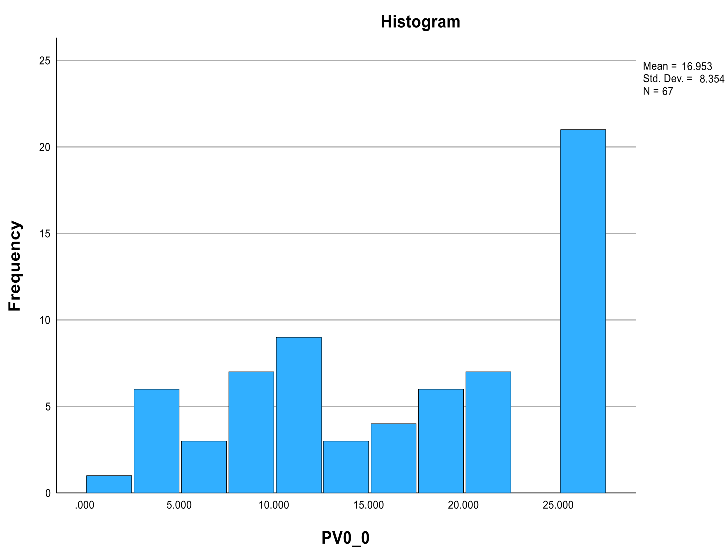


Figure A3. *Normality Plot (Q-Q plot) of Level-1 Residuals for the Hierarchical Linear Model*

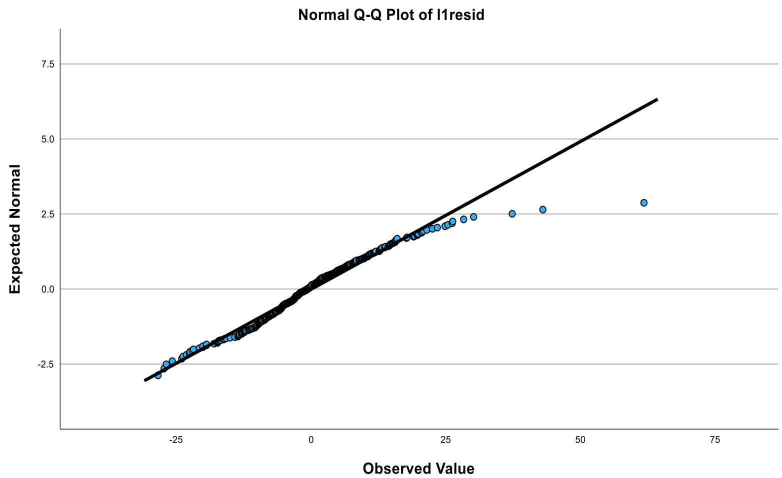


Figure A4. *Normality Plot (Q-Q plot) of Level-2 Residuals for the Hierarchical Linear Model*

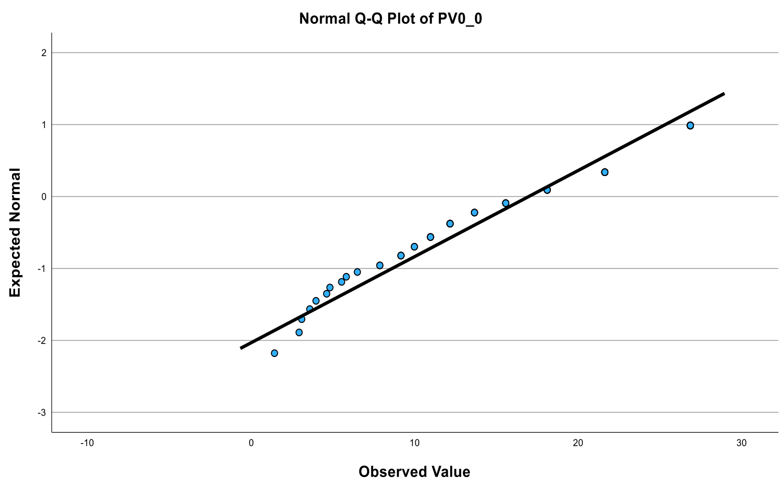


Table A1. *Tests of Normality Level-1 Residuals*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	*p*	*Statistic*	*df*	*p*
l1resid	0.70	492	<0.001	0.962	492	<0.001

[a] Lilliefors significance correction

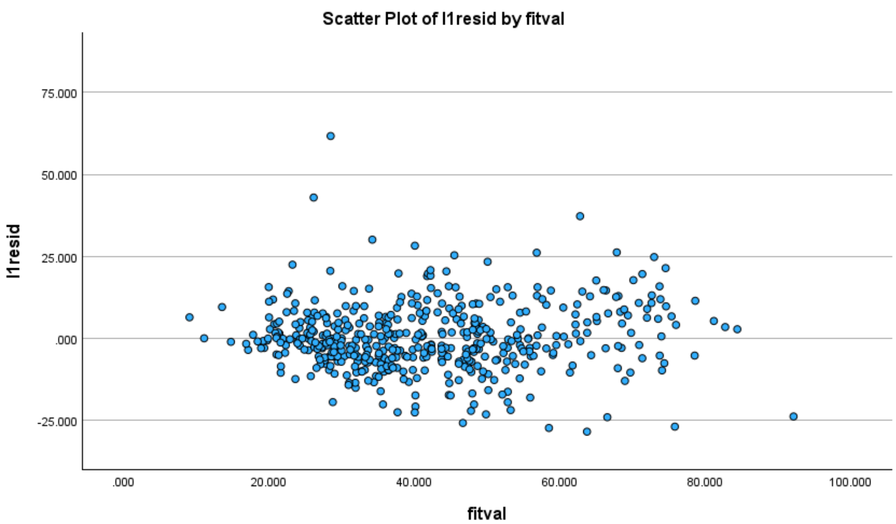
Table A2. *Tests of Normality Level 2-Residuals*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	*p*	*Statistic*	*df*	*p*
l2resid	0.195	67	<0.001	0.891	67	<0.001

[a] Lilliefors significance correction

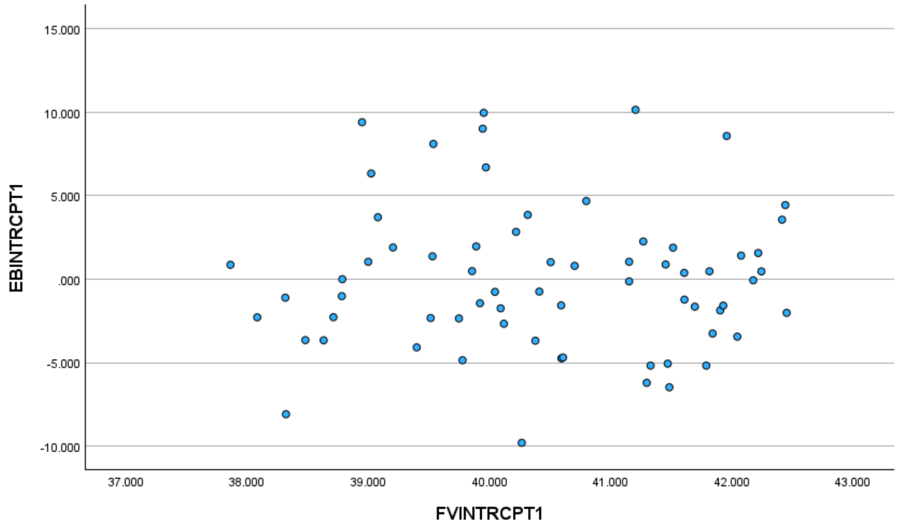
The assumption of normality was evaluated at Level 1 (school level) and Level 2 (county level) by examining residuals through Q-Q plots, histograms, and the Shapiro-Wilk test. While slight deviations from normality were observed, the residuals approximated a normal distribution, and the large sample size of 492 schools minimizes concerns about non-normality at Level 1 due to the central limit theorem. For Level 2 residuals, although deviations from normality were detected, the inclusion of 67 counties ensured that the deviations did not critically affect the model's validity. Because fixed slopes were used for all predictors, it reduces the reliance on the assumption of normality for Level 2 random effects. Furthermore, with 67 counties included in the analysis, the sample size provides sufficient robustness to deviations from normality at Level 2, ensuring reliable estimates for fixed effects and cross-level interactions.

Figure A5. *Scatterplot of Level-1 Residuals (l1resid) versus Fitted Values (fitval)*



In this plot, the residuals appear fairly randomly distributed around 0, with no evidence of systematic patterns. This suggests that the linearity assumption is reasonably met. However, there are a few points with larger residuals (e.g., above 50,000 and below –25,000), which could indicate potential outliers or influential observations. The spread of residuals appears fairly consistent across most of the range of the fitted values. However, there is slightly more variability at higher fitted values (e.g., above 60,000), which might indicate mild heteroscedasticity, but this is not severe enough to warrant major concerns.

Figure A6. *Scatterplot of Level-2 Residuals (EBINTRCPT1) versus Fitted Values (FVINTRCPT1)*



The scatterplot revealed a random distribution of residuals with no discernible patterns or systematic changes in variance across the range of fitted values. While slight increases in residual spread were observed at higher fitted values (above FVINTRCPT1 = 41), the variability was minimal and did not indicate significant heteroscedasticity. Overall, the residuals at Level 2 satisfy the assumption of constant variance, supporting the robustness of the hierarchical linear model at this level.