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"How You Spend Your Money is Your Strategy": Education Spending and the Academic Achievement of Students with and without Disabilities in Virginia, 2018-2025

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"How You Spend your Money is Your Strategy": Education Spending and the Academic Achievement of Students with and without Disabilities in Virginia, 2018-2025

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Abstract

Virginia experienced a boost in federal and state education funding from 2020-2025 and launched the Virginia Literacy Act in 2023. These policy events prompted our study of the impact of education spending by school divisions on growth in academic pass rates in reading and mathematics for students with and without disabilities in grades three through eight (2018-2025). To do this, we estimated two-level latent growth curve models to examine how reading and mathematics pass rates changed over time, both within and between school divisions. We also examined whether there were school division-level demographic differences in the growth patterns in pass rates and whether K-12 per pupil spending decisions affected those growth patterns. Using publicly available administrative data, we addressed the effects of spending at two time points: 2021-2022 (the first two rounds of federal pandemic relief) and 2023-2024 (the final round of federal pandemic relief plus targeted state funds). We found that pass rates for both reading and math displayed nonlinear growth patterns over time. These growth patterns differed by student characteristics, as students with disabilities and those in school divisions with a higher percentage of minority (non-White) students and families in poverty had significantly lower pass rates. With few exceptions, we also identified negative effects of spending on pass rates in reading and mathematics for students with and without disabilities.

Keywords: Education Finance; Education Spending; Education Policy; Special Education Policy; Local Policy Variation; Latent Growth Curve Models; Descriptive Policy Analysis; Reading and Mathematics Achievement

Policy research in education, particularly research addressing spending and student achievement, has the potential to inform decision-making by federal, state, and local leaders on behalf of children and youth. We know that money matters: financial resources to public schools can improve students' test scores and advance their educational attainment and wages in adulthood (Jackson et al., 2016, 2020; Kreisman & Steinberg, 2019; Lafortune et al., 2018). But how those resources are used is critical; namely, the extent to which their use is informed by strategic decision-making and implementation that will lead to academic improvement (Bryk et al., 2010; Handel & Hanushek, 2023; Rauscher et al., 2025a; 2025b). "How you spend your money is your strategy" is a common post-hoc interpretation of financial decision-making (Edunomics Lab, 2017, p. 2). But according to education leaders, a proactive approach is better than a reactive one. These leaders advise their colleagues to maximize the effectiveness of spending by building better connections between financial processes and academic goals. In that way, education leaders can tackle year-to-year budgeting challenges as well as sustain long-term strategies to improve student outcomes (Kurtz et al., 2024; 2025).

At the same time, concerns about the sustainability of funding make it challenging for education leaders to plan for the future (Kurtz et al., 2025). Federal pandemic relief funding has ended, and the future of federal education funding is uncertain (Goldhaber & Falken, 2025). Both of these truths have disrupted the ability of district leaders to make strategic decisions about allocating resources for improvement in student achievement (Kurtz et al., 2025). This financial uncertainty has occurred at the same time that overall student enrollment in Virginia has declined. According to the University of Virginia, population growth in the state has slowed, and

90 of Virginia's 131 school divisions[1] (68.7%) are experiencing enrollment declines (McKenzie, 2026). Yet, even as overall student enrollment has declined in Virginia, special education enrollment has increased, both with regard to the total number of students and percentage of total student enrollment (Edunomics Lab, 2025). Because funding is frequently tied to student enrollment, education leaders likely face an uncertain and challenging fiscal environment going forward (DiNapoli & Griffith, 2025; Goldhaber & Falken, 2025; Roza & Anderson, 2025). In this context, school district leaders have to balance competing priorities to make strategic, if difficult, spending decisions (Roza & Knight, 2022).

To inform proactive, strategic decision-making in challenging times, we can learn from the past. And the past six years were full of change, beginning with federal funding designed to mitigate the harms caused by the COVID-19 pandemic. In March of 2020, Congress passed the Coronavirus Aid, Relief, and Economic Security Act (CARES), wherein they appropriated significant funding for Elementary and Secondary School Emergency Relief, also known as ESSER I (Goldhaber & Falken, 2025). ESSER I was the first of three waves of funding in response to the pandemic and was designed primarily to address health and safety in schools; it was available for spending from Spring 2020 through the end of September 2022. The second round of funding (ESSER II) was primarily focused on supporting a return to in-person learning, and was available for spending from December 2020 through September 2023. The third round of funding (ESSER III) was designed to support long-term academic recovery, highlighting the need for evidence-based strategies to advance student learning and well-being. ESSER III was

[1] School divisions in Virginia are roughly equivalent to school districts in other states (see Code of Virginia, 1950).

available for spending from Spring 2022 through September 2024 (Dewey et al., 2026; Goldhaber & Falken, 2025; National Conference of State Legislators, n.d.).

In Virginia, school division leaders reported that 71% of ESSER funding from the three waves went toward "Other" expenses (e.g., cleaning supplies, air purifiers, tools for digital instruction, school buses, salaries for bus drivers and substitutes) and capital improvements (e.g., HVAC systems, building projects, and other infrastructure needs). Fifteen percent of funds were spent on instruction (e.g., high quality tutoring, summer school, afterschool programming) and 14% were spent on staff support (e.g., recruitment and retention and performance bonuses [Virginia Department of Education, 2025]). Given these spending decisions, policymakers might not expect to see direct benefits to student achievement from ESSER spending, particularly ESSER I and II.

But during this same time period, significant state policy initiatives were also enacted. In the state of Virginia in 2022, legislators passed the Virginia Literacy Act (VLA), a comprehensive multi-pronged approach designed to (a) close achievement gaps in literacy and address pandemic learning loss; (b) accelerate literacy achievement; (c) ensure K-3 learners meet reading benchmarks; (d) support at-risk readers; and (e) provide instruction grounded in science-based reading research (SB 616 Virginia Literacy Act, 2022). The VLA was implemented in phases from 2023-2026. In 2023, the legislature and the governor authorized the targeting of state funds for school divisions to spend on high dosage tutoring, or the "ALL In VA" initiative (Saltmarsh et al., 2026). Of those targeted funds, 65% were spent by school divisions on high-intensity tutoring; 23% were spent on planning for implementation of the VLA; 10% were spent on addressing chronic absenteeism; and 2% were spent on additional operations and infrastructure support (Virginia Department of Education, 2025). Given these spending decisions with targeted state funds, alongside the third wave of ESSER funding, policymakers might expect to see benefits to achievement in 2023-2024.

But these policymakers and school leaders also needed to demonstrate the benefits of funding for all students, particularly those students who were likely to experience the most harmful effects of the pandemic to their education, such as students with disabilities (Fuchs et al., 2023), students from low income communities (Dewey et al., 2026), and students from minority backgrounds who also lived in segregated communities (Brown's Promise, n.d.).

Even in the best of times, we know that special education is expensive (Edunomics Lab, 2025). However, investing in special education has resulted in significant improvement in students' academic achievement over time, particularly for youth with mild disabilities in general education classes (Hanushek et al., 2002). In contrast, divesting in special education in the form of removing current students from programs and placing artificial caps on new student enrollment in special education has led to educational harm for students with mild disabilities, resulting in declines in their high school completion rates and likelihood of college enrollment (Ballis & Heath, 2021).

Similarly, investing in the educational achievement of students from low income communities has consistently yielded academic benefits for these students and mitigated the harmful effects of the pandemic on student achievement (Dewey et al., 2026; Jackson & Mackevicius, 2024). Likewise, investing in schools that are desegregated by family income and student race has resulted in long-term educational benefits for students, including a 30% increase in high school graduation for Black students, a 20% increase in graduation for Hispanic students, and a 22% decrease in poverty for Black families (Brown's Promise, n.d.). Therefore, our study is designed to examine the effects of spending on academic pass rates in Virginia at key funding time points, and to inform state policy and spending decisions for all students, including students with disabilities, students from low income communities, and students from minority backgrounds who are more likely than their peers to attend segregated schools (Brown's Promise, n.d.)

Purpose, Research Questions, and Hypotheses

The purpose of our study was to explore how education spending decisions at two time points - the first aligned with ESSER I and II funding (2020-2021) and the second aligned with ESSER III funding - as well as targeted state funding and passage of the VLA (2023-2024), affected academic pass rates for third through eighth graders with and without disabilities in reading and mathematics from 2018-2025. We hypothesized that growth in student pass rates would be correlated with spending decisions from these funding boosts, particularly during the later rounds of spending (2023-2024), as school division leaders became aware of the extent of pandemic-related learning losses (Silberstein & Roza, 2023). We also hypothesized that academic growth was likely to differ for students with and without disabilities and across different community demographic characteristics (i.e., locality, diversity, and poverty). Using publicly available administrative data, we addressed the effects of spending at two time points (2020-2021 and 2023-2024) to determine whether changes in pass rates differed before and after the policy changes (Collins, 2006; Gilmour & Stiefel, 2025; Shadish et al., 2002). To do this, we addressed four research questions using publicly available data from the Virginia Department of Education.

Research Question 1a: How did pass rates in English (reading) and mathematics (math) for students with and without disabilities in third through eighth grade change from 2018-2025, and what is the overall shape of those growth patterns?

Research Question 1b: Are there differences in the growth patterns in reading and math pass rates between students with and without disabilities?

Research Question 2: Are there school division-level demographic differences (i.e., location, poverty, and diversity) in the growth patterns in reading and math pass rates for students with and without disabilities?

Research Question 3: Did K-12 school division per pupil spending decisions (for administration, instruction, attendance and health, transportation, and operations/maintenance) with different spending sources (federal [Individuals with Disabilities Education Act (IDEA) and non-IDEA]; state and local) at key time points (2020-2021 and 2023-2024) affect the growth patterns in reading and math pass rates for students with and without disabilities?

Method

Participants

Study participants included students with and without disabilities in third through eighth grades from all school divisions in Virginia (*N* = 131) who completed the annual English (reading) and/or mathematics (math) achievement tests (Standards of Learning [SoL] assessments) in 2018-2025. These students represented a subset of the total population of K-12 students in Virginia. An average of 538,608 (*SD* = 66,974) students in grades 3-8 took the reading tests over the course of the study period, whereas an average of 475,829 (*SD* = 51,919) students in grades 3-8 took the math tests. The percentage of students with disabilities who took the annual achievement tests in reading ranged from 12.26% in 2020-2021 to 14.02% in 2024-2025, and the percentage of students with disabilities who took the annual achievement tests in math ranged from 13.3% in 2020-2021 to 14.98% in 2024-2025. In Table 1, we compare reading and math pass rates for students with and without disabilities in grades 3-8 across school division locations, poverty, and diversity characteristics.

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School Divisions

Student participants were nested within *N* = 131 school divisions serving students in grades K-12. Sixty-six (50.38%) school divisions were located in rural communities, 23 (17.56%) in small towns, 27 (20.61%) in suburban communities, and 15 (11.45%) in cities (National Center for Education Statistics, n.d.). In Table 2, we summarize the demographic characteristics of these school divisions. In addition to total enrollment for students with and without disabilities in K-12, we provide data summarizing student diversity, teachers per 1,000 students, and community poverty statewide in each of the study years. Total enrollment reflected the average daily attendance of K-12 students in school divisions across the school year, and total special education enrollment reflected the total number of students served under IDEA. Notably during the study period, the total enrollment of K-12 students with disabilities increased from 176,268 (13.7% of all K-12 students) in 2018-2019, to 189,786 (15% of all K-12 students) in 2024-2025. That increase occurred as the total overall enrollment of K-12 students declined during the same period: from a total of 1,290,513 students in 2018-2019 to a total of 1,261,387 students in 2024-2025 (a decline of 29,126 students).

Student diversity within K-12 school divisions reflected the average number of students enrolled from the following racial/ethnic groups: White, Black, Hispanic, and “Other.” Students in the “Other” category included those students from American Indian, Asian, Native Hawaiian or Pacific Islander, non-Hispanic, and mixed race (two or more) backgrounds. We combined students from these racial/ethnic groups under the category of “Other” due to low numbers in each group. Notably, the K-12 enrollment of both White and Black students declined from 2018-2019 to 2024-2025, with White students showing a decline of 77,819 students (5% decline) and Black students showing a decline of 17,277 students (1% decline) during the study period. At the same time, the numbers of Hispanic students and students in the “Other” category increased from 2018-2019 to 2024-2025, with Hispanic students showing an increase of 45,151 students (4% increase) and students in the “Other” category showing an increase of 50,819 students (2% increase) during the study period.

Teachers per 1,000 students reflected the number of instructional staff divided by the total K-12 enrollment and multiplied by 1,000. Notably, this teacher:student ratio decreased from 2018-2019 to 2024-2025, with the mean number of teachers per 1,000 students in 2018-2019 at 81.8 (*SD* = 11.4), reflecting a teacher:student ratio of 12:1, and the mean number of teachers per 1,000 students in 2024-2025 at 84.6 (*SD* = 12.6), reflecting a teacher:student ratio of 11.8:1. This increase in numbers of teachers serving students in Virginia occurred even as the overall enrollment of students in K-12 declined over the study period.

Data for community poverty reflected the estimated percentage of school-aged children (ages 5-17) who were living in poverty within each school division from the U.S. Census Bureau (n.d.). The percentage of students living in poverty in Virginia declined over the study period, with an average of 17.9% (*SD* = 8.1) of students living in poverty in 2018-2019, and an average of 15.5% (*SD* = 7.1) of students living in poverty in 2024-2025. Note that these income data are more accurate compared to free and reduced lunch estimates, which have been shown to inflate the percentages of students in poverty (Camera, 2019).

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Procedure

We retrieved student-level and division-level data from the publicly available Virginia state longitudinal data system (Virginia Department of Education, n.d.), as well as from the Virginia Department of Education website (2024-2025). We retrieved data on income (community poverty levels) associated with each of the school divisions from the Small Area Income and Poverty Estimates (U.S. Census Bureau, 2025), and data describing school division localities from the National Center for Education Statistics (NCES, n.d.). We used ChatGPT (OpenAI, 2024-2025) to write R code to clean data, merge datasets, and conduct initial descriptive analyses (R version 4.3.3.; R Core Team 2024). All AI-assisted output was reviewed and independently evaluated by the authors for accuracy.

Measures

Academic Pass Rates

We captured pass rates on annual standards of learning (SoL) achievement tests in reading and math for students in grades 3-8 in each year of the study, except for 2019-2020 when tests were not given due to the COVID-19 pandemic. These pass rate data (for students in grades 3-8) represented data available to the public from the elementary and middle school years. We did not include results for students in high school (grades 9-12), as achievement tests at that level were not comparable to those from the younger grades. Achievement pass rates were calculated as the percentage of students in grades 3-8 with or without disabilities, respectively, who obtained passing scores on achievement tests at a given grade level relative to all students with or without disabilities, respectively, who took the test at each grade level.

School Division Covariates

School division covariates were available at the K-12 division-level and were coded as dichotomous variables. Covariates included (a) school division locality (combining rural and town in the rural category, and urban and suburban in the urban category); (b) diversity (reflecting high-diversity divisions as those in the top 25% with enrollment of students from non-White backgrounds, and low diversity representing all other divisions); and (c) poverty (reflecting high-poverty divisions as those in the top 25% with regard to the number of families living in poverty in the community, and low poverty representing all other divisions).

Spending Decisions and Sources of Funding

We retrieved K-12 per pupil spending data for each school division during each year of the project. Division leaders spent allocated funds for the following costs: administration, instruction, attendance and health, transportation, and operations / maintenance. Spending on administration reflected activities associated with administering policy, including school board services, executive administration, information, personnel, planning, fiscal, purchasing, and reprographics. Spending on instruction reflected activities associated with classroom instruction, guidance and social work, homebound instruction, improvement, media services, and the work of the principal's office. Spending on attendance and health reflected activities associated with promoting and improving school attendance, plus medical, dental, psychology, and nursing care. Spending on transportation reflected activities associated with conveying students between home and school and to and from school activities, including the costs of vehicle maintenance and management. Spending on operations reflected activities associated with grounds-keeping and safety. Furthermore, the sources of funding included federal dollars (for IDEA and non-IDEA spending), as well as state and local dollars (Virginia Department of Education, 2024-2025).

Data Analysis Plan

We used publicly available administrative data to examine the effects of spending decisions and funding sources at two time points: (a) 2021-2022 (ESSER I and II funding) and (b) 2023-2024 (ESSER III and targeted state funding) on changes in reading and math pass rates for students with and without disabilities. Given that repeated measures of students' SoL pass rates (level 1) were nested within school divisions (level 2), we estimated two-level latent growth curve models (LGCMs; Little, 2013; Preacher et al., 2008) in Mplus version 8.4 (Muthén & Muthén, 1998-2019) to examine how reading and math pass rates changed over time from 2018 to 2025. This approach allowed us to separate variability into within- (i.e., change in pass rates over time) and between- (i.e., differences between school divisions) level components. Random effects (i.e., intercepts and slopes) were modeled as latent variables at the between-level, and were allowed to covary. For Research Questions 1-2, the latent intercept factor was centered at Time 4 (2021-2022) to capture potential changes in pass rates following the COVID-19 pandemic; for Research Question 3, we centered the latent intercept factor at two time points: (a) at Time 4 (2021-2022) to capture the effects of ESSER I and II funding, and (b) at Time 7 (2023-2024) to capture the effects of ESSER III and targeted state funding.

We used ChatGPT (Open AI, 2024-2025) to assist with the development and troubleshooting of Mplus syntax, and to clarify the interpretation of statistical results; all analyses were executed by the authors using Mplus. All AI-assisted outputs were reviewed and independently evaluated by the authors, and the authors made all final decisions regarding the analyses, interpretation of findings, and content of the manuscript.

Missing Data

Data were considered missing if pass rate data were available for fewer than 10 students within the school division. The frequency of this missingness was minimal (1.5% to 5.3%) and only occurred in pass rates for students with disabilities, driven largely by two small rural school divisions where no data were reported for students with disabilities (Virginia School Quality Profile, 2025). Missingness at each time point was not correlated with any of the school division covariates and was not predicted by pass rates in the preceding year (e.g., missing data were not more likely within school divisions with lower pass rates). As is common in longitudinal studies, missing data were correlated across years and within reading and math tests administered in the same year. Multilevel LGCMs are particularly well-suited to managing these missing data patterns, as these models utilize all available repeated measures and do not require complete data at all time points (Singer & Willett, 2003). Therefore, all models were estimated with the MLF estimator in Mplus, a maximum likelihood estimator that calculates standard errors from the first-order derivative and provides computational efficiency with complex multilevel models. Similar to other maximum likelihood estimators, MLF uses all available data under the assumption that the data are missing at random (MAR).

Descriptive Analyses

Descriptive analyses explored how average reading and math pass rates differed between disability status, timepoints, and school characteristics. First, we conducted two sets of paired samples *t*-tests: (1) to determine if there were any differences in average pass rates between students with and without disabilities, and (2) to examine if pass rates between adjacent time points significantly increased or decreased across the six school years examined in the current study. Second, we conducted independent samples *t*-tests to determine if pass rates differed between three school characteristics – location (urban/suburban vs. rural/town), poverty (low vs. high poverty), and diversity (low vs. high diversity). These analyses were conducted separately for reading and math pass rates and for students with and without disabilities, respectively.

Research Questions 1a and 1b

To address our first question, we estimated four separate unconditional LGCMs – one each for reading and math pass rates for students with and without disabilities – to determine the growth patterns and their overall shape. Considering the possibility that changes in pass rates might display nonlinear growth trends, we estimated both linear and quadratic slope factors and examined ΔAIC and ΔBIC values to determine which provided the best model fit (lower values indicate a better fit). After determining the best fitting unconditional LGCMs, we next modeled pass rates for students with and without disabilities jointly within two separate two-level parallel process LGCMs – one for reading and one for math. Within these LGCMs, we tested for differences in the intercept and slope(s) factors of pass rates for students with and without disabilities using parameter constraints.

Research Question 2

Following estimation of these unconditional multilevel LGCMs, we examined whether there were any school division-level demographic differences (i.e., location, poverty, and diversity) in the growth patterns of reading and math pass rates for students with and without disabilities. Specifically, we tested whether each demographic variable predicted the intercept and slope(s) factors, allowing us to explore whether there were any differences in initial levels of (intercepts) as well as change in (slopes) pass rates over time, depending on the demographic characteristics of the school divisions within which students resided.

Research Question 3

We examined whether the different K-12 per pupil spending categories affected the growth patterns of reading and math pass rates for students with and without disabilities. We entered each individual spending category, total spending, and funding spending source as predictors of both initial levels of (intercepts) and change in (slopes) pass rates for students with and without disabilities. Spending amounts were scaled (i.e., divided by 1,000) for model estimation purposes. As noted above, we conducted two sets of these analyses: (1) with the latent intercept centered at Time 4 (2021-2022) and spending variables measured in 2020-2021, to examine whether the influx of ESSER I and II funds affected growth patterns in pass rates; and (2) with the latent intercept centered at Time 7 (2024-2025) and spending variables measured in 2023-2024 to examine whether ESSER III and targeted state funding (i.e., to implement high dosage tutoring, address absenteeism, and prepare for the VLA) affected pass rate growth patterns.

Correcting for Multiple Comparisons

Given the number of comparisons made across various *t*-tests and regression models, all *p*-values from these analyses were adjusted using the Benjamini-Hochberg false discovery rate (FDR) correction (Benjamini & Hochberg, 1995). See individual table notes for how FDR corrections were employed for each set of analyses.

Results

Descriptive Analyses

As visualized in Figure 1, reading and math pass rates for students with disabilities were significantly lower than the pass rates for students without disabilities at all six time points (all adjusted *p*s from paired samples *t*-tests < .001). As shown in Table 3, paired samples *t*-tests conducted between adjacent time points indicated a significant decrease in reading and math pass rates from 2018-2019 to 2020-2021 for all students. Following this initial decrease, pass rates generally increased across adjacent years, with a few exceptions. Specifically, pass rates for students with disabilities appeared to plateau, as indicated by the nonsignificant mean differences for some of the later adjacent time points. We also found no significant change in reading pass rates for students without disabilities from 2021-2022 to 2022-2023.

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As shown in Table 1, overall findings from the independent samples *t*-tests indicated that reading and math pass rates were significantly lower in school divisions with a higher percentage of communities in poverty and a higher percentage of minority (i.e., non-White) students. Reading and math pass rates were also significantly lower in rural/town school divisions compared to school divisions located in urban/suburban areas, but only for students with disabilities; there were no significant differences in pass rates between these two geographic locations for students without disabilities.

Research Questions 1a and 1b: Two-Level Parallel Process LGCMs

For all of the four unconditional LGCMs, the models with the quadratic slope factors provided a better fit to the data (see Table 4). This pattern is also evident in Figure 1. The quadratic slope factors alter the interpretation of the growth curves, as the linear slope factor is the rate of change at the intercept and not at other time points. The intercept and slope factors all influence the overall shape of the curve, as they shift the curve up or down (for the intercept), tilt it up or down (for the linear slope), and change the curvature of the growth curve (for the quadratic slope). A positive linear slope indicates that the curve is tilting upwards/increasing, while a negative linear slope indicates that the curve is tilting downwards/decreasing. A positive quadratic slope factor indicates that the curve is accelerating over time, while a negative quadratic slope indicates that the curve is decelerating.

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INSERT TABLE 4 AND FIGURE 1 ABOUT HERE

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In Table 5 we present the findings and unstandardized coefficients from the two-level parallel process LGCMs for reading and math pass rates.

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Reading Pass Rates

Reading pass rates displayed different growth patterns for students with and without disabilities. For students with disabilities, there was no significant growth trend (i.e., a nonsignificant linear slope factor) but the significant, positive quadratic slope factor indicated an upward curvature; that is, pass rates were relatively flat until 2021-2022, after which they started accelerating. Conversely, for students without disabilities, a significant negative linear slope plus a positive quadratic slope defined a U-shaped trajectory: reading pass rates decreased, reached a minimum point shortly after 2021-2022, and then began to accelerate.

The intercept and slope factors were also significantly associated in the LGCM of reading pass rates for students without disabilities. These associations indicated that higher reading pass rates in 2021-2022 for these students were associated with less of a decline but a weaker acceleration in the growth curve (i.e., a flatter growth curve). Stated another way, lower reading pass rates at this timepoint were associated with greater declines but a stronger rebound (i.e., more acceleration in the curve) over time for students without disabilities. In addition, significant variance coefficients in both LGCMs indicated that school divisions varied in their linear growth rates and 2021-2022 reading pass rates for students with and without disabilities. Significant residual variances also indicated that school divisions fluctuated around their own estimated growth curves, suggesting additional within-division variability at each time point that was not accounted for by the growth model.

Math Pass Rates

Similar to the LGCMs for reading pass rates, the growth patterns of math pass rates for students with and without disabilities were relatively different. Specifically, for students with disabilities, a significant negative linear slope plus a positive quadratic slope defined a U-shaped trajectory; that is, math pass rates for these students decreased until they reached a minimum point shortly after 2021-2022, after which they began to accelerate. The relatively strong quadratic slope factor for this model suggested a pronounced rebound in this growth. In contrast, for students without disabilities, there was no significant growth trend (i.e., a nonsignificant linear slope factor), but the significant, positive quadratic slope factor indicated a strong upward curvature. That is, math pass rates for students without disabilities were relatively flat until 2021-2022, after which they started accelerating at a relatively quick rate.

Similar to the LGCM for reading pass rates for students without disabilities, the intercept and slope factors were significantly associated in the LGCM of math pass rates for students without disabilities. These associations indicated that higher math pass rates in 2021-2022 for these students showed less negative linear change with a weaker upward curvature (i.e., more stability in the growth curve). Stated another way, lower math pass rates at this timepoint were associated with greater declines but a strong acceleration after 2021-2022 for students without disabilities. In addition, significant variance coefficients in both LGCMs indicated school divisions varied in their 2021-2022 math pass rates for students with and without disabilities; linear growth rates in math pass rates for students with disabilities also varied across school divisions. Significant residual variances indicated additional within-division variability that was not accounted for by the growth model.

Differences in LGCM Factors Between Students With and Without Disabilities

Several parameter constraints were significant within the parallel process LGCMs. Specifically, the intercept factors for students with and without disabilities were significantly different in the LGCMs for both reading, $b = 46.45$, $SE = 3.77$, $p < .001$, and math pass rates, $b = 39.53$, $SE = 4.33$, $p < .001$. These differences indicated significantly lower 2021-2022 reading and math pass rates for students with disabilities as compared to those without disabilities. In addition, the quadratic slope factors for students with and without disabilities were significantly different from each other in the LGCMs of math pass rates, $b = 0.49$, $SE = 0.17$, $p = .003$, indicating a stronger rebound/acceleration in these pass rates for students without disabilities.

Research Question 2: School Division-Level Demographic Differences in LGCMs

The two-level parallel process LGCMs with school division-level demographics entered as predictors revealed consistency in slope coefficients across groups, as no demographic characteristics predicted either the linear or quadratic slopes in any of the models. However, both poverty and diversity characteristics significantly predicted the intercept factors in both LGCMs. Specifically, school division-level poverty significantly predicted the intercept factors of reading pass rates for students with ($b = -9.67$, $SE = 3.99$, $p = .015$) and without ($b = -9.21$, $SE = 1.78$, $p < .001$) disabilities, and also predicted the intercept factors of math pass rates for students with (b

= -8.30, *SE* = 3.59, *p* = .021) and without (*b* = -11.81, *SE* = 3.09, *p* < .001) disabilities. Similarly, school division-level diversity significantly predicted the intercept factors of reading pass rates for students with (*b* = -11.54, *SE* = 4.74, *p* = .015) and without (*b* = -14.76, *SE* = 1.55, *p* < .001) disabilities, and also predicted the intercept factors of math pass rates for students with (*b* = -10.25, *SE* = 4.93, *p* = .038) and without (*b* = -21.34, *SE* = 3.10, *p* < .001) disabilities. Overall, these findings indicate lower pass rates in 2021-2022 for school divisions with a higher percentage of communities in poverty and a higher percentage of minority (i.e., non-White) students.

Research Question 3: Spending Predictors of Intercept and Slope Factors in LGCMs

Due to the exploratory nature of these analyses, we first identify which effects were significant prior to correcting for multiple comparisons in order to identify patterns in how spending predicted changes in math and reading pass rates across time. After discussing those patterns, we indicate which effects remained significant after applying the Benjamini-Hochberg FDR correction.

Time 1: Impact of ESSER I and II Funding (2020-2021)

The majority of models examining the predictive effects of ESSER I and II federal funding (measured in 2020-2021) on the growth trajectories of reading and math pass rates for students with and without disabilities were nonsignificant, indicating no effects of spending on either initial levels of or change in pass rates over time (see Table 6). Of the few effects that were significant, most indicated a *negative* effect on several intercepts, such that more spending in 2020-2021 predicted lower pass rates in 2021-2022. We identified these effects for the following spending *sources*: federal (non-IDEA), IDEA, and state sources predicting lower reading and math pass rates in 2021-2022 for students without disabilities. We also identified these effects for the following spending *categories*: (a) administration spending predicting lower 2021-2022 math pass rates for students without disabilities; and (b) administration, transportation, federal (non-IDEA), IDEA, and total spending source predicting lower 2021-2022 reading and math pass rates for students with disabilities. In addition, administration and attendance and health spending in 2020-2021 negatively predicted the linear slope of reading pass rates for students with disabilities, indicating that increased spending in these domains predicted slower rates of improvement in reading pass rates for these students over time. In contrast, transportation spending in 2020-2021 positively predicted the quadratic slope of reading pass rates for students with disabilities, such that increased spending in this category predicted a greater acceleration in reading growth over time, after 2021-2022, for these students.

The following effects remained significant after correcting for multiple comparisons: (a) federal (non-IDEA) and IDEA spending predicting lower 2021-2022 reading and math pass rates for students without disabilities; (b) IDEA spending predicting lower 2021-2022 reading and math pass rates for students with disabilities; and (c) administration spending predicting lower 2021-2022 math pass rates for students with disabilities.

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Time 2: Impact of ESSER III and Targeted State Funding (2023-2024)

As with the models examining the impact of spending with ESSER I and II dollars, most of the predictive effects of ESSER III and targeted state funds (measured in 2023-2024) on the growth trajectories of reading and math pass rates for students with and without disabilities were nonsignificant (see Table 7). Of the few effects that were significant, we again observed a negative effect of spending on several intercepts, such that more spending predicted lower pass rates in 2024-2025. Specifically, these effects were identified for (a) attendance and health spending, (b) federal (non-IDEA) spending, and (c) IDEA spending predicting lower 2024-2025 reading and math pass rates for students without disabilities. We identified similar effects for (a) total spending and state spending source predicting lower 2024-2025 reading pass rates for students without disabilities, (b) spending on administration and IDEA spending source predicting lower 2024-2025 reading and math pass rates for students with disabilities, and (c) spending on transportation, operations and maintenance, total spending, and federal (non-IDEA) spending source predicting lower 2024-2025 reading pass rates for students with disabilities. We also identified positive predictive effects on three slope parameters in the models of reading pass rates for students without disabilities. Specifically, increased transportation spending in 2023-2024 predicted a faster growth (i.e., effect on the linear slope) in reading pass rates over time for students without disabilities. Increased federal (non-IDEA) spending in 2023-2024 also predicted faster growth (i.e., effect on the linear slope) as well as a greater acceleration (i.e., effect on the quadratic slope) in reading pass rates, after 2024-2025, for students without disabilities. After correcting for multiple comparisons, only the negative effects of attendance & health, federal (non-IDEA), state, and IDEA spending on 2024-2025 reading pass rates (i.e., the intercept) remained significant.

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Discussion

We examined the effects of federal and state spending in Virginia before, during, and after the COVID-19 pandemic to ascertain the extent to which federal and state investments at critical time periods affected pass rates for students with and without disabilities on state achievement tests in reading and math. Although researchers have conducted comparable studies of the effects of ESSER funding (Dewey et al., 2026; Goldhaber & Falken, 2025; Kuhfeld et al., 2022), these studies have not identified students with disabilities as part of their analyses, nor have they examined the timing of specific funding initiatives to include state as well as federal spending. To our knowledge, there is no comparable longitudinal analysis of the academic progress of students with disabilities during this period, even as we know that these students were likely to experience significant challenges in their education and development through reduced access to services (Spencer et al., 2023). For example, Fuchs and colleagues (2023) found that for students with co-occurring reading and math difficulties, declines in achievement (standard deviations below expected growth) were approximately three times larger than those reported for the general population and for students in high-poverty schools.

Beyond the COVID-19 period, we need to know how well the academic achievement of students with disabilities has recovered over time, from “learning recession to learning recovery” (Dewey et al., 2026, p. 1). To that end, we obtained findings that were both surprising and not surprising. We discuss each of those below, along with their implications. We also describe limitations of the present study and provide future directions for research.

Growth Patterns in Reading and Math Pass Rates

To address our first research question, we examined the overall shape of separate growth curves (i.e., changes in pass rates) in reading and math (respectively) for students with and without disabilities in third through eighth grades over the course of the study period (2018-

2025). We found that quadratic slope factors provided a better fit to the data (compared with linear factors), indicating that changes in reading and math pass rates displayed a nonlinear growth pattern over time as pass rates began to accelerate/rebound following the COVID-19 pandemic. These U-shaped curves have been identified in a previous study during the same period for students without disabilities (Dewey et al., 2026); here, we extend those findings by identifying the same overall shape in growth curves for students with disabilities as for their peers without disabilities. Indeed, we found that student scores rebounded in a positive (and U-shaped) fashion for both groups of students in both subject areas.

Differences in Growth Patterns in Reading and Math for Students with and without Disabilities

Consistent with nationally representative survey data (National Center for Education Statistics [NCES], 2025a, 2025b), we identified significant gaps in academic performance for students with disabilities as compared to students without disabilities. In both descriptive and growth curve analyses, reading and math pass rates for students with disabilities were significantly lower compared to the pass rates for students without disabilities. Significant associations between the intercept and slope factors in the growth curve models also indicated a stronger rebound for students who started at lower pass rates in 2021-2022, but only for students without disabilities. In previous longitudinal research with a national sample of students with disabilities (aged 7 to 17), Xie and colleagues (2011; 2012) also found that student growth in reading and math standardized test scores was nonlinear (quadratic), and that in both subjects, academic growth for students with disabilities reached a plateau in adolescence.

The growth curves of reading and math pass rates also revealed differences in the overall growth patterns between students with and without disabilities. Specifically, for reading, pass rates were relatively flat for students with disabilities until 2021-2022, after which they began accelerating. In contrast, for students without disabilities, reading pass rates had already begun decreasing prior to the COVID-19 pandemic, after which they began to accelerate. Similarly, Dewey and colleagues (2026) found that growth in grade level units in reading was relatively flat for students in Virginia from 2022-2025 compared to students in seven states who experienced growth. Strikingly, in their analysis, students in 25 states experienced a loss in grade-level growth in reading during that period.

To address this low growth in reading for students, policymakers passed the Virginia Literacy Act in 2022. The VLA is a comprehensive education policy with a multi-pronged approach designed to (a) close achievement gaps in literacy and address pandemic learning loss; (b) accelerate literacy achievement; (c) ensure K-3 learners meet reading benchmarks; (d) support at-risk readers; and (e) provide instruction grounded in science-based reading research. The VLA has mandated approaches that are both universal (i.e., evidence-based instruction for all students) and targeted (i.e., screening and intervention for students with reading difficulties) and has required that school divisions document their selection of high quality curricula, assessment of student progress, training of reading specialists, and engagement with families and communities to advance literacy. Therefore, we do expect the VLA to benefit students both with and without disabilities beyond the time period of the current study. In fact, our team will study student growth in reading test scores through a recently funded grant from the Institute of Education Sciences (Talbott et al., 2026-2029). This work will address the reading performance of students in specific subgroups, including students who identify as a racial/ethnic minority; students who are English learners; students from economically disadvantaged communities; and students identified with literacy difficulties and disabilities in these subgroups.

For math pass rates, the growth patterns showed the opposite than what we observed for reading pass rates. Specifically, for students with disabilities, pass rates in math had already begun decreasing before the COVID-19, after which they began accelerating/rebounding at a relatively fast rate. Math pass rates for students without disabilities did not demonstrate any significant linear growth but did evidence a rebound in a U-shaped pattern that was significantly more pronounced than the rebound for students with disabilities. Dewey and colleagues (2026) had found stronger improvements in grade level growth in math compared to reading growth in their analysis of 37 states, with only 4 of these states experiencing declines in math growth. Unfortunately, Virginia was not included in their analysis of grade level growth in math.

In order to improve mathematics achievement for students with and without disabilities, education leaders have begun to explore implementation of policies and procedures associated with the “science of math;” namely, using evidence about how students learn math to make educational decisions on their behalf, informing both policy and practice (Codding et al., 2023; Powell et al., 2025). Education researchers recognize that the state of mathematics achievement in the United States is of deep concern (Darling-Hammond & Fitz, 2025). For example, although U.S. students ranked seventh among participating nations on the Program in International Student Assessment (PISA) in reading in 2022, these same U.S. students scored lower than their peers from 30 other nations in mathematics. In fact, U.S. students mathematics’ scores were below the average of countries with similar democracies and market-based economies, and revealed large achievement gaps associated with income (Darling-Hammond & Fitz, 2025). But despite agreement among education scientists about the current state of math achievement, these same scientists do not agree about how to address it (see Powell et al., 2025).

Our findings regarding patterns in math achievement for students with and without disabilities in Virginia reflect these same concerning patterns and suggest that interventions aligned with “the science of math” could be a reasonable policy solution. But as is the case with reading, new policies need to address both universal (i.e., evidence-based instruction for all students) and targeted (i.e., screening and intervention for students with math difficulties) approaches, along with the use of high quality curricula, assessment of student progress, training of educators, and engagement with families and communities. Implementation of such comprehensive policies is urgent, even as debates continue between education scientists and professional organizations about the best ways to teach math (see Powell et al., 2025).

School Division-Level Demographic Differences

We identified overall lower reading and math pass rates for students with and without disabilities initially, at the 2021-2022 time point, in those school divisions with a higher percentage of communities in poverty and a higher percentage of minority (i.e., non-White) students, demonstrating stubborn achievement gaps immediately following the pandemic. These findings were similar to those obtained by Dewey and colleagues (2026), where academic learning losses over the course of the pandemic were approximately twice as large for students in high poverty compared to low poverty districts. In descriptive analyses, pass rates were also significantly lower among school divisions located in rural/town areas as compared to urban/suburban areas, but only for students with disabilities. This finding is likely associated with persistent challenges that rural school divisions experience in recruiting and retaining special education teachers (Ruppar et al., 2024).

In Virginia, as in many states, students from minority backgrounds (particularly Black and Hispanic students) are more likely to live in low income neighborhoods compared to White and Asian students. For example, in 2023, 55% of Black students in Virginia lived in high poverty neighborhoods and 32% of Hispanic students lived in high poverty neighborhoods, compared to 25% of White students and 10% of Asian students who lived in high poverty neighborhoods (University of Southern California Equity Research Institute, n.d.). For this reason, ESSER funds were designed to disproportionately benefit students who attended schools in high poverty neighborhoods (Dewey et al., 2026; Goldhaber & Falken, 2025). And in Dewey's (2026) analysis, this funding paid off. For example, they identified the largest academic improvements for students in districts at both the highest and the lowest income levels, attributing recovery in the highest poverty districts to ESSER funding. Without that funding, Dewey and colleagues (2026) predicted that the average high-poverty district would have remained at 2022 levels of achievement.

Impact of ESSER I and II Funding (2020-2021) on Academic Pass Rates at 2022-2023

Surprisingly, we did not observe significant improvements in academic pass rates as a result of district spending in Virginia. To address this question, we examined K-12 school division per pupil spending decisions (for administration, instruction, attendance and health, transportation, and operations/maintenance) using different sources of spending (federal [IDEA and non-IDEA]; state and local) at the time of the first influx of federal dollars (ESSER I and II in 2020-2021). We did so to determine whether these spending decisions affected the growth curves (change in pass rates) in reading and math for students with and without disabilities.

Unfortunately, we found very few significant effects of spending on either initial levels of or changes in pass rates over time, especially after correcting for multiple comparisons. In cases where spending effects were significant, most indicated a negative effect. This was certainly a surprising finding, except when one examines the report from the Virginia Department of

Education (2025) about how those funds were spent: 71% of division leaders reported spending funds for other, COVID-related expenses, such as cleaning supplies and air filters, along with capital improvements to HVAC systems and other infrastructure needs. Undoubtedly, "how you spend your money is your strategy" was in effect here. Unfortunately, in many districts, spending plans were developed before leaders understood the magnitude of declines in academic outcomes, particularly for students in the middle grades, as well as the large declines experienced by students with high needs in many districts (Silberstein & Roza, 2023). Therefore, once initial data came in showing significant learning loss in the state, as well as problems with chronic absenteeism, Virginia policymakers agreed to invest $418 million to tackle those losses, address chronic absenteeism, and accelerate the implementation of the VLA (Virginia Department of Education, 2025). Those funds were dedicated by the state even as ESSER III funding was also available.

Impact of ESSER III and Targeted State Funding (2023-2024) on Academic Pass Rates in 2024-2025

We also sought to determine the impact of spending decisions using this later influx of both federal (ESSER III) and targeted state funding. Similar to the previous findings, we mostly found no significant effects of spending on either initial levels of or change in pass rates over time. In cases where spending effects were significant, most indicated a negative effect. However, we did identify a few interesting slope effects, with increases in spending predicting either a faster rate of improvement and/or greater acceleration in pass rates. These largely occurred in the models of 2023-2024 spending predicting 2024-2025 reading pass rates for students without disabilities (with one exception in the 2020-2021 spending models, with increased transportation spending predicting a greater acceleration in 2021-2022 reading pass rates for students with disabilities). Spending did not appear to be particularly effective in improving pass rates in math or for students with disabilities, particularly in the year immediately following the COVID-19 pandemic. But, we acknowledge that predictor effects on slopes, particularly nonlinear slope parameters, can be more difficult to estimate (as compared to predictor effects on intercepts) due to the required power to identify those effects (Diallo et al., 2014; Feingold, 2021; Singer & Willett, 2003). In addition, it is important to note that none of these slope effects remained significant after correcting for multiple comparisons in the regression models. We emphasize that these findings are exploratory and hypothesis-generating, and warrant further exploration and replication.

In sum, the majority of significant effects we observed were on the intercepts, with increased spending predicting lower pass rates, both for math and reading, for students with and without disabilities, for spending at both 2020-2021 (predicting pass rates in 2021-2022) and 2023-2024 (predicting pass rates in 2024-2025). This type of result can indicate several possibilities: (a) that the process of improvement was relatively stable, where all students were changing at approximately the same rate, or (b) that there may be insufficient variability in slopes, or (c) that our study may have limited power. That is, although we examined results for all students in third through eighth grades, these students were nested within a relatively small sample size of school divisions ($N = 131$). In addition, the significant effects that we did find should be interpreted with caution given the number of comparisons made across the different spending categories.

Limitations

We report several limitations in the current study that require us to interpret our findings with caution. First, we were limited to using student pass rates on Virginia's annual state achievement tests as our outcome variable, as these were the data that were publicly available. Clearly, pass rate data are limited in their interpretability and usefulness, particularly for low performing students and students with disabilities. Pass rates indicate the proportion of students with or without disabilities (respectively) who have met a baseline proficiency threshold, compared to achievement test scores which are more sensitive to change over time (National Center for Education Statistics, n.d.). For example, even if a student may not have passed the annual state achievement test, that student may still be showing significant growth. That type of information provides invaluable feedback to teachers and school leaders, particularly about whether and how to change course in instruction. Having access to anonymous student test score data, such as through our Institute of Education Sciences grant, will allow us to examine variability in student growth over time in order to provide feedback to educators and school leaders about how their students' academic progress.

The use of pass rates, compared to actual test scores, might also explain why we did not obtain the positive effects of spending on achievement for students in low income communities identified in previous studies (Dewey et al., 2026; Jackson, 2020; Jackson & Mackevicius, 2024). In addition, missing data only occurred in pass rates for students with disabilities. While our analytic approach is well-suited to managing missing data, it is possible that this pattern of missingness skewed our findings. Efforts to quantify and collect data on how students with disabilities demonstrate academic progress is needed, and will be addressed in our future grant work. Lastly, large standard errors, particularly for predictor effects, suggest some model instability and limited precision in estimating longitudinal change, which may be due to restricted slope variability, low power, or limited information across time.

Future Directions

Ours was an exploratory study, an initial look at the effects of spending on student achievement in Virginia. We have highlighted future directions for research through our upcoming study of the VLA. In that project, we will study growth in K-8 students' annual achievement in reading, as well as growth throughout the year for students in grades 3-8 on more frequent assessments. We also look forward to studying student literacy progress for all students in Kindergarten through third grade, as well as for students with reading difficulties, using a newly developed tool linked to the science of reading: the Virginia Language and Literacy Screening System ([VALLSS], University of Virginia, n.d.).

At the same time, the need to address students' math achievement remains urgent, even as research in the science of math lags behind that of reading and literacy. The Center for Reinventing Public Education (CRPE, 2025) offers the following perspective on the crisis in math achievement, describing it as solvable as student math achievement is highly responsive to teacher training and improvements in instruction—perhaps more so than reading (CRPE, 2025). The authors point to the following factors as key to improving math outcomes: quality of instruction, strength of the teacher workforce, and availability of timely support for students. They cite the steady progress and narrowed achievement gaps in math observed in the late 1990s and early 2000s as evidence. Yet, as we have noted, education scientists still debate the most effective approaches to math instruction (see Powell et al., 2025). Education and special education scientists look to progress in advancing the science of reading to guide their advocacy work, now legislated in 44 states and Washington, DC (Sayag & Gendill, 2024). Within the science of math, research-backed strategies include explicit instruction in basic concepts, wherein teachers demonstrate procedures for struggling students, followed by teachers and students working together, and finally by students working independently, with plenty of opportunity for practice and feedback (Archer & Hughes, 2011). Rigorous research supports an emphasis on learning math facts, procedural knowledge, and deeper conceptual thinking, along with the use of explicit instruction (CPRE, 2025).

In addition to employing systematic, explicit instruction to teach mathematics, CPRE authors also recommend a continued emphasis on standards and accountability, as well as recruitment and training of highly qualified teachers, particularly for students in high-poverty districts. Schools must be equipped to meet the needs of students from disadvantaged backgrounds, as well as students with reading and math difficulties and disabilities, so that these students are prepared to enroll in college-track courses, expanding their career opportunities to fields that require advanced math skills (CPRE, 2025).

We conclude our discussion where we began, with a reminder that "how you spend your money is your strategy" (Edunomics Lab, 2017, p. 2). Education leaders are charged with making key economic decisions of behalf of their students (Loeb & McEwan, 2006). To adopt a proactive approach to this decision making, Kurtz and colleagues (2025) have turned to district and school leaders, who identified the following recommendations: (a) engage external partners in outcomes-based contracts focused on boosting student achievement (e.g., for tutoring); (b) discuss priorities with different constituents early in the budget process; (c) develop a plan to ensure coherent budgetary decision-making; (d) promote leaders from within and view staffing as a source of new ideas; (e) evaluate sustainability of funding to prepare contingency plans; and (f) provide technical assistance and training for budgetary decision-making.

Furthermore, school leaders, teachers, families, and students will find that wise spending decisions and hard work pay off when teachers and school leaders focus on steady and consistent improvement in academic achievement in reading and math as their "north star," directing funds toward evidence-based approaches to instruction, assessment of student progress over time, clear communication to families about that progress, and instructional changes and adaptations designed to improve student performance (Fletcher & Vaughn, 2009; Wyckoff, 2025). Our students deserve nothing less.

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Table 1

Comparing Reading and Math Pass Rates for Students With and Without Disabilities in Grades 3-8 Across School Division Locations, Poverty, and Diversity Characteristics

Year	Test	*N* Students Tested (% w/ Disabilities)	School Characteristic	Group	Mean Pass Rate, %: Students w/o Disabilities	*t* (*df*)	Students w/ Disabilities	*t* (*df*)
2018-2019	Reading	572,071 (12.77)	Location	Urban/Suburban	78.76	-0.61	37.53	3.31**
				Rural/Town	79.78	(129)	28.55	(126)
			Poverty	Low Poverty	81.23	3.95***	33.86	2.70**
				High Poverty	74.19	(129)	24.70	(126)
			Diversity	Low Diversity	82.31	8.80***	34.60	3.63***
				High Diversity	70.98	(129)	22.55	(126)
	Math	509,222 (13.90)	Location	Urban/Suburban	82.63	-1.38	45.11	2.57*
				Rural/Town	85.07	(129)	37.83	(126)
			Poverty	Low Poverty	85.89	2.96**	41.91	1.89
				High Poverty	79.52	(129)	35.34	(126)
			Diversity	Low Diversity	87.41	7.10***	43.45	3.74***
				High Diversity	75.03	(129)	30.92	(126)
2020-2021	Reading	414,435 (12.26)	Location	Urban/Suburban	68.65	-0.04	29.62	3.45***
				Rural/Town	68.74	(129)	19.30	(122)
			Poverty	Low Poverty	71.14	3.93***	24.34	1.87
				High Poverty	61.51	(129)	17.96	(122)
			Diversity	Low Diversity	72.77	9.11***	25.54	3.35**
				High Diversity	56.67	(129)	14.56	(122)
	Math	369,923 (13.30)	Location	Urban/Suburban	49.68	0.45	19.61	3.42***
				Rural/Town	48.13	(129)	11.75	(122)
			Poverty	Low Poverty	51.84	3.97***	15.80	2.19*
				High Poverty	39.11	(129)	10.09	(122)
			Diversity	Low Diversity	54.55	8.73***	16.46	4.06***
				High Diversity	31.05	(129)	8.27	(122)
2021-2022	Reading	542,774 (12.93)	Location	Urban/Suburban	72.05	-0.56	33.43	4.09***
				Rural/Town	73.28	(129)	22.47	(125)

			Poverty	Low Poverty	75.24	4.18***	28.61	3.07**
				High Poverty	65.91	(129)	18.62	(125)
			Diversity	Low Diversity	76.50	8.45***	28.71	3.20**
				High Diversity	62.17	(129)	18.34	(125)
	Math	492,700 (13.83)	Location	Urban/Suburban	61.84	-1.10	27.75	3.44***
				Rural/Town	65.15	(129)	18.33	(125)
			Poverty	Low Poverty	67.04	3.82***	23.54	2.75*
				High Poverty	55.32	(129)	15.25	(125)
			Diversity	Low Diversity	69.37	9.38***	23.61	2.85*
				High Diversity	48.40	(129)	15.02	(125)
2022-2023	Reading	541,879 (13.45)	Location	Urban/Suburban	71.54	-0.76	34.56	4.39***
				Rural/Town	73.22	(129)	22.71	(125)
			Poverty	Low Poverty	74.80	3.76***	29.04	2.79**
				High Poverty	66.38	(129)	19.76	(125)
			Diversity	Low Diversity	76.16	8.05***	29.45	3.29**
				High Diversity	62.34	(129)	18.60	(125)
	Math	492,987 (14.35)	Location	Urban/Suburban	65.41	-1.19	31.63	2.80*
				Rural/Town	68.73	(129)	23.44	(124)
			Poverty	Low Poverty	70.37	3.37**	15.20	2.58*
				High Poverty	59.64	(129)	16.61	(124)
			Diversity	Low Diversity	72.44	8.27***	15.92	3.89***
				High Diversity	53.49	(129)	12.25	(124)
2023-2024	Reading	539,966 (13.83)	Location	Urban/Suburban	72.35	-0.97	34.70	3.42**
				Rural/Town	74.48	(129)	25.69	(125)
			Poverty	Low Poverty	75.86	4.22***	30.72	2.49*
				High Poverty	67.67	(129)	22.59	(125)
			Diversity	Low Diversity	77.24	8.11***	31.59	3.74***
				High Diversity	63.57	(129)	19.62	(125)
	Math	493,324 (14.66)	Location	Urban/Suburban	67.27	-1.23	32.01	2.28*
				Rural/Town	70.60	(129)	25.72	(125)
			Poverty	Low Poverty	71.96	3.09**	29.95	2.59*
				High Poverty	62.33	(129)	21.43	(125)
			Diversity	Low Diversity	73.97		30.64	

				High Diversity	56.34	6.62*** (129)	19.01	3.57*** (125)
2024-2025	Reading	543,403 (14.02)	Location	Urban/Suburban	73.41	-1.20 (129)	35.20	3.04** (127)
				Rural/Town	76.02		26.58	
			Poverty	Low Poverty	77.16	3.48** (129)	31.33	2.48* (127)
				High Poverty	69.32		23.71	
			Diversity	Low Diversity	78.72	8.84*** (129)	32.40	3.96*** (127)
				High Diversity	64.67		20.62	
	Math	493,144 (14.98)	Location	Urban/Suburban	69.72	-1.41 (129)	32.19	2.21* (127)
				Rural/Town	73.26		25.82	
			Poverty	Low Poverty	74.54	3.36** (129)	30.31	3.11** (127)
				High Poverty	64.96		20.87	
			Diversity	Low Diversity	76.42	6.86*** (129)	30.85	3.88*** (127)
				High Diversity	59.39		19.28	

Note. No state achievement tests were administered in 2019-2020. *t*-tests compare the first listed group (i.e., urban/suburban, low poverty, low diversity) with the second listed group (i.e., rural/town, high poverty, high diversity), respectively, within each school characteristic. Benjamini-Hochberg FDR adjustments made within each combination of test and disability status, across the six time points and three school characteristics (i.e., 4 families, 18 comparisons per family).
Adjusted *p*-values: $^*p<.05$ $^{**}p<.01$ $^{***}p<.001$

Table 2

Demographic Characteristics of K-12 School Divisions in Virginia: 2018-2025

	2018-19	**2019-20**	**2020-21**	**2021-22**	**2022-23**	**2023-24**	**2024-25**
Total Enrollment K-12[a]	1,290,513	1,298,083	1,252,752	1,251,970	1,263,367	1,262,011	1,261,387
Total SpEd Enrollment[b] (%)	176,268 (13.7)	180,219 (13.9)	174,404 (13.9)	173,671 (13.9)	178,608 (14.1)	185,284 (14.7)	189,786 (15)
Diversity[c]							
N White	624,660	617,310	580,618	573,619	568,485	557,791	546,841
(%)	(48.4)	(47.6)	(46.3)	(45.8)	(45)	(44.2)	(43.4)
N Black	285,910	283,426	276,930	273,166	273,503	270,980	268,633
(%)	(22.2)	(21.8)	(22.1)	(21.8)	(21.6)	(21.5)	(21.3)
N Hispanic	208,705	220,968	218,752	226,208	236,793	244,903	253,856
(%)	(16.2)	(17)	(17.5)	(18.1)	(18.7)	(19.4)	(20.1)
N Other	171,238	176,379	176,452	178,977	184,586	188,337	192,057
(%)	(13.3)	(13.6)	(14.1)	(14.3)	(14.6)	(14.9)	(15.2)
	Mean (*SD*)	**Mean (*SD*)**	**Mean (*SD*)**	**Mean (*SD*)**	**Mean (*SD*)**	**Mean (*SD*)**	**Mean (*SD*)**
Teachers Per 1,000 Students[d]	81.8 (11.4)	81.2 (10.9)	83.5 (12.0)	83.6 (14.5)	83 (13.8)	83.3 (13.3)	84.6 (12.6)
Community Poverty %[e]	17.9 (8.1)	17.7 (8.1)	15.9 (7.1)	17.4 (7.6)	16.8 (7.4)	17.2 (7.3)	15.5 (7.1)
Interquartile Range	12.6	12.5	10.2	10.9	11.1	10.8	9.5

Note. [a]Total Enrollment represents the average daily attendance of K-12 students in Virginia across all days of the school year. [b]Total SpEd enrollment reflects the total count of students in K-12 served under IDEA, and the percentage of students with disabilities who comprise total enrollment. [c]Students in “Other” racial categories include students from American Indian, Asian, Native Hawaiian or Pacific Islander, Non-Hispanic, and Mixed Race (two or more) backgrounds. [d]Number of instructional staff are divided by total enrollment and multiplied by 1,000. [e]Estimated percentage of children ages 5-17 living in poverty within each school division (U.S. Census Bureau Small Area Income and Poverty Estimates).

Table 3

Comparing Reading and Math Pass Rates for Students With and Without Disabilities in Grades 3-8 Across Adjacent School Year Timepoints

Comparison	Mean Difference in Pass Rates, % (*SD*)	*t* (*df*)	Mean Difference in Pass Rates, % (*SD*)	*t* (*df*)	Mean Difference in Pass Rates, % (*SD*)	*t* (*df*)	Mean Difference in Pass Rates, % (*SD*)	*t* (*df*)
	READING PASS RATES				**MATH PASS RATES**			
	Students w/o Disabilities		**Students w/ Disabilities**		**Students w/o Disabilities**		**Students w/ Disabilities**	
2018-2019 vs. 2020-2021	10.74 (*5.10*)	24.10*** (130)	8.79 (*10.54*)	9.26*** (122)	35.66 (*11.42*)	35.74*** (130)	26.27 (*12.69*)	22.97*** (122)
2020-2021 vs. 2021-2022	-4.17 (*4.31*)	-11.07*** (130)	-3.56 (*10.21*)	-3.87*** (122)	-15.45 (*7.63*)	-23.20*** (130)	-7.38 (*8.33*)	-9.83*** (122)
2021-2022 vs. 2022-2023	0.21 (*3.03*)	0.79 (130)	-0.54 (*8.32*)	-0.73 (125)	-3.58 (*4.23*)	-9.68*** (130)	-4.55 (*8.26*)	-6.19*** (125)
2022-2023 vs. 2023-2024	-1.12 (*2.75*)	-4.66*** (130)	-1.86 (*6.11*)	-3.40*** (124)	-1.86 (*3.92*)	-5.44*** (130)	-1.53 (*7.76*)	-2.20* (124)
2023-2024 vs. 2024-2025	-1.39 (*2.29*)	-6.92*** (130)	-1.18 (*8.85*)	-1.50 (126)	-2.60 (*3.98*)	-7.47*** (130)	-0.53 (*10.43*)	-0.57 (126)

Note. No state achievement tests were administered in 2019-2020. *t*-tests compare the pass rate for the first year listed as compared to the second year listed. Benjamini-Hochberg FDR adjustments made within each combination of test and disability status (i.e., 4 families, 5 comparisons per family).
Adjusted *p*-values: *p<.05 **p<.01 ***p<.001

Table 4

Model comparisons for unconditional LGCMs with linear versus quadratic slopes

	AIC linear slope	**AIC quad slope**	**Δ AIC**	**BIC linear slope**	**BIC quad slope**	**Δ BIC**	**Best model**
Reading Pass Rates, Students w/o Disabilities	5077.61	4721.37	356.24	5086.56	4736.28	350.27	Quadratic
Reading Pass Rates, Students w/ Disabilities	5686.07	5609.12	76.952	5694.84	5623.73	71.11	Quadratic
Math Pass Rates, Students w/o Disabilities	6470.27	6035.18	435.087	6479.22	6050.10	429.121	Quadratic
Math Pass Rates, Students w/ Disabilities	6152.35	5897.32	255.03	6161.10	5911.91	249.193	Quadratic

Note. Sample-size adjusted BIC values provided.

Table 5

Findings and unstandardized coefficients from two-level parallel process LGCMs of reading and math pass rates for students with and without disabilities

Effect Type	Parameter	*b* (*SE*)	95% CI	*p*	*b* (*SE*)	95% CI	*p*
		STUDENTS WITHOUT DISABILITIES			STUDENTS WITH DISABILITIES		
		READING PASS RATES					
Fixed Effects	Intercept	71.18 (*1.80*)	[67.65, 74.70]	**< .001[a]**	24.73 (*2.35*)	[20.12, 29.33]	**< .001[a]**
	Linear Slope	-0.38 (*0.13*)	[-0.63, -0.12]	**.004**	0.02 (*0.20*)	[-0.38, 0.42]	.914
	Quadratic Slope	0.68 (*0.06*)	[0.56, 0.81]	**< .001**	0.64 (*0.12*)	[0.40, 0.87]	**< .001**
	Intercept-Linear Association	2.65 (*0.98*)	[0.72, 4.57]	**.007**	-1.49 (*2.96*)	[-7.29, 4.31]	.615
	Intercept-Quadratic Association	-2.33 (*0.74*)	[-3.79, -0.88]	**.002**	-0.59 (*1.65*)	[-3.82, 2.65]	.723
	Linear-Quadratic Association	-0.02 (*0.04*)	[-0.10, 0.06]	.581	-0.07 (*0.12*)	[-0.30, 0.16]	.534
Random Effects	Between-District Variance (Intercept)	106.32 (*20.04*)	[67.04, 145.59]	**< .001**	225.19 (*53.64*)	[120.05, 330.33]	**< .001**
	Between-District Variance (Linear Slope)	0.43 (*0.10*)	[0.23, 0.63]	**< .001**	1.10 (*0.44*)	[0.24, 1.96]	**.013**
	Between-District Variance (Quadratic Slope)	0.06 (*0.04*)	[-0.03, 0.14]	.176	0.02 (*0.07*)	[-0.12, 0.16]	.812
	Residual (Within-District)	10.93 (*0.76*)	[9.43, 12.42]	**< .001**	47.47 (*2.35*)	[42.86, 52.08]	**< .001**
		MATH PASS RATES					
Fixed Effects	Intercept	59.52 (*2.57*)	[54.49, 64.55]	**< .001[b]**	19.99 (*2.54*)	[15.01, 24.97]	**< .001[b]**
	Linear Slope	-0.59 (*0.36*)	[-1.29, 0.11]	.100	-0.93 (*0.28*)	[-1.48, -0.38]	**.001**
	Quadratic Slope	2.10 (*0.30*)	[1.51, 2.69]	**< .001[c]**	1.60 (*0.21*)	[1.20, 2.01]	**< .001[c]**

	Intercept-Linear Association	7.90 (*3.09*)	[1.85, 13.96]	**.011**	3.94 (*3.21*)	[-2.35, 10.23]	.219
	Intercept-Quadratic Association	-7.34 (*2.70*)	[-12.63, -2.04]	**.007**	2.07 (*1.44*)	[-0.75, 4.89]	.150
	Linear-Quadratic Association	-0.32 (*0.36*)	[-1.02, 0.39]	.381	-0.25 (*0.15*)	[-0.54, 0.05]	.105
Random Effects	Between-District Variance (Intercept)	182.54 (*40.00*)	[104.15, 260.93]	**< .001**	147.88 (*30.68*)	[87.75, 208.02]	**< .001**
	Between-District Variance (Linear Slope)	0.36 (*0.59*)	[-0.80, 1.52]	.544	1.64 (*0.67*)	[0.33, 2.95]	**.014**
	Between-District Variance (Quadratic Slope)	0.30 (*0.26*)	[-0.21, 0.80]	.247	0.12 (*0.11*)	[-0.11, 0.34]	.303
	Residual (Within-District)	82.67 (*6.48*)	[69.96, 95.38]	**< .001**	78.62 (*5.07*)	[68.69, 88.55]	**< .001**

Note. Matching subscripts indicate parameter estimates are significantly different from each other at $p < .05$. *SE* = standard error, CI = confidence interval

Table 6

Separate multilevel growth models examining the impact of ESSER I and II funding (measured in 2020-2021) on reading and math pass rate growth curves for students with and without disabilities (time centered at 2021-2022).

	Intercept		Linear Slope		Quadratic Slope		Intercept		Linear Slope		Quadratic Slope	
Spending Predictor	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI
	STUDENTS WITHOUT DISABILITIES						**STUDENTS WITH DISABILITIES**					
	READING PASS RATES											
Spending Decisions												
Administration	-2.71 (*2.56*)	-7.72, 2.31	-0.02 (*0.37*)	-0.73, 0.70	-0.06 (*0.20*)	-0.46, 0.34	-16.10** (*6.04*)	-27.93, -4.27	-1.21* (*0.62*)	-2.43, 0.01	0.36 (*0.31*)	-0.25, 0.97
Instructional	-0.17 (*0.46*)	-1.07, 0.72	0.02 (*0.07*)	-0.12, 0.15	-0.01 (*0.03*)	-0.09, 0.05	-0.88 (*1.03*)	-2.91, 1.14	-0.03 (*0.10*)	-0.23, 0.17	0.03 (*0.06*)	-0.09, 0.15
Attendance & Health	-11.51 (*7.04*)	-25.32, 2.29	-0.33 (*0.99*)	-2.27, 1.62	0.23 (*0.38*)	-0.51, 0.97	-0.08 (*14.98*)	-29.44, 29.29	-2.89* (*1.24*)	-5.31, -0.46	-0.04 (*0.57*)	-1.15, 1.08
Transportation	-1.96 (*3.36*)	-8.55, 4.62	-0.02 (*0.23*)	-0.48, 0.43	0.30 (*0.18*)	-0.05, 0.64	-19.23** (*7.22*)	-33.37, -5.09	-0.05 (*0.63*)	-1.28, 1.18	0.53* (*0.26*)	0.02, 1.04
Operations/Maintenance	-1.07 (*2.43*)	-5.84, 3.70	-0.08 (*0.29*)	-0.64, 0.49	0.10 (*0.09*)	-0.07, 0.27	-9.70 (*5.70*)	-20.87, 1.48	-0.88 (*0.62*)	-2.09, 0.34	0.26 (*0.29*)	-0.30, 0.82
Total	-0.24 (*0.31*)	-0.84, 0.37	-0.001 (*0.05*)	-0.10, 0.09	-0.004 (*0.02*)	-0.04, 0.03	-1.41 (*0.79*)	-2.95, 0.14	-0.03 (*0.06*)	-0.16, 0.09	0.04 (*0.04*)	-0.04, 0.13
Funding Source												
Federal	-7.63***† (*1.27*)	-10.12, -5.13	-0.03 (*0.15*)	-0.32, 0.25	0.16 (*0.11*)	-0.05, 0.37	-7.86* (*3.30*)	-14.33, -1.40	-0.11 (*0.35*)	-0.79, 0.58	0.04 (*0.20*)	-0.35, 0.44
State	-1.41** (*0.53*)	-2.45, -0.38	-0.11 (*0.09*)	-0.29, 0.08	0.02 (*0.03*)	-0.05, 0.09	-0.87 (*1.27*)	-3.37, 1.63	0.01 (*0.13*)	-0.24, 0.26	-0.03 (*0.06*)	-0.13, 0.08
Local	0.35 (*0.28*)	-0.20, 0.90	0.02 (*0.04*)	-0.05, 0.09	-0.01 (*0.02*)	-0.04, 0.02	-0.32 (*0.55*)	-1.38, 0.75	-0.03 (*0.05*)	-0.14, 0.07	0.02 (*0.03*)	-0.03, 0.08
Total	-0.32 (*0.36*)	-1.03, 0.39	-0.002 (*0.05*)	-0.10, 0.09	0.01 (*0.02*)	-0.03, 0.04	-1.60* (*0.81*)	-3.19, -0.001	-0.07 (*0.08*)	-0.23, 0.09	0.04 (*0.05*)	-0.05, 0.13
IDEA	-14.64***† (*3.19*)	-20.89, -8.39	-0.20 (*0.20*)	-0.59, 0.19	0.28 (*0.18*)	-0.07, 0.63	-21.64***† (*5.89*)	-33.19, -10.10	0.77 (*0.65*)	-0.49, 2.04	0.11 (*0.35*)	-0.57, 0.79

MATH PASS RATES

Spending Decisions												
Administration	-7.41* (*3.52*)	-14.31, -0.50	0.21 (*1.32*)	-2.37, 2.79	0.37 (*0.84*)	-1.27, 2.01	-14.62**† (*4.43*)	-23.30, -5.93	-1.07 (*0.99*)	-3.01, 0.87	0.05 (*0.61*)	-1.16, 1.25
Instructional	-0.72 (*0.86*)	-2.41, 0.98	0.06 (*0.30*)	-0.52, 0.64	0.02 (*0.20*)	-0.37, 0.41	-0.66 (*1.04*)	-2.69, 1.37	-0.06 (*0.20*)	-0.46, 0.33	0.003 (*0.15*)	-0.30, 0.30
Attendance & Health	-14.94 (*10.64*)	-35.79, 5.91	-1.96 (*3.38*)	-8.58, 4.65	0.52 (*2.45*)	-4.28, 5.32	-3.34 (*16.94*)	-36.55, 29.86	-0.32 (*2.12*)	-4.47, 3.82	-0.82 (*1.61*)	-3.97, 2.33
Transportation	-4.91 (*4.74*)	-14.20, 4.38	0.27 (*1.03*)	-1.75, 2.28	0.58 (*0.92*)	-1.22, 2.38	-14.06* (*6.12*)	-26.06, -2.07	-0.53 (*0.83*)	-2.15, 1.09	0.54 (*0.69*)	-0.82, 1.89
Operations/Maintenance	-2.69 (*3.36*)	-9.27, 3.90	-0.27 (*0.79*)	-1.82, 1.28	0.16 (*0.77*)	-1.36, 1.67	-8.27 (*4.43*)	-16.95, 0.41	-1.18 (*1.09*)	-3.32, 0.96	0.13 (*0.51*)	-0.87, 1.14
Total	-0.66 (*0.61*)	-1.87, 0.54	0.02 (*0.19*)	-0.36, 0.39	0.02 (*0.15*)	-0.26, 0.31	-1.18 (*0.63*)	-2.40, 0.05	-0.02 (*0.15*)	-0.31, 0.27	0.01 (*0.12*)	-0.29, 0.23
Funding Source												
Federal	-9.63***† (*2.64*)	-14.80, -4.47	-0.17 (*0.63*)	-1.40, 1.06	0.32 (*0.55*)	-0.75, 1.40	-7.99* (*3.12*)	-14.10, -1.88	-0.57 (*0.50*)	-1.55, 0.42	0.05 (*0.36*)	-0.67, 0.76
State	-2.02* (*1.02*)	-4.01, -0.02	-0.12 (*0.31*)	-0.72, 0.49	0.09 (*0.21*)	-0.32, 0.50	-0.91 (*1.08*)	-3.03, 1.21	-0.07 (*0.22*)	-0.50, 0.37	-0.003 (*0.15*)	-0.29, 0.28
Local	0.24 (*0.52*)	-0.79, 1.26	0.03 (*0.15*)	-0.27, 0.33	-0.01 (*0.10*)	-0.21, 0.20	-0.21 (*0.48*)	-1.15, 0.72	-0.02 (*0.11*)	-0.24, 0.20	0.01 (*0.08*)	-0.15, 0.17
Total	-0.86 (*0.58*)	-2.00, 0.28	0.004 (*0.21*)	-0.41, 0.41	0.04 (*0.14*)	-0.23, 0.30	-1.33* (*0.65*)	-2.60, -0.06	-0.11 (*0.15*)	-0.41, 0.18	0.01 (*0.11*)	-0.20, 0.22
IDEA	-20.27***† (*5.25*)	-30.57, -9.97	-0.25 (*0.75*)	-1.71, 1.21	0.78 (*0.85*)	-0.89, 2.45	-17.89***† (*4.94*)	-27.57, -8.21	0.28 (*0.85*)	-1.39, 1.95	-0.37 (*0.72*)	-1.79, 1.05

Note. Each predictor was entered in a separate multilevel growth model. Coefficients represent unadjusted associations with the intercept and slope factors of reading and math pass rates for students with and without disabilities over time. *SE* = standard error; CI = confidence interval. Benjamini-Hochberg FDR adjustments made within each combination of test and disability status (i.e., 4 families, 33 comparisons per family).

*$p \leq .05$ **$p < .01$ ***$p < .001$ †Statistically significant after Benjamini-Hochberg FDR correction

Table 7

Separate multilevel growth models examining the impact of ESSER III funding and targeted state funds (measured in 2023-2024) on reading and math pass rate growth curves for students with and without disabilities (time centered at 2024-2025)

	Intercept		Linear Slope		Quadratic Slope		Intercept		Linear Slope		Quadratic Slope	
Spending Predictor	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI	*b* (*SE*)	95% CI
	STUDENTS WITHOUT DISABILITIES						**STUDENTS WITH DISABILITIES**					
	READING PASS RATES											
Spending Decisions												
Administration	-1.49 (*2.36*)	-6.12, 3.15	0.22 (*0.66*)	-1.08, 1.52	0.03 (*0.10*)	-0.17, 0.23	-9.99** (*3.23*)	-16.31, -3.66	0.15 (*0.87*)	-1.56, 1.85	0.10 (*0.15*)	-0.20, 0.40
Instructional	-0.78 (*0.45*)	-1.66, 0.09	0.12 (*0.16*)	-0.19, 0.44	0.01 (*0.03*)	-0.04, 0.06	-0.87 (*0.91*)	-2.66, 0.92	0.09 (*0.31*)	-0.51, 0.69	-0.01 (*0.05*)	-0.10, 0.09
Attendance & Health	-16.71***† (*4.71*)	-25.94, -7.47	1.90 (*1.48*)	-1.00, 4.80	0.45 (*0.25*)	-0.05, 0.95	-11.69 (*12.23*)	-35.65, 12.28	1.09 (*3.34*)	-5.45, 7.62	0.39 (*0.53*)	-0.65, 1.43
Transportation	-0.87 (*2.33*)	-5.44, 3.70	1.35* (*0.69*)	-0.01, 2.69	0.20 (*0.12*)	-0.02, 0.43	-9.55* (*4.34*)	-18.05, -1.05	1.62 (*1.09*)	-0.51, 3.74	0.26 (*0.17*)	-0.06, 0.59
Operations/Maintenance	-1.58 (*1.43*)	-4.40, 1.23	0.65 (*0.37*)	-0.06, 1.37	0.09 (*0.07*)	-0.04, 0.23	-6.96* (*3.11*)	-13.05, -0.87	0.58 (*0.83*)	-1.04, 2.20	0.20 (*0.13*)	-0.06, 0.46
Total	-0.59* (*0.30*)	-1.17, -0.01	0.14 (*0.10*)	-0.05, 0.33	0.02 (*0.02*)	-0.01, 0.05	-1.34* (*0.67*)	-2.66, -0.01	0.12 (*0.22*)	-0.32, 0.56	0.02 (*0.04*)	-0.05, 0.09
Funding Source												
Federal	-3.41***† (*0.74*)	-4.85, -1.97	0.63* (*0.29*)	0.06, 1.20	0.10* (*0.05*)	-0.001, 0.20	-4.11* (*1.77*)	-7.58, -0.63	0.10 (*0.61*)	-1.09, 1.29	-0.01 (*0.09*)	-0.18, 0.17
State	-1.50**† (*0.45*)	-2.38, -0.62	0.09 (*0.15*)	-0.20, 0.39	0.03 (*0.03*)	-0.03, 0.08	-0.95 (*0.92*)	-2.75, 0.85	-0.05 (*0.23*)	-0.51, 0.40	-0.01 (*0.04*)	-0.08, 0.06
Local	0.43 (*0.29*)	-0.14, 0.99	-0.01 (*0.09*)	-0.19, 0.17	-0.01 (*0.01*)	-0.03, 0.02	-0.03 (*0.48*)	-0.96, 0.90	0.11 (*0.14*)	-0.16, 0.39	0.02 (*0.02*)	-0.02, 0.07
Total	-0.58 (*0.31*)	-1.19, 0.03	0.13 (*0.11*)	-0.09, 0.35	0.02 (*0.02*)	-0.02, 0.05	-1.23 (*0.69*)	-2.58, 0.13	0.18 (*0.23*)	-0.28, 0.64	0.03 (*0.04*)	-0.05, 0.11
IDEA	-13.20***† (*2.20*)	-17.51, -8.89	1.06 (*1.16*)	-1.20, 3.32	0.26 (*0.19*)	-0.11, 0.62	-17.07** (*5.96*)	-32.41, -5.39	0.54 (*1.94*)	-3.27, 4.34	0.01 (*0.33*)	-0.63, 0.65

	MATH PASS RATES											
Spending Decisions												
Administration	-2.51	-9.19,	1.62	-3.96,	0.27	-0.69,	-10.00*	-18.43,	-0.71	-5.52,	-0.001	-0.79,
	(*3.41*)	4.17	(*2.85*)	7.21	(*0.49*)	1.23	(*4.30*)	-1.57	(*2.46*)	4.10	(*0.40*)	0.79
Instructional	-0.97	-3.01,	0.36	-1.45,	0.05	-0.26,	-1.17	-4.44,	-0.19	-1.71,	-0.04	-0.27,
	(*1.04*)	1.08	(*0.92*)	2.17	(*0.16*)	0.36	(*1.67*)	2.10	(*0.78*)	1.33	(*0.12*)	0.19
Attendance & Health	-20.77*	-41.66,	4.84	-9.33,	1.04	-1.23,	-13.78	-44.98,	-0.35	-12.33,	0.23	-1.62,
	(*10.66*)	0.12	(*7.23*)	19.00	(*1.15*)	3.30	(*15.92*)	17.42	(*6.11*)	11.62	(*0.94*)	2.07
Transportation	-0.30	-9.91,	2.66	-4.84,	0.38	-0.86,	-7.84	-22.39,	1.40	-4.72,	0.32	-0.67,
	(*4.91*)	9.32	(*3.83*)	10.16	(*0.63*)	1.63	(*7.43*)	6.71	(*3.12*)	7.52	(*0.51*)	1.31
Operations/Maintenance	-2.31	-8.10,	1.03	-3.97,	0.16	-0.71,	-6.74	-15.19,	0.04	-3.60,	0.07	-0.50,
	(*2.95*)	3.48	(*2.55*)	6.03	(*0.44*)	1.02	(*4.31*)	1.71	(*1.86*)	3.68	(*0.29*)	0.64
Total	-0.75	-2.11,	0.36	-0.85,	0.05	-0.15,	-1.45	-3.58,	-0.09	-1.12,	-0.01	-0.17,
	(*0.70*)	0.62	(*0.62*)	1.57	(*0.10*)	0.26	(*1.09*)	0.68	(*0.53*)	0.95	(*0.08*)	0.15
Funding Source												
Federal	-3.81*	-7.63,	1.41	-1.61,	0.23	-0.28,	-5.00	-10.35,	-0.41	-2.75,	-0.03	-0.40,
	(*1.95*)	0.02	(*1.54*)	4.44	(*0.26*)	0.75	(*2.73*)	0.35	(*1.20*)	1.94	(*0.19*)	0.34
State	-1.74	-3.64,	0.34	-1.33,	0.07	-0.20,	-1.11	-3.98,	-0.06	-1.30,	-0.003	-0.19,
	(*0.97*)	0.17	(*0.86*)	2.02	(*0.14*)	0.34	(*1.47*)	1.77	(*0.63*)	1.19	(*0.10*)	0.19
Local	0.41	-0.83,	-0.03	-1.11,	-0.01	-0.19,	0.002	-1.97,	0.04	-0.88,	0.01	-0.13,
	(*0.63*)	1.65	(*0.55*)	1.06	(*0.09*)	0.16	(*1.00*)	1.97	(*0.47*)	0.96	(*0.07*)	0.15
Total	-0.79	-2.21,	0.35	-0.89,	0.06	-0.15,	-1.39	-3.64,	-0.02	-1.08,	0.01	-0.16,
	(*0.73*)	0.63	(*0.64*)	1.60	(*0.11*)	0.26	(*1.15*)	0.86	(*0.54*)	1.04	(*0.09*)	0.18
IDEA	-14.57**	-24.07,	3.82	-4.15,	0.72	-0.62,	-19.78**	-34.69,	-2.63	-9.75,	-0.39	-1.51,
	(*4.85*)	-5.07	(*4.07*)	11.80	(*0.69*)	2.07	(*7.61*)	-4.87	(*3.63*)	4.49	(*0.57*)	0.74

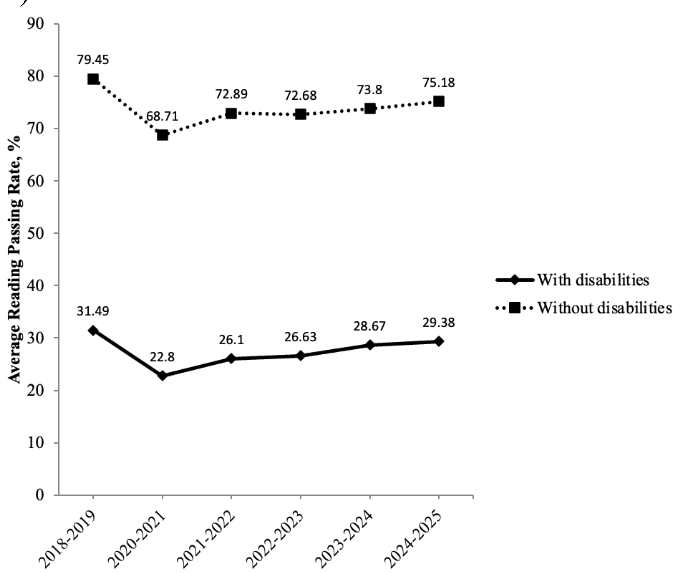
Note. Each predictor was entered in a separate multilevel growth model. Coefficients represent unadjusted associations with the intercept and slope factors of reading and math pass rates for students with and without disabilities over time. *SE* = standard error; CI = confidence interval. Benjamini-Hochberg FDR adjustments made within each combination of test and disability status (i.e., 4 families, 33 comparisons per family).

**p*≤.05 ***p*<.01 ****p*<.001 †Statistically significant after Benjamini-Hochberg FDR correction

Figure 1

Average reading (Panel A) and math (Panel B) pass rates (%) for students with and without disabilities from 2018 to 2025 (note that tests were not administered in 2019-2020 due to the COVID-19 pandemic). ESSER I funds were obligated from March 2020 through Sept. 2022; ESSER II funds were obligated from Dec. 2020 through Sept. 2023; ESSER III funds were obligated through Sept. 2024 at the same time as targeted state funding. Paired samples *t*-tests indicated that pass rates for students with disabilities were significantly lower than pass rates for students without disabilities for both reading and math at all six time points (all *p*s<.001).

(A)



(B)