

# Growth Trajectories in Florida's Mathematics Scores Among Virtual School Students

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## Abstract

This study examines the growth trajectories of math scores among full-time virtual school students in Florida before and after the COVID-19 pandemic. While academic achievement across the United States generally declined during the pandemic, this study found that students enrolled in a full-time virtual school maintained higher math achievement. The study also highlights the performance of students with disabilities (SWDs) compared to students without disabilities to determine whether their math achievement followed national trends. The full-time virtual school student sample demonstrated higher math achievement than those reported by in-person schools. Findings reveal that although virtual SWDs had lower baseline math scores, their growth trajectories were consistent with those of their peers. Results suggest that virtual schooling models effectively maintain learning continuity during disruptions and emphasize the need for effective online instruction and support for diverse learning needs.

**Keywords:** virtual schools, math achievement, growth curve models, K–12 education, educational disparities

## Introduction

Amid the unprecedented disruptions in education brought about by the COVID-19 pandemic, researchers and practitioners have reported concerning declines in academic achievement among K–12 students in the United States. The aftermath of widespread school closures revealed an alarming trend, with various studies indicating a significant decrease in math proficiency (Clark et al., 2020; Dorn et al., 2021; Engzell et al., 2021; Maldonado & De Witte, 2022; Schult et al., 2021; Tomasik et al., 2020). Some studies also suggest that specific student groups, such as students with disabilities (SWDs), were more vulnerable to the disruptions caused by physical school closures (Sherwood, 2023). These academic declines underscore one of the many challenges attributable to the sudden shift to virtual learning, as schools that lacked online teaching experiences struggled to provide effective resources and teacher training (Johnson et al., 2023).

While studies indicate that SWDs generally score lower than their peers on academic assessments (Ladner, 2021), there is a significant gap in our understanding of the impact of the pandemic on math achievement among SWDs. Some researchers speculate that school closures and distance learning disproportionately impacted SWDs who could not receive specialized services, further exacerbating existing educational disparities (Battistin et al., 2021; Gaines, 2020; Sherwood, 2023). However, most published research is limited to educator and parent perceptions of behavioral or functional changes among SWDs (e.g., Yakut, 2021) rather than longitudinal changes in standardized test scores. This gap in the literature underscores the need for our study, which aims to fill this void by examining the academic achievement trajectories of SWDs in a virtual school setting before and after the pandemic.

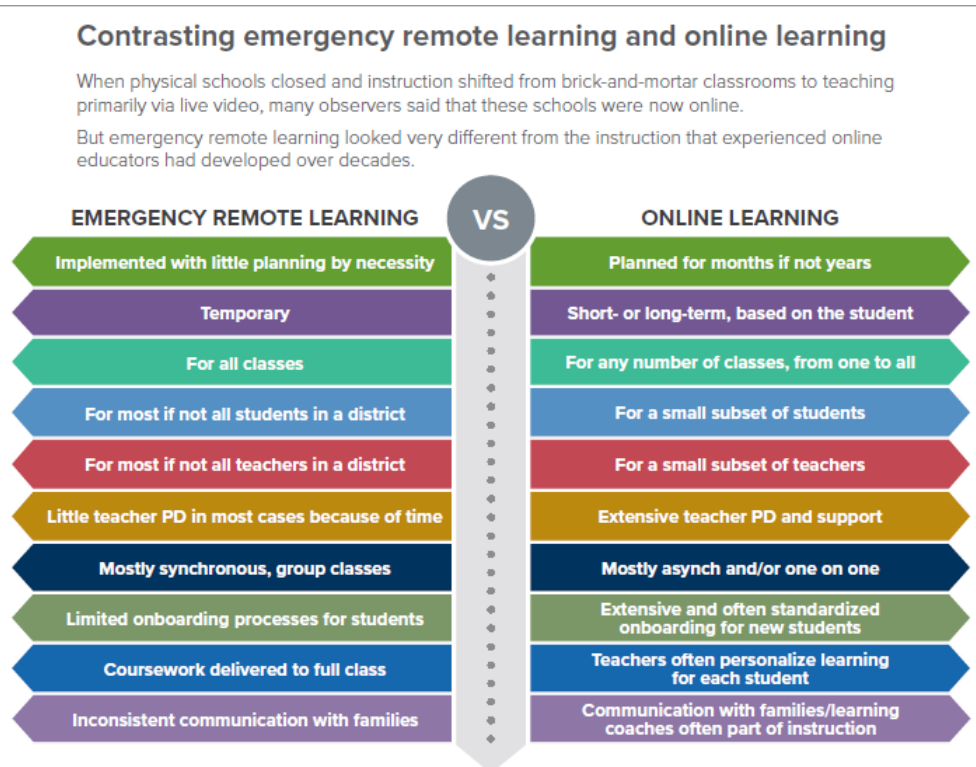
Despite widespread reports of learning loss in the United States due to the pandemic, many virtual school programs stood out as an exception. Students who were already familiar with online learning before the pandemic demonstrated higher math achievement than students who had to adapt to a new learning environment (Meeter, 2021; Spitzer & Musslick, 2021; van der Velde et al., 2021). However, the broader educational landscape highlights the urgency of addressing the disparities and challenges in online math instruction, with implications for future strategies and policies to ensure equitable and effective learning experiences for students. This study, with its unique focus on the academic achievement of students with and without disabilities before and after the COVID-19 pandemic in a well-established full-time virtual school, provides valuable insights into the implications for effective online teaching and learning, thereby contributing significantly to the field of education.

### Rationale and Background

The COVID-19 pandemic triggered a significant transformation in K–12 education in the United States, and the aftermath of widespread school closures and other learning disruptions led to a concerning decline in math achievement among students at all grade levels (Dorn et al., 2021; Kuhfeld et al., 2022). This decline highlighted the complexities posed by the abrupt shift from traditional in-person learning to the ad hoc implementation of online instruction. It is important to note, however, that recent literature underscores stark contrasts between the learning environments of schools that implemented emergency remote teaching (Hodges et al., 2020) with those schools that were already grounded in online instruction (Digital Learning Collaborative [DLC], 2024).

DLC (2024) researchers noted these contrasts early in the pandemic and published the figure below in 2021, but inconsistencies in current publications and policy discussions are still apparent. Please note that any references to online learning or virtual learning in this paper align with the criteria listed on the right side of Figure 1 from the DLC.

**Figure 1. Emergency Remote Learning Versus Online Learning**



Source: DLC (2024).

The sudden transition to virtual learning posed challenges for schools unfamiliar with virtual instruction (Johnson et al., 2023), those characterized on the left in Figure 1 (DLC, 2024). In-person schools' limited experience with online teaching methods resulted in inadequate resources, insufficient teacher training, and technological hurdles, leading to struggles in engaging students effectively, particularly in math.

Consequently, students' math achievement experienced a decline during the 2020–21 school year (Jack et al., 2023). Among the affected groups, SWDs encountered even greater difficulties adapting to the virtual format due to their specialized support needs (Spencer et al., 2023). For example, a study published by Streich and colleagues (2021) found that special education students in Grades 7 and 8 had more unfinished learning than students not in special education classes. The absence of in-person interaction and tailored assistance may have exacerbated their learning challenges and contributed to lower achievement. In general, the shift from in-person to online learning impacted different demographic groups unevenly. Although the decline in math achievement was evident across grades, regions, and student proficiency levels, students from disadvantaged backgrounds faced more significant challenges, contributing to existing educational inequalities (Jack et al., 2023; Meeter, 2021).

Lessons learned from these experiences will likely shape future instructional strategies, emphasizing the need for effective online teaching methodologies and support for diverse student populations (Eadens et al., 2022). This study sought insights into the achievement journeys of students who were established in a virtual school before and after the pandemic, with the goal of adding to the conversation contrasting emergency remote learning (DLC, 2024) that was unplanned and temporary with online learning in seasoned educational systems.

## Method

This study utilized a prospective cohort design in which the sample was comprised of full-time virtual school students who met the following criteria: (1) enrolled in Grade 3 in 2017–18, and (2) had a valid Florida Standards Assessment (FSA) Math scale score in spring 2018. By following a cohort longitudinally, we aimed to investigate the impact of the pandemic on math achievement among elementary school students in this statewide virtual school.

To achieve this aim, the study addressed the following research questions:

1. How did the math achievement of students enrolled in a full-time virtual school change over time, comparing their performance before and after the COVID-19 pandemic?
2. How did one full-time virtual school's mainstream students and SWDs compare to national trends where online students maintained higher levels of math achievement during the COVID-19 pandemic compared to traditional school students?

The decision to analyze math achievement exclusively in this study is grounded in several factors. Math proficiency has been widely reported as more significantly impacted by the COVID-19 pandemic compared to other subjects, making it a critical area of focus for understanding learning loss and recovery trajectories (Dorn et al., 2021). Additionally, math skills are foundational for academic success and future career opportunities, particularly in STEM fields. Including English language arts (ELA) would indeed provide a more comprehensive view of academic performance; however, the scope of this study was narrowed to math to allow for a more detailed analysis of this crucial subject area.

Regarding the focus on third graders from the 2017–18 academic year, this cohort was selected because they were at a formative stage in their education, transitioning from early elementary learning to more advanced content, and were the earliest cohort for which longitudinal data could be tracked through to the seventh grade. This choice allows for an examination of the long-term impacts of the pandemic on a group of students likely to be familiar with the virtual education space at this school.

## Research Design

This study used two secondary data sources. Student assessment data were matched with demographic data from the virtual school's enrollment records using a unique identifier. The demographic data of the students in 2017–18 were used to construct categorical predictor variables for the descriptive analysis and statistical models.

## Data Sources

All students included in the analysis were enrolled in Grade 3 during the 2017–18 academic year in a statewide virtual school serving grades K–12. A total of 329 students had valid assessment data for that year. A majority of students were male (54%) and white (55%). Over a third of students were eligible for free or reduced-price lunch, which indicates the concentration of low-income students at the school. Table 1 describes the demographic characteristics of the student cohort.

**Table 1.** *Demographic Characteristics of Third Grade 2017–18 Cohort (N = 329)*

| Characteristic                           | N   | %    |
|--|-----|------|
| Female                                   | 152 | 46.2 |
| Ethnicity                                |     |      |
| Black                                    | 42  | 12.8 |
| Hispanic                                 | 70  | 21.3 |
| Multiracial                              | 28  | 8.5  |
| White                                    | 181 | 55.0 |
| Other or missing                         | 8   | 2.4  |
| Limited English proficiency              | 10  | 3.0  |
| Students with disabilities (SWD)         | 34  | 10.3 |
| Eligible for free or reduced-price lunch | 118 | 35.9 |
| Complete data for all years              | 18  | 5.5  |

## Measurement

The Florida Statewide Assessment (FSA) Math is a standardized assessment that was administered annually to students in the state of Florida at the time of this study. It was designed to evaluate students' proficiency and understanding of mathematical concepts aligned with the Florida Standards, covering various mathematical topics, including arithmetic, algebra, geometry, statistics, and problem-solving skills.

One of the essential features of the FSA Math test is its utilization of a continuous metric. A continuous metric ensures that students' performance is quantified on a consistent scale across different grades and academic years. This aspect is crucial for accurately measuring growth trajectories and assessing progress over time. The FSA achieves this by employing a scaled scoring system that translates raw test scores into a standardized metric (FLDOE, 2022).

The scaled scoring system employed by the FSA Math test allows for a direct comparison of student performance across various grade levels and academic years. Raw test scores are transformed into scaled scores with consistent ranges and interpretations throughout the assessment years. This scaling process takes into account the difficulty level of individual test items and adjusts the scores accordingly, ensuring that the scores are comparable and meaningful across different administrations of the test.

## **Procedure**

Growth curve models (GCMs) allow researchers to examine change over time in a dependent variable as a function of time for each participant. These models offer numerous advantages over repeated-measures ANOVA. They can account for partially missing data under certain conditions and do not require equal spacing between time points (Curran et al., 2010; Curran & Bauer, 2011; Francis et al., 1991; Willett, 1988), which was important in the current study because there were no testing data for Spring 2020 due to the pandemic. GCMs can also account for linear or nonlinear change over time. Moreover, GCMs do not require observations to be independent, which is rarely true with longitudinal data, and are robust to violations of the homogeneity of variance assumption (Maas & Hox, 2004).

Growth curve models are a type of mixed or multilevel model in which measurement time points (Level 1) are clustered within participants (Level 2). All multilevel models partition variance into their appropriate levels. In the case of GCMs, we can determine how much of the variability in scores is due to the passage of time, participant characteristics, and possible interactions between time and characteristics (i.e., cross-level interactions). As with ordinary least squares regression, the intercept in a GCM represents the initial starting value, and the slope represents the increase or decrease in the dependent variable over time.

Several decisions need to be made before and during this type of model-building process. First, researchers must decide whether to apply maximum likelihood estimation (ML) or restricted maximum likelihood estimation (REML) for the estimation of variance components. REML is generally preferred because it provides more unbiased estimates, particularly for small sample sizes (Hoyle & Gottfredson, 2015). Second, researchers must determine if the intercepts and slopes appear to be random (varying across participants) or fixed (constant across participants). This question can be answered using a sequential model-building approach as outlined in the results. Third, researchers must determine if there is a predictable pattern to the errors. A variety of covariance matrix types can be selected. An unstructured matrix is commonly used with GCMs, but multiple models with different matrix structures can be tested to find one that fits the data best.

This study used REML and an unstructured covariance matrix in addition to the Kenward-Roger adjustment due to the small sample size. This adjustment provides more precise estimates of fixed effects than would result without it. We also made sure to consider the value of the intraclass correlation coefficient (ICC), which is the proportion of total variance in the DV that is accounted for by the clustering—in this case, multiple observations for the same individual. Lastly, we considered model fit by determining the change in the absolute value of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) with each new model.

A cohort was created from the assessment data that consisted of all students, including mainstream and SWDs, who were enrolled in Grade 3 at the full-time virtual school during the 2017–18 school year. Because the cohort was generated from the assessment data, all students in the cohort had a valid Math FSA score in spring 2018. The outcome measure was each student's scale score, which ranged from 240 to 376 in Grade 3 and 269 to 375 in Grade 7. The selected independent variables were dummy-coded predictors representing student demographic characteristics. A series of models were applied to the data to determine if there were statistically significant differences between the intercepts and slopes across groups, with a particular focus on SWDs.

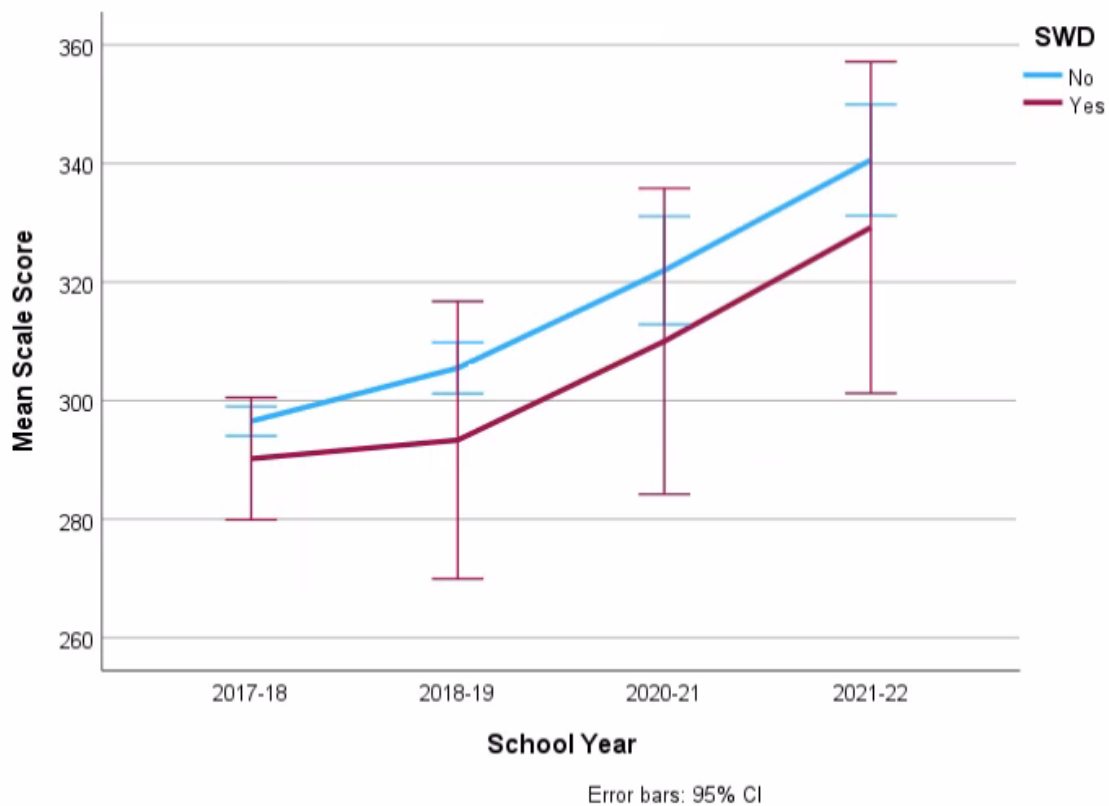
## **Results**

Table 2 and the following figures display the results of this study's analysis. Table 2 differentiates findings by all students and SWDs, and Figures 2 and 3 detail student growth patterns by disability status.

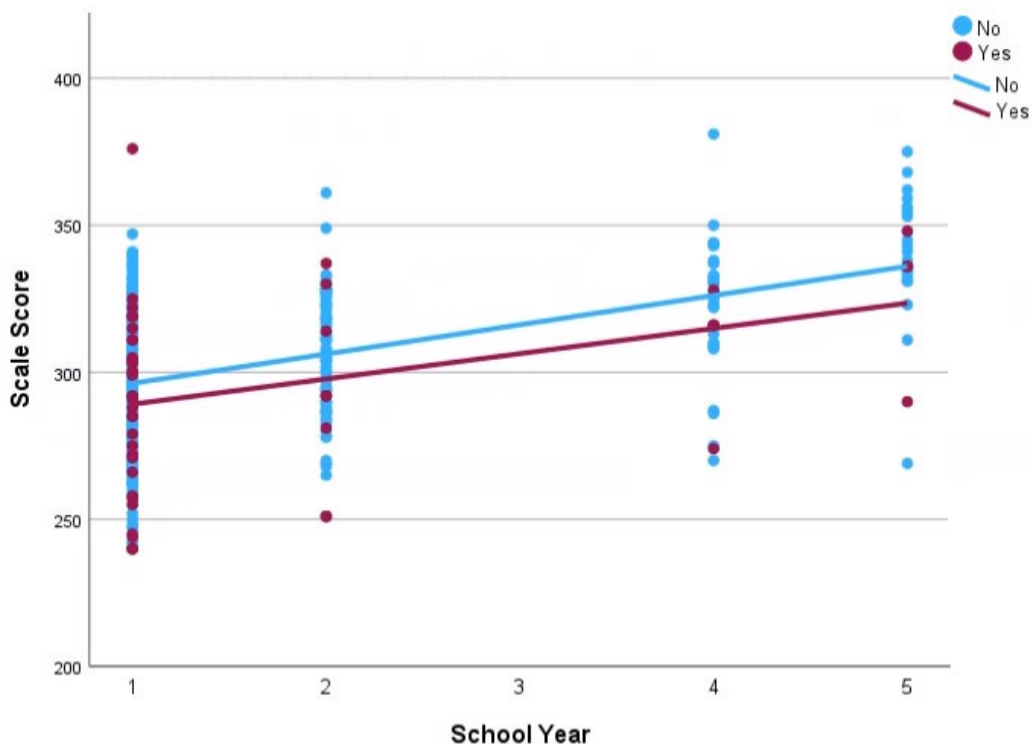
**Table 2.** Observed FSA Mathematics Scale Scores for Students by Disability Status

|                     | Grade<br>(School Year) |                |                |                |                |
|---------------------|------------------------|----------------|----------------|----------------|----------------|
|                     | 3<br>(2017–18)         | 4<br>(2018–19) | 5<br>(2019–20) | 6<br>(2020–21) | 7<br>(2021–22) |
| <b>All students</b> |                        |                |                |                |                |
| N tested            | 329                    | 101            | -              | 33             | 28             |
| % of cohort tested  | 100.00                 | 30.70          | -              | 10.03          | 8.51           |
| M                   | 295.87                 | 304.42         | -              | 320.15         | 338.54         |
| SD                  | 22.60                  | 21.93          | -              | 23.23          | 21.86          |
| <b>SWD</b>          |                        |                |                |                |                |
| N tested            | 34                     | 9              | -              | 5              | 5              |
| % of cohort tested  | 100.00                 | 26.47          | -              | 14.71          | 14.71          |
| M                   | 290.21                 | 293.33         | -              | 310.00         | 329.20         |
| SD                  | 29.59                  | 30.46          | -              | 20.79          | 22.52          |

**Figure 2:** Observed Scores of Students by Disability Status



**Figure 3:** OLS Regression Growth Trajectories by Disability Status



### Results of GCM Modeling Building Procedures

The results of the GCM building procedures offer insights into the fit of various models to the data and the key findings regarding student achievement trajectories. These models explore factors such as the stability of math scores over time, the potential impact of the COVID-19 pandemic on student performance, and the influence of demographic variables on math achievement.

#### Model 1

The goal of Model 1 is to compute a fixed intercept model. In this model, no growth parameters are specified. Across all students, the predicted math scale score averaged over time was 301.69. This model is unlikely to fit the data well because it assumes that all students had similar scores and that these scores were stable over time.

#### Model 2

This model modifies Model 1 by estimating student-level variance in the intercept (baseline) scores. In other words, Model 2 allows baseline scores to vary across students, but it assumes that students have similar scores at each time point. This model also allows for the calculation of the intraclass correlation (0.67), which indicates that most of the variability in math scores is between different students rather than fluctuations within the same student. When we allow the intercept to vary across students, the average baseline value decreases from 301.69 to 298.64.

This model provided a better fit to the data than Model 1, which can be determined by comparing the values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where decreasing values indicate a better fit (Bollen & Long, 1993). The AIC for Model 1 was 4554.32, whereas the AIC for Model 2 was 4422.90. The BIC for Model 1 was 4558.51, whereas the BIC for Model 2 was 4431.29.

**Table 3.** *Model 2*

| Effect        | Estimate | SE   | 95% CI    |           | <i>p</i> |
|---------------|----------|------|-----------|-----------|----------|
|               |          |      | <i>LL</i> | <i>UL</i> |          |
| Fixed effects |          |      |           |           |          |
| Intercept     | 298.64   | 1.30 | 296.09    | 301.20    | <.001    |

*Note.* CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

### Model 3

This model modifies Model 2 by including a linear slope parameter for time, which means that time now becomes a predictor and is interpreted as the annual change in student math scores. It is important to note that students were not tested in Grade 5 due to the COVID-19 pandemic. Results indicate that students' math scores are predicted to increase by 9.62 points each year beyond the baseline year. The predicted math score for students in Grade 3 is 285.97. The predicted math score in Grade 4 is calculated as  $285.97 + 9.62 = 295.59$ , and so on. These results show that students in the virtual school demonstrated a positive growth trajectory in their math scores over the study period, with an average annual increase of 9.62 points. This finding indicates a steady improvement in math achievement despite the pandemic-related disruptions, addressing our first research question by showing that the virtual school's students were able to maintain and even improve their performance over time.

**Table 4.** *Model 3*

| Effect   | Estimate | SE    | 95% CI    |           | <i>p</i> |
|--|----------|-------|-----------|-----------|----------|
|  |          |       | <i>LL</i> | <i>UL</i> |          |
| Fixed effects                                    |          |       |           |           |          |
| Intercept  | 285.97   | 1.77  | 282.50    | 289.43    | <.001    |
| Time   | 9.62     | 0.88  | 7.88      | 11.35     | <.001    |
| Random effects                                   |          |       |           |           |          |
| Intercept variance (within students across time) | 505.14   | 32.31 | 445.63    | 572.60    | <.001    |

*Note.* CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

### Model 4

This model is known as an unconditional linear growth model and has been specified to include randomly varying intercepts and slopes as well as an unstructured covariance matrix. The degrees of freedom were estimated with the Kenward Roger adjustment to account for the small sample size, which is important when random effects are included in the model. Table 5 shows that the random variance estimates for Level 1 (time) and the Level 2 (student) intercepts are significant, but the random slope variance and error covariance estimates are not.



**Table 5. Model 4**

| Effect   | Estimate | SE    | 95% CI |        | p     |
|--|----------|-------|--------|--------|-------|
|  |          |       | LL     | UL     |       |
| Fixed effects                                    |          |       |        |        |       |
| Intercept  | 287.79   | 1.40  | 285.04 | 290.54 | <.001 |
| Time   | 7.85     | 0.52  | 6.82   | 8.89   | <.001 |
| Random effects                                   |          |       |        |        |       |
| Time variance                                    | 51.24    | 7.03  | 39.17  | 67.04  | <.001 |
| Intercept variance (within students across time) | 478.78   | 50.23 | 389.79 | 588.08 | <.001 |
| Slope variance (between students across time)    | -11.01   | 12.69 | -35.89 | 13.86  | .39   |
| Intercept-slope covariance                       | 5.70     | 2.98  | 2.05   | 15.88  | .06   |

Note. CI = confidence interval; LL = lower limit; UL = upper limit.

### Model 5

For Model 5, we added Level 2 predictors of variation in students' intercepts and slopes. We first added SWD (yes/no) because of the widely reported educational disparities for this population. As shown in Table 6, the intercept (288.85) is the predicted math score for students who were not SWD. The time slope (7.52) is the predicted increase in math scores each year for students who were not SWD. The SWD slope (-9.13) means that SWDs were predicted to score 9.13 points lower in Grade 3 than those who were not SWD, which represents a statistically significant difference between SWDs and their peers in baseline math scores ( $p = .04$ ). However, the cross-level interaction between SWD and time was not significant ( $p = .14$ ), indicating that SWD status in third grade did not account for significant variation in growth trajectories. In other words, SWDs did not experience a drop in learning gains, although their math scores were consistently lower than their peers. The values of the ICCs for this model indicate that 11% of the variance in math scores is attributable to differences between students, and 10% is attributable to differences over time.

**Table 6. Model 5**

| Effect   | Estimate | SE    | 95% CI |        | p     |
|--|----------|-------|--------|--------|-------|
|  |          |       | LL     | UL     |       |
| Fixed effects                                    |          |       |        |        |       |
| Intercept  | 288.85   | 1.46  | 285.97 | 291.73 | <.001 |
| Time   | 7.52     | 0.55  | 6.41   | 8.62   | <.001 |
| SWD  | -9.13    | 4.46  | -17.90 | -0.36  | .04   |
| Time x SWD                                       | 2.28     | 1.52  | -0.79  | 5.36   | .14   |
| Random effects                                   |          |       |        |        |       |
| Time variance                                    | 51.13    | 6.98  | 39.13  | 66.81  | <.001 |
| Intercept variance (within students across time) | 465.59   | 49.71 | 377.69 | 573.96 | <.001 |
| Slope variance (between students across time)    | -5.86    | 12.81 | -30.98 | 19.25  | .65   |
| Intercept-slope covariance                       | 5.29     | 2.91  | 1.80   | 15.53  | .07   |

Note. CI = confidence interval; LL = lower limit; UL = upper limit.

As the covariance in Table 6 shows, there is no significant variation in the model that still needs to be accounted for, but we decided to run a final model with the complete set of predictors.

## Model 6

As expected, the set of demographic variables were not significant predictors of students' baseline scores or trajectories. Although SWDs had significantly lower baseline scores, their growth trajectories were not statistically different from their counterparts. This finding addresses our second research question, as it suggests that the virtual school environment provided a supportive framework for SWDs, allowing them to achieve growth patterns comparable to their non-disabled peers, aligning with national trends that highlighted the advantages of established virtual learning environments during the pandemic (Spitzer & Musslick, 2021).

**Table 7.** *Model 6*

| Effect             | Estimate | SE   | 95% CI |        | p     |
|--------------------|----------|------|--------|--------|-------|
|                    |          |      | LL     | UL     |       |
| Fixed effects      |          |      |        |        |       |
| Intercept          | 288.94   | 2.72 | 283.58 | 294.29 | <.001 |
| Time               | 7.26     | 1.25 | 4.77   | 9.76   | <.001 |
| Male               | 1.18     | 2.93 | -4.58  | 6.94   | .69   |
| Black              | -5.53    | 4.33 | -14.05 | 3.00   | .20   |
| Hispanic           | 4.47     | 3.51 | -2.44  | 11.39  | .20   |
| Multiracial        | 0.05     | 5.11 | -10.01 | 10.11  | .99   |
| FRL                | -5.01    | 2.97 | -10.85 | 0.83   | .09   |
| SWD                | -9.40    | 4.62 | -18.51 | -0.30  | .04   |
| Dense              | 5.61     | 3.71 | -1.68  | 12.91  | .13   |
| Time x Male        | -0.11    | 1.22 | -2.55  | 2.34   | .93   |
| Time x Black       | -1.07    | 1.73 | -4.56  | 2.41   | .54   |
| Time x Hispanic    | 0.57     | 1.32 | -2.08  | 3.22   | .66   |
| Time x Multiracial | 1.72     | 1.97 | -2.26  | 5.70   | .39   |
| Time x FRL         | 0.29     | 1.15 | -2.03  | 2.61   | .80   |
| Time x SWD         | 2.41     | 1.72 | -1.09  | 5.90   | .17   |
| Time x Dense       | -0.20    | 1.26 | -2.75  | 2.34   | .87   |

*Note.* CI = confidence interval; LL = lower limit; UL = upper limit.

## Conclusions and Implications

Our study uncovered insightful patterns of academic achievement by examining the growth trajectories of full-time virtual school students' mathematics scores before and after the COVID-19 pandemic. Notably, full-time virtual school students in this study had higher math achievement during the pandemic than those reported elsewhere, which is likely attributable to their familiarity with online learning formats.

A recent survey comparing the experiences of students enrolled in virtual schools versus those in traditional brick-and-mortar schools during the pandemic supports this claim. Kingsbury (2020) found that respondents were almost 6.5 times more likely to report that their child "learned a lot" in Spring 2020 if they were enrolled in a virtual school. These results support the effectiveness of virtual education in maintaining student engagement and learning continuity during times of crisis (Kingsbury, 2020).

Although the sample in this study is relatively small, it is important to consider that it reflects young students who attended virtual school prior to the pandemic and then remained in this learning environment to successfully progress during a time when other students in different circumstances were unable to maintain growth. The disparities in performance between virtual and reported by brick-and-mortar schools across various facets of schooling, including active learning, effective communication, classroom management, and instructional quality, underscore the potential of well-

established virtual schooling models to outperform traditional institutions in online instruction. Moreover, the results of this study revealed that while SWDs exhibited lower baseline math scores compared to their peers, their growth trajectories remained consistent. This observation emphasizes the importance of effective online instruction to support diverse learning needs, even in challenging circumstances such as those brought by the pandemic. The experiences of SWDs highlight the need for tailored support and accommodations in virtual learning environments to ensure equitable opportunities for students.

The findings of this study also carry important implications for educational policy and practice. The decline in math achievement during the pandemic underscores the need for targeted interventions to address the challenges posed by online learning for students who are not accustomed to these types of learning environments. Well-established virtual schools, as demonstrated here and echoed by Molnar et al. (2023), offer a potential blueprint for effective online education. The study argues that while virtual schools have demonstrated potential, particularly in maintaining continuity during disruptions like the COVID-19 pandemic, their success hinges on appropriate policy frameworks. These frameworks should include measures to ensure educational quality, such as setting maximum teacher-to-pupil ratios and aligning curricula with state standards, as well as providing robust support for SWDs through Individualized Education Plans (IEPs; Molnar et al., 2023).

Further, the results of this study suggest that well-designed online platforms and resources may help mitigate the negative effects of disruptions, such as those caused by the pandemic, for students with or without disabilities. The study demonstrated the effectiveness of virtual schooling in maintaining learning continuity, highlighting the potential of online education to complement traditional classroom instruction even under normal circumstances (Kingsbury, 2020). As such, policymakers may consider exploring learning models that utilize virtual instruction to provide students with more flexible and personalized learning experiences. By adopting strategies that promote equitable access, ensure teacher quality, and align virtual school practices with educational standards, policymakers can harness the benefits of virtual schooling to address educational challenges effectively and enhance educational resilience in times of crisis (Beck, 2023).

## Limitations

A limitation of this study is the high percentage of attrition within the cohort over time. Only 8% of the original sample was tested in the final year. Although attrition is not necessarily problematic, we did not test for differences between those who remained at, or withdrew and returned to, the school versus those who left permanently. Additionally, the initial sample size was small, and it is possible that the attrition rate has resulted in unstable model estimates, so results should be interpreted cautiously.

Additionally, it is important to note that while the findings offer valuable insights, their generalizability to other grades may require further investigation. Factors such as the presence of learning guides in earlier grades and the shift toward more independent learning in subsequent years were not directly accounted for in this study but represent important considerations for future research.

Another limitation was that we did not replicate the study with a different sample or include more than one outcome measure. It would be helpful to know if these findings are similar for different standardized tests and different grade levels statewide and nationally.

Future research should address attrition and attempt a replication study to enhance the generalizability of findings. Another aspect to consider is the diverse nature of exceptionalities among SWDs. Conducting targeted investigations in the future could help develop a deeper understanding of how various exceptionalities interact with virtual learning environments and their influence on math achievement.

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