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Predictors and Outcomes of Eighth Grade Math Acceleration in a Florida District

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Students who take higher level math coursework during high school have increased chances of entering a four-year college or university, specifically in the science, technology, engineering, and mathematics (STEM) related fields (Miller 2012; Schneider et al., 1990). Students demonstrating exceptional mathematics performance are often encouraged to take algebra during Grade 8, setting them on a pathway to complete higher-level college-level mathematics coursework in high school (Clotfelter et al., 2015; Dougherty et al., 2017; McEachin et al., 2020; Penner et al., 2015). For several decades, there has been a nationwide push to increase student enrollment in advanced math coursework during middle school (Loveless et al., 2008). The impacts of math acceleration in Grade 8 (e.g., taking algebra or higher by Grade 8) has demonstrated heterogeneous effects across studies, with some demonstrating unintended negative consequences of acceleration (e.g., Clotfelter et al., 2015; Penner et al., 2015) compared with positive long-term impacts to math performance and even English language arts (Rickles, 2013; McEachin et al., 2020). Moreover, the relations of acceleration to later achievement may vary considerably across schools as acceleration decisions may be somewhat dependent on contextual factors that shape individual schools' decision-making criteria (McEachin et al., 2020).

Algebra has long been viewed as a "gatekeeper" to future educational and economic opportunities, though there is mixed evidence for the success of policies instituting college preparatory math requirements early in high school (Allensworth et al., 2009; Nomi & Allensworth, 2009) or earlier (Clotfelter et al., 2015). Importantly, the impacts of math acceleration may largely depend on students' exposure to high-quality pre-algebra coursework; uniform requirements for all students to take algebra in Grade 8 may fall short of their intended consequences because this coursework does not make up for instructional and performance gaps preceding Grade 8 (Penner et al., 2015). These potential issues facing math acceleration programs can be framed within the diamond multi-tiered systems of support (MTSS) model (Green et al., 2013), which emphasizes tiered strategies of enrichment for students' strengths in addition tiered intervention and prevention strategies for academic, behavioral, and mental health difficulties. High-quality core mathematics coursework throughout middle school is necessary to increase the likelihood that students are successful within accelerated programs and not inadvertently discouraged from enrichment coursework. By viewing math acceleration through this diamond approach that emphasizes prevention and enrichment for all students (Bianco, 2010; Green et al., 2013; Robertson & Pfieffer, 2016), it may possible simultaneously shore up the lower tails of the achievement distribution by providing tiered preventative and remedial supports while also promoting tiered enrichment for students demonstrating excellence beyond the core curriculum expectations (Rollins et al., 2009).

Nevertheless, increased Grade 8 algebra opportunities may reshape not only average performance but the distribution of performance, particularly by lowering performance at upper quantiles of math performance (Penner et al., 2015). However, Penner et al., (2015) note that these results may stem from short-term disruptions of typical practices, which further emphasizes the need to carefully attend to the system-wide practices in place when implementing large curricular changes. The authors highlight that system-wide impacts (e.g., improved average math performance) often do not emulate the impacts on a given individual (e.g., an individual student being accelerated). These findings are important in light of framing acceleration as a form of MTSS given that efforts to substantially reform course taking opportunities or criteria to accelerate may not reveal immediate and uniform short-term benefits, but this may be a byproduct of the implementation process rather than the curriculum itself.

Algebra in Grade 8 and Achievement Outcomes

According to the National Center for Educational Statistics, approximately 26% of students during the 2020-2021 school year took algebra I in Grade 8. Since 2023, the percentage of students taking algebra during Grade 8 has remained relatively stable but has decreased to 24% (National Center for Education Statistics, 2025). Evidence from the Trends in International Math and Sciences Study indicated that with students from the United States in Grade 8, performing below average, falling behind 21 other countries (von Davier et al., 2024). Moreover, despite economic affluence in the United States and more districts pushing to enroll students in these higher-level math courses during Grade 8, there are present difficulties with student achievement. However, by providing opportunities for math acceleration earlier in middle school to high-achieving students, schools provide an additional mechanism to attain college preparatory achievement benchmarks earlier in schooling (Dougherty et al., 2015).

Several patterns consistently emerge regarding students who are successful in Grade 8 Algebra. These patterns typically include a combination of academic, socio-economic, behavioral, and institutional factors (Stein et al., 2011; Loveless, 2008; Hattie, 2009). Loveless (2008) found that the students who were successful in Grade 8 Algebra were more likely to come from suburban or rural White and affluent families. However, California's recent efforts to reduce racial disparities in math coursework demonstrate potential unintended consequences in more advanced coursework (Huffaker et al., 2023). For example, Peters and Cater (2023) found that

Black and Hispanic students and students from low-income households have lower enrollment in accelerated math courses, despite these courses being offered. External factors such as teacher educational level and teaching experience and school district access to enrichment opportunities are outside the students' control but related to access to algebra coursework in Grade 8 and successful completion of the course (Burris et al., 2004; Peters & Carter, 2023).

Evidence on impacts of math acceleration in middle school from a large, southeastern public school district demonstrated that a quantitative acceleration criterion in middle school increased the number of students projected to meet algebra benchmarks by Grade 8 and also reduced the relation between student demographic characteristics and acceleration opportunities (Dougherty et al., 2015). However, studies of acceleration enrollment patterns and acceleration impacts have also not traditionally attended to the between-school variation in enrollment patterns and acceleration outcomes. McEachin et al. (2020) demonstrated noticeable between-school variation in Grade 8 algebra impacts to subsequent high school math and ELA achievement.

A key feature of Dougherty et al. (2015) and McEachin et al. (2020) is the use of regression discontinuity designs, which leverage a strict quantitative criterion for Grade 8 math acceleration and allows a clearer inference (at the score cutoff) acceleration impacts to later achievement. The stringency with which districts adhere to quantitative criteria to determine acceleration may vary across school contexts for myriad reasons, resulting in other systematic and random factors affecting decisions of teachers, parents, and school administrators to recommend students' acceleration in math, even if they meet quantitative criteria. Indeed, Dougherty et al. (2015) demonstrated that stricter quantitative criteria for acceleration reduced racial-ethnic acceleration opportunity gaps. Districts with strict adherence to these acceleration cutoffs lend themselves to clearer causal evaluation of acceleration's impact on math achievement, but noncompliance with acceleration criteria muddies the impact of acceleration on achievement. Substantial between-school variation within a district may compound the complexity of understanding how schools fare in promoting students' success in math acceleration (and for whom) at the system level.

In the context of a diamond MTSS approach, the criteria for acceleration can have an important impact on how resources are allocated toward enrichment opportunities, much like intervention entry/exit criteria for Tier 2 or 3 intervention. Within a district, strict acceleration cutoffs may result in stability of the proportion of accelerated students if achievement levels remain somewhat stable over time. The use of more qualitative factors in combination with achievement cutoffs to determine acceleration may have some advantages, such as promoting students who may not perform as well on achievement measures but otherwise demonstrate exceptional mathematical thinking skills. The downside of this is that there is less predictability in accelerated math placement and the process may involve too much subjectivity, which could result in students ending up in acceleration courses that may not demonstrate the requisite skills, which can strain the tiered enrichment system. Students who were otherwise eligible may also not be accelerated.

In addition, instructional quality within accelerated courses is important to ensure that these opportunities are incentivizing for students and encourage their persistence in advanced coursework. Evidence from a recent Grade 9 Algebra de-tracking study (Dee & Huffaker, 2024) indicated that providing differentiated support for low-performing students enrolled in Grade 9 algebra resulted in markedly higher math achievement later in high school. Earlier enrichment opportunities like math acceleration can be successful for a wide range of students with proper differentiation of instructional strategies and content, which is particularly necessary if districts opt to implement requirements for more eighth graders to take Algebra (or higher). Appropriate differentiation may also be necessary to ensure that students of a variety of backgrounds with potentially heterogenous prior math courses are able to successfully access the core Algebra curriculum.

The Current Study

The current literature on Grade 8 math acceleration into algebra coursework suggests that impacts are likely heterogenous and attributable to numerous contextual factors, including instructional context and course availability throughout elementary and middle school as well as the type of acceleration criteria used (e.g., strictness of prior achievement criteria). However, there remains a gap in understanding who receives access to acceleration opportunities in lieu of strict achievement cutoffs and, thereby, the likelihood of meeting achievement benchmarks in accelerated math relative to grade-level math coursework.

In the current study, we examined math acceleration enrollment patterns based on student demographic characteristics as well as the relation between math acceleration enrollment in Grade 8 to the attainment of end-of-year achievement benchmarks. We use data from 30 middle schools and approximately 3,500 students in a Florida district to investigate these patterns with particular attention to the between-school variation in acceleration patterns and achievement. We address the following exploratory research questions:

> **Research Question 1 [RQ1]:** Is there demographic variation in accelerated math placement and to what extent does this vary across middle schools within the school district?
>
> **Research Question 2 [RQ2]:** What is the relation between placement in a math acceleration course (algebra or geometry) in Grade 8 and meeting Grade 8 end-of-year achievement benchmark?

Method

Sample and Procedure

The current sample included 3,470 Grade 8 students from 30 middle schools in a large, suburban Florida school district. Sample demographic factors are reported in Table 1. Deidentified data were shared with the authors by the school district. The authors' institutional review board determined this study did not meet criteria for human subjects research.

Table 1
Sample Demographic Characteristic Percentages.

Female	48.44%

White	59.33%
Hispanic	21.72%
Black	6.62%
Asian	6.58%
Multiple Races/Ethnicities or American Indian or Pacific Islander	5.28%
English Learner	8.49%
Has IEP	17.74%
Eligible for Free/Reduced Price Lunch	33.17%

Note. Racial/ethnic indicator names are those provided in the district data. IEP = individualized education plan.

We define two comparison groups to examine RQ 1: *unaccelerated students* (n = 1,507) and *accelerated students* (1,963). Unaccelerated students consisted of eight graders who scored 3 (out of 5) or higher on the prior year (2022-23) state summative math assessment (Florida Assessment of Student Thinking (FAST) but did not take any algebra or geometry in 2024. The FAST system provides coordinated screening and progress monitoring to assess how well students are mastering the state's Benchmarks for Excellent Student Thinking (B.E.S.T.) Standards (Figueroa, 2025). Accelerated students consisted of those that attained a 3 or higher and did take algebra or geometry in 2024. In Florida, schools are provided an acceleration "score" that reflects the proportion of students that attain a 3 or higher on the end-of-course (EOC) assessments in accelerated math (*acceleration numerator*) over the total number of students in acceleration courses (*acceleration denominator*). Schools with a larger share of students successful in math acceleration will receive higher acceleration scores from the state department of education. For RQ2, we use a slightly smaller sample size due to differences in eligibility for end-of-year summative assessment.

Measures

Outcome. The math achievement measures in this study include either (a) FAST Math or (b) End-of-Course (EOC) assessments. As noted above, the Grade 8 acceleration criterion is based on prior year FAST Math scores (scoring ≥3 out of 5). We used observed accelerated course enrollment in Grade 8 as the outcome for RQ1.

Once students are in an accelerated math course, they take the EOC for that specific course, which also result in an achievement level ranging from 1-5. Students who do not take an accelerated math course in Grade 8 take FAST Math, which again provides the same achievement levels. In addition to the math acceleration score, Florida Department of Education (FLDOE) defines an achievement score for schools that consists of the number of students scoring ≥3 on FAST Math or the EOC (numerator) over the number of students taking FAST or EOC in the school (denominator). As a result, the *achievement numerator* serves as a key indicator for districts and schools in judging students' success on their respective summative assessments (Florida Department of Education, 2024). Following from this, for RQ2, we use the *achievement numerator* as the primary outcome in this study (1.7% of students were not in the achievement denominator and thus not eligible to be in the numerator, resulting in an analytic sample of 3,411). In other words, we are interested in whether taking accelerated math in Grade

8 makes it more likely that a student reaches the state achievement numerator criterion on their respective assessments (Algebra or Geometry EOC or Grade 8 FAST Math).

Predictors and Covariates. For RQ1, our predictors include the demographic characteristics listed in Table 1, Grade 7 FAST Math score, and Grade 7 FAST Math Grade Level (because some students in Grade 7 were taking either above- grade FAST [Grade 8] or on-grade FAST [Grade 7], which also accounts for prior likelihood of acceleration if students were already taking above-grade math in prior years).

For RQ2, the primary predictor is students' acceleration status (enrolled in accelerated math or not). For RQ2, we also adjust for background demographic characteristics, prior (Grade 7) achievement, and prior FAST grade level.

Analytic Plan

RQ1

For RQ, we used the following multilevel logistic regression model:

$$\log\left(\frac{p(Accelerated\ Math_{ij})}{1-(p[Accelerated\ Math_{ij}])}\right) \tag{1}$$
$$= \beta_0 + \beta_1 FRL_{ij} + \beta_2 Race/Ethnicity_{ij} + \beta_3 EL\ Status_{ij} + \beta_4 Female_{ij} + \beta_5 SwD_{ij} + \beta_6 Prior\ FAST\ Math_{ij} + \beta_7 Prior\ FAST\ Grade\ 8_{ij} + u_{0_j} + u_{X_j}X_{ij} + e_{ij}$$

In this model, we estimate the log of the odds of student *i* being placed in accelerated math in Grade 8 in school j in as a function of binary demographic factors (β_{1-4}), disability status (β_6) prior FAST Math standardized scores (β_6), and binary prior FAST Math grade level (β_7). β_2 actually comprises five separate coefficients, each representing one demographic factor with White (and a small number of Pacific Islander students) serving as the reference group. u_{0_j} represents the between-school variability in the proportion of students in algebra/geometry (i.e., the random intercept). We allow all predictors to vary across schools as random slopes, which we indicate as $u_{X_j}X_{ij}$, where *X* represents the vector of predictors that vary across schools j. e_{ij} is the latent scale of the logistic function. All predictor variables were school mean-centered in order to yield within-school estimates of each predictor (Hoffman & Walters, 2022).

RQ2

For RQ2, we used the following model (Model 2):

$$\log\left(\frac{p(In\ Numerator_{ij})}{1-p(In\ Numerator_{ij})}\right) \tag{2}$$
$$= \beta_0 + \beta_1 Alg/Geo_{ij} + \beta_2 FRL_{ij} + \beta_3 Race/Ethnicity_{ij} + \beta_4 EL\ Status_{ij} + \beta_5 Female_{ij} + \beta_6 SwD_{ij} + \beta_7 Prior\ FAST\ Math_{ij} + \beta_8 Prior\ FAST\ Grade\ 8_{ij} + u_{0_j} + u_{1_j} Alg/Geo_{ij} + e_{ij}$$

The predictor Alg/Geo_{ij} is a school-mean centered binary indicator of whether a student i in school j was enrolled in algebra or geometry in Grade 8. We also added the school random slope term $u_{1_j}Alg/Geo_{ij}$, which estimates the between-school variability in the relation of algebra/geometry to numerator status.

This modeling approach differs substantially from prior studies employing regression discontinuity designs (RDD; e.g., Dougherty et al., 2017; McEachin et al., 2020). In the current study, acceleration did not depend on a sharp cut score of prior achievement, and the lack of adherence to a cut score was too strong to justify a fuzzy RDD approach that accounts for noncompliance to the cut score. As a result, we take a more standard regression approach that adjusts for demographic factors that may be related to the probability of being accelerated and the probability of reaching the achievement criterion at the end of Grade 8.

Model Interpretation

Because these Models (1) and (2) are multilevel, they include estimates of relations that reflect the average within the sample as well as between-school variability in relations. We quantify between-school variability in relations using random slopes that are included in Models (1) and (2), which allow us to estimate relations for specific schools in addition to the overall sample average estimate.

We used Bayesian estimation for models (1) and (2) (Kaplan et al., 2023) in the `brms` R package (Bürkner, 2017). Bayesian methods allow the incorporation of prior distributions into the model estimation process (i.e., distributional constraints placed on model parameters based on prior information; Kaplan, 2023). In our case, we used weakly information priors for each log-odds regression coefficient by placing a normal distribution prior of ~*N*(0, 3) on each fixed effect regression parameter (fixed, or constant, effects are the average regression parameters across all upper-level [i.e., schools] units). This merely implies that coefficients closer to 0 are somewhat more likely than those at the tails (e.g., </> +/- 6). We used the default priors of ~ *half-t* (3, 0, 2.5) for random effects, which is a general weak prior for random effects (Bürkner, 2017).

We applied Bayesian methods for practical convergence reasons as well as the interpretation advantages over traditional maximum likelihood estimation (MLE). Fully Bayesian multilevel modeling is advantageous because it facilitates convergence of more complex models by "feeding" the model with additional parameter information contained in prior distributions (compared to MLE that estimates all model information based only on the available data). Bayesian estimation also results in intuitive estimates of parameter uncertainty in the form of posterior distributions and credible intervals. This facilitates more straightforward and flexible interpretation of posterior estimates compared to *p*-values that emphasize only statistical "significance" rather than the full breadth of parameter uncertainty.

We report key parameter estimates with their average estimate, their posterior standard deviation (*p*SD) and the 95% credible interval (this interval value is arbitrary but is used for convention; McElreath, 2020). For fixed effect parameters (i.e., the average parameter estimates across all schools), we also present an estimate of the percentage of posterior estimates that fall in the *region of practical equivalence* (ROPE; Kruschke, 2018), which we calculated using the bayestestR package (Makowski et al., 2019). The percentage of posterior estimates that fall inside the ROPE (-0.18 – 0.18 in log-odds, a typical ROPE range for logistic regression coefficients; Kruschke, 2018) can provide one indication of the certainty that an estimate is equivalent to 0 or not (we use the 89% highest density interval [HDI] for all ROPE calculations, which is the ROPE default in bayestestR). Given the exploratory nature of the study and the desire to be more conservative in our inferences, we defined any log-odds estimates in which the 95% credible interval includes 0 (1 for odds ratios) as not detectably different from zero. However, it is not necessary to bifurcate statistically significance in Bayesian analyses (Kruschke, 2018), so the percentage of estimates in the ROPE can be used in conjunction with credible intervals to understand the broader range of uncertainty in the parameter estimates when using different posterior interval methods and widths (89% HDI and 95% CI).

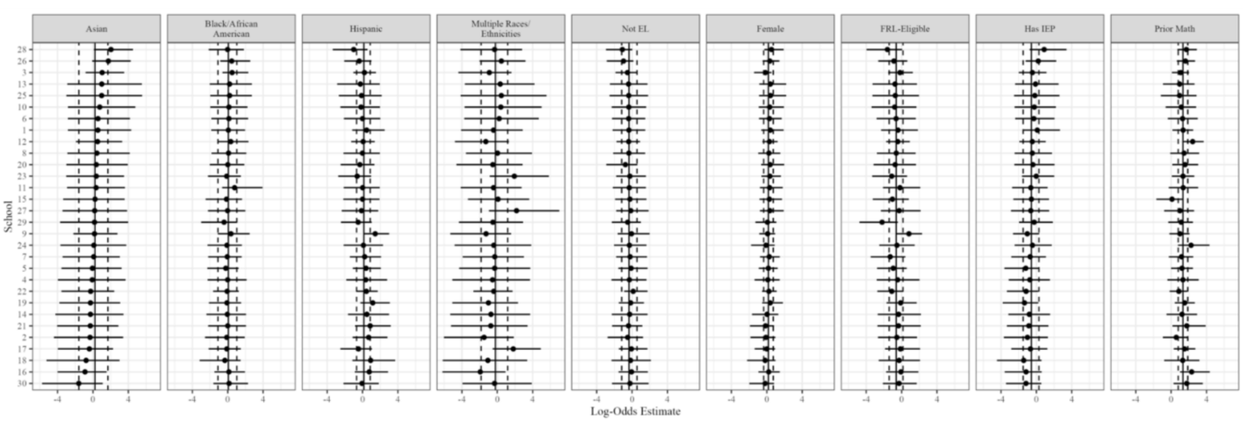
Results

RQ1

The results of this regression analysis are presented in Table 1 and Figure 1. When we adjust for prior FAST grade level, the only statistically detectable predictors of math acceleration are prior FAST Math performance and prior FAST grade level. Scoring 14 points higher (1 standard deviation) on FAST Math in the prior year corresponds to being about 3.5 times more likely to be in accelerated math even when students have the same demographic characteristics and had the same FAST grade level. However, the strongest predictor of acceleration was whether a student was already accelerated (adjusting for their prior math achievement). Previously accelerated students were >100,000 times more likely to be in accelerated math in Grade 8.

Figure 1

Model 1 Constant and School Varying Effect Estimates of Demographic Factors Predicting Math Acceleration



Note. School-specific estimates ordered by magnitude of first panel. FRL = free/reduced price lunch, IEP = individualized education plan, EL = English learner. Prior math is the FAST score Grade 7. FAST grade level coefficient (the grade level of the FAST assessment the student took) not displayed. Race/ethnicity coefficients are relative to primarily White students and a small number of American Indian or Pacific Islander students. School numbers are random.

Between-School Variation

In Figure 1, we present school-specific log-odds estimates from the multilevel model for each demographic factor and prior math scores. The vertical lines in Figure 1 represent the sample-average estimates (solid line) and 95% credible interval range (dotted lines). Some demographic factors have substantially more between-school variability in their estimates. There are few instances in which a school-specific demographic estimate's 95% credible interval does not include zero, indicating that the amount of between-school variation in these predictors is not substantial. The school-specific estimates of prior math are more precise, although the variability in these effects is comparable to other predictors. The narrower credible intervals for prior math results in prior math being a more detectable predictor of enrollment in some contexts but not others. Nevertheless, no prior math school-specific estimates are substantially different from the average estimate.

RQ2

For the second research analysis, we examined if it was more likely that accelerated students in Grade 8 would score ≥3 on the respective assessments (EOC or FAST). We estimated two versions of Model 2: the model presented previously (Model 2a) as well as a model that removes prior math performance and math grade level. Table 2 provides the log-odds and odds ratio coefficients for the two models. In the model that adjusts for prior FAST Math performance (Model 2a), accelerated students were not substantially more likely to obtain ≥3 on their EOC than students in grade-level math taking FAST (b = 0.46, pSD = 0.35, 95% CI = -0.21 – 1.15, OR = 1.58). Twenty percent of the 89% HDI of this estimate falls in the ROPE; however, math acceleration demonstrates some potential multicollinearity with prior FAST grade level (i.e., those who were already accelerated remain accelerated), so this ROPE estimate is not accurate (Kruschke, 2014). This estimate has 91% chance of exceeding zero given a pSD of 0.35; however, the 95% CI substantially covers 0, so the estimate does not meet the desired level of certainty.

Without adjusting for prior FAST Math and math grade level, the likelihood that accelerated students scored ≥3 is substantially larger (b = 1.12, pSD = 0.19, 95% CI = 0.84 – 1.41, OR = 3.06). Accelerated students are already by definition higher-performing, so when prior performance is not adjusted, they are noticeably more likely to score ≥3 on their EOC than students in grade-level math who take FAST. The 95% interval of this effect falls 100% outside the ROPE.

Table 2
Multilevel Logistic Model Parameters for Predicting Algebra/Geometry Enrollment in Grade 8

Parameter	Estimate	Posterior Standard Deviation	95% Credible Interval Low	95% Credible Interval High	Odds Ratio	% Inside ROPE
Model 1						
Constant Effects	Log-odds					
Intercept	3.67	0.80	2.17	5.32	39.25	0.00%
EL	-0.33	0.45	-1.17	0.60	0.72	23.58%
FRL-Eligible	-0.60	0.40	-1.42	0.19	0.55	11.99%
Has IEP	-0.57	0.46	-1.51	0.29	0.56	15.50%
Female	0.18	0.28	-0.38	0.75	1.20	43.76%
Asian	0.24	0.83	-1.60	1.68	1.27	16.32%

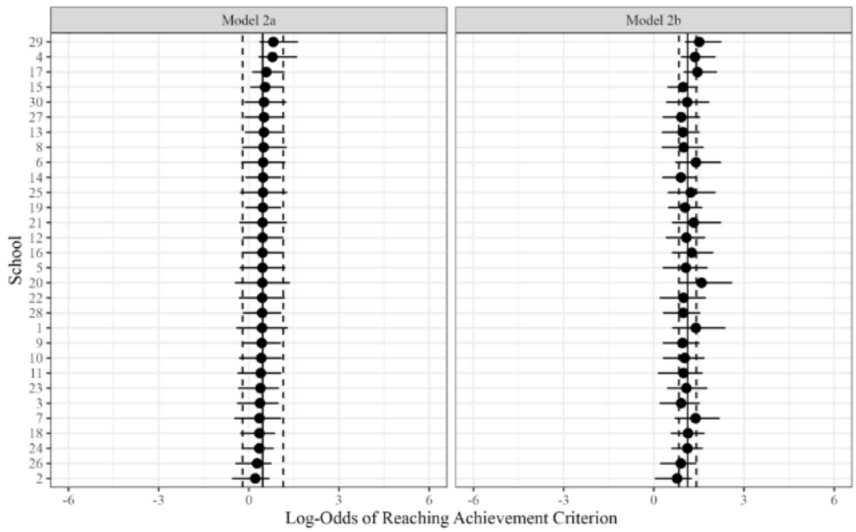
Black	0.05	0.55	-1.13	1.06	1.05	27.53%
Hispanic	0.16	0.40	-0.67	0.91	1.17	33.46%
Multiple Races/Ethnicities	-0.22	0.77	-1.84	1.20	0.81	20.00%
Prior FAST Math (Standardized)	1.34	0.27	0.81	1.87	3.80	0.00%
Prior FAST Math Grade Level	11.82	1.12	9.82	14.19	135495.78	0.00%
Varying Effects	*SD*					
Intercept	3.52	0.64	2.42	4.93		
EL	0.77	0.49	0.05	1.90		
FRL-Eligible	1.13	0.45	0.30	2.08		
Has IEP	1.03	0.55	0.08	2.15		
Female	0.53	0.39	0.02	1.46		
Asian	1.66	0.82	0.21	3.46		
Black	0.81	0.61	0.03	2.26		
Hispanic	1.03	0.46	0.17	1.99		
Multiple Races/Ethnicities	1.94	0.93	0.20	3.93		
Prior FAST Math (Standardized)	0.89	0.33	0.30	1.60		
Prior FAST Math Grade Level	1.31	0.97	0.05	3.59		
Model 2a						
Constant Effects						
Intercept	2.29	0.23	1.84	2.75	9.87	0.00%
Enrolled in Algebra/Geometry	0.46	0.35	-0.21	1.15	1.58	19.58%*
Varying Effects						
Intercept	1.13	0.19	0.81	1.55		
Enrolled in Algebra/Geometry	0.32	0.19	0.02	0.72		
Model 2b						
Constant Effects						
Intercept	1.82	0.19	1.45	2.20	6.17	0.00%
Enrolled in Algebra/Geometry	1.12	0.14	0.84	1.41	3.06	0.00%
Varying Effects						
Intercept	0.94	0.16	0.67	1.30		
Enrolled in Algebra/Geometry	0.38	0.18	0.05	0.75		

Note. ROPE = region of practical equivalence using 89% highest density interval of posterior distribution. White students (in addition to a small percent of American Indian or Pacific Islander students) are the race/ethnicity reference group. EL = English learner, FRL= free/reduced lunch, IEP = individualized education plan.

Between-school Variation

Table 2 provides the estimates of $u_{1_j}Alg/Geo_{ij}$ (school varying effect $\beta_1 Alg/Geo_{ij}$), and Figure 2 school-specific log-odds estimates $\beta_1 Alg/Geo_{ij}$ in Models 2a and 2b. In both cases, the lower bound of the 95% CI of $u_{1_j}Alg/Geo_{ij}$ is close to zero, and this is also reflected in the minimal between-school variation in log-odds estimates in Figure 2. Most school-specific estimates are close to the model average estimate, and in Model 2a, most school-specific 95% CIs also cover zero (except for a few), suggesting that there is minimal between-school variability in the relation between acceleration and achievement level.

Figure 2
Model 2a and 2b Constant and School Varying Effect Estimates



***Note*.** School-specific estimates ordered by Model 2a panel. Model 2a corresponds to the Model 2 equation provided in the text. Model 2b removes prior math achievement and prior math grade level as predictors. School numbers are random.

Discussion

The current study expands previous research on math acceleration enrollment patterns by providing new evidence from a large, suburban school district. Moreover, this study builds upon prior research on acceleration enrollment patterns and outcomes by attending specifically to between-school variation in relations between demographics and enrollment as well as the relations of acceleration to achievement level (McEachin et al., 2020). Our findings suggested no detectable relations of demographic factors (race/ethnicity, EL status, disability status, FRL eligibility, or sex) to math acceleration after accounting for prior math performance and students' prior math grade level. This suggests that students who are already accelerated in Grade 7 continue to remain accelerated in Grade 8. Nevertheless, there is a small but robust relation between prior FAST scores and subsequent acceleration, suggesting that despite the substantial stability in accelerated students, prior achievement does predict some mobility in acceleration. However, this varies to some extent across schools, suggesting that in some settings prior math scores carry more weight in acceleration decisions than others (McEachin et al., 2020).

When we adjust for students' prior math performance and prior FAST grade level, accelerated and unaccelerated students have similar odds of scoring ≥ 3 on their respective end-of-year assessments. Accelerated students may have a slight advantage in odds, but this estimate did not meet our desired level of certainty, and the advantage in odds is quite small (1.58x greater odds). In other words, students with similar prior performance have similar probability of scoring ≥ 3 on the end-of-year assessment regardless of which assessment and class (algebra/geometry or grade-level math) they took. The between-school variation in this relation is minimal with schools only at the far tails of the distribution showing estimates demonstrably different from the average.

Implications for Applied Research

In this study, we addressed similar research questions as previous work with the added nuance of examining variability of acceleration enrollment and outcomes across schools. Our findings demonstrate that demographic factors were generally not related to acceleration enrollment over and above prior math scores and prior acceleration. However, Grade 8 acceleration is highly downstream as an indicator of math enrichment need. For example, Koon and Davis (2019) used data from Mississippi to demonstrate that Grade 5 math achievement was a stronger predictor of attaining Grade 11 college readiness benchmarks than students' math course-taking patterns through middle and high school. This suggests considerable stability in math attainment across late elementary and middle school. In addition, Hall et al. (2025) demonstrated that math growth between Grades 6-8 demonstrated substantial between-person stability; students that performed high in Grade 6 were highly likely to remain in that relative position by Grade 8. Moreover, there was a small, positive correlation between growth slopes and intercepts, potentially suggesting that students "fan out" across middle school, widening individual differences in math performance. Math growth is highly stable within the school year in Grades 6 and 7 and Fall math performance in each grade also demonstrates a strong correlation with Fall reading performance (r = .7-.8; Clark & Hall, 2025), which indicates general stability in students' achievement at these grade levels. Deceleration of math growth across elementary and middle school is common (Shanley et al., 2016; Shi et al., 2023), further underscoring the increasing between- and within-person stability of math gains as students transition to adolescence.

These developmental trends are key to consider in developing tiered enrichment models parallel to tiered intervention models. With the increasing stability in math performance, students are unlikely to make gains in math competence comparable to that in early elementary years. This is likely due in part to an interaction between typical course-taking pattern mobility in addition to the developmental deceleration during this period where students who are not accelerated early in math are much less likely to be accelerated later in middle school. The stability in acceleration patterns between Grades 7-8 in the current study provide further evidence for this, although students who score 1*SD* higher on prior year state exams are twice as likely to be accelerated. Additional research is needed to understand how MTSS structures for math can both enrich learning opportunities beyond typical expectations while supporting essential grade-level competencies for all students. This is particularly essential in late elementary school as students encounter increasingly higher expectations for prealgebra and rational number competencies, both of which are key predictors of later algebra success (Booth & Newton, 2012; Siegler & Braithwaite, 2017).

Continued investigation of mechanisms to support students within late middle school enrichment is necessary, particularly at the school-wide level, to ensure that adequate supports are in place to promote students' success once they are accelerated (or continue to be accelerated). This may be particularly the case for students who are newly accelerated by Grade 8, who may then be transitioning to assessment on EOC exams instead of typical grade level performance. McCoy (2005) reported that the students with higher success during Grade 8 algebra had teachers who were more experienced in teacher high level concepts, perceived usefulness in mathematics, and were more inclined to motivate students taking math coursework.

Implications for Practice

The current work demonstrates that schools should attend to both the upstream and downstream patterns of acceleration and link tiered enrichment supports across grade levels to ensure continuity in coursework access opportunities. The natural differentiation of math coursework through middle school can easily stabilize course taking patterns that may unnecessarily limit enrichment opportunities. However, the combination of tiered enrichment and alternative math pathways must be implemented carefully in order to avoid disincentivizing students from taking advantage of enrichment opportunities or inadvertently creating more barriers. Large-scale course-taking pathway reforms may not enact the intended disparity-reducing changes (Huffaker et al., 2023). Sources of within-district heterogeneity are key to consider when enacting acceleration policies (McEachin et al., 2023), particularly when considering that system-wide impacts to these policies may not reflect acceleration patterns among individual students (Penner et al., 2015).

Altogether, our current findings suggest that continued tiered math enrichment through middle school with data-based decisions to inform acceleration can provide added opportunities and acceleration mobility even as math gains tend to slow down. Nevertheless, a large share of accelerated students are likely exposed to those enrichment opportunities much earlier than the end of middle school. Districts should focus establishing continuity across elementary and secondary school in the continuum of tiered math prevention, intervention, and enrichment services. This is particularly important to consider given that fifth grade math achievement may be a stronger indicator of later math college readiness than middle and high school math courses (Koon & Davis, 2019). Proactive instructional supports can facilitate access to early high school algebra and promote later achievement (Dee & Huffaker, 2024).

Limitations

Several key factors limit the current work. First, this study provides evidence from a single district. Although diverse across several demographic dimensions, generalizability is limited due to the specific district and state policies governing acceleration, math instruction, and assessment methods. Moreover, the current work cannot be interpreted as causal evidence for the impact of math acceleration given the numerous unexplained factors determining placement of students within accelerated math coursework. Adherence (even approximate) to a specific prior score for acceleration eligibility was not evident, limiting the use of more rigorous techniques like regression discontinuity methods. Finally, the outcome measurement differs across accelerated and nonaccelerated classes, further confounding the relation of acceleration to achievement. Similar performance levels on FAST and EOC do not imply measurement invariance, so inferences about how acceleration impacts similar dimensions of math skills are untenable.

Conclusions

Math acceleration is an important feature of tiered support models that emphasize enrichment and preventative supports for all students. However, opportunities for acceleration are often not equally distributed across demographics or grade level given the confluence of decelerating achievement over time as well as stabilizing individual and group differences in math attainment.

The current work provides another source of evidence demonstrating that acceleration opportunities were invariant to demographic factors in this context, and students with similar prior math performance were approximately equally likely to reach end-of-year benchmarks in either accelerated or unaccelerated courses. More attention in research and practice is needed to understand how an effective continuum of support for math enrichment and prevention can be implemented across elementary and secondary schooling to support high expectations and access to rigorous, core curricula for all students.

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