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Heterogeneous Effects of Early Algebra across California Middle Schools

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Abstract

How should schools assign students to more rigorous math courses so as best to help their academic outcomes? We identify several hundred California middle schools that used 7th-grade test scores to place students into 8th-grade algebra courses and use a regression discontinuity design to estimate average impacts and heterogeneity across schools. Enrolling in 8th-grade algebra boosts students' enrollment in advanced math in ninth grade by 30 percentage points and eleventh grade by 16 percentage points. Math scores in tenth grade rise by 0.05 standard deviations. Women, students of color, and English-language learners benefit disproportionately from placement into early algebra. Importantly, the benefits of 8th-grade algebra are substantially larger in schools that set their eligibility threshold higher in the baseline achievement distribution. This suggests a potential tradeoff between increased access and rates of subsequent math success.

INTRODUCTION

Between 1990 and 2015, the proportion of eighth graders in United States public schools enrolled in algebra or a more advanced mathematics course more than doubled to 44 percent. This increase was particularly pronounced in California, where 8th-grade algebra enrollment rates peaked at 68 percent in 2013, in the wake of a decades-long policy effort to make algebra the default mathematics course for eighth graders. The push to enroll more students in 8th-grade algebra is predicated on the idea that exposing students to more advanced material accelerates their skills acquisition (Allensworth et al., 2014; Hemelt, Schwartz, & Dynarski, 2019; Kurlaender, Reardon, & Jackson, 2008) and improves their labor market outcomes (Goodman, 2019). Yet evidence on the effects of course acceleration is mixed. Both high-achieving and low-achieving students can thrive in well-designed algebra classrooms (Cortes, Goodman, & Nomi, 2015; Heppen et al., 2012). However, recent quasi-experimental evaluations suggest that, on average, algebra policies administered

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at scale have modest or even negative average effects on students' mathematics achievement (Clotfelter, Ladd, & Vigdor, 2015; Domina et al., 2015; Dougherty et al., 2017).

In this paper, we argue that, in order to understand the effects of 8th-grade algebra courses, it is essential to explicitly model cross-school variation in the effects of course exposure. Schools differ considerably in the ways they approach 8th-grade algebra (Domina et al., 2016; Rickles, 2011). We thus expect the effects of 8th-grade algebra exposure to vary considerably across schools. We use data from all eighth graders in California public schools across four cohorts to identify schools in which students' rates of enrolling in 8th-grade algebra varied discontinuously at a threshold in the 7th-grade math test score achievement distribution. We then use a fuzzy regression discontinuity design to examine the average local effect of 8th-grade algebra on achievement and course-taking outcomes, as well as the extent to which these effects vary across schools and student demographics.

Our analyses indicate that the average effects of 8th-grade algebra enrollment on students' advanced math course enrollment are substantial and positive, while the average effects on mathematics and English language arts (ELA) test scores are modest. Enrolling in 8th-grade algebra boosts students' enrollment in advanced math in ninth grade by 30 percentage points and eleventh grade by 16 percentage points. Math scores in tenth grade rise by 0.05 standard deviations (sd). Encouragingly, we find that women, students of color, and English-language learners benefit disproportionately from accelerated coursework.

Importantly, however, we find substantial cross-school variation in the achievement effects of 8th-grade algebra. For example, we find that approximately 38 percent of the site-specific effects of 8th-grade algebra on students' math achievement on the 10th-grade California High School Exit Exam (CAHSEE) are negative. The benefits of 8th-grade algebra are substantially larger in schools that set their eligibility threshold higher in the baseline achievement distribution. This suggests a potential tradeoff between increased access and rates of subsequent math success.

Our paper makes two major contributions. First, we contribute to the educational policy literature by providing unbiased estimates of the effects of accelerated coursework drawn from a wide range of educational settings as well as showing how these effects vary across students and schools. Several studies indicate that enrolling in advanced courses improves students' achievement and their likelihood of success in both higher education and in careers involving advanced quantitative skills net of a rich set of observational controls (Attewell & Domina, 2008; Gamoran et al., 1997; Gamoran & Hannigan 2000; Long, Conger, & Iatarola, 2012; Rose, & Betts, 2004; Schmidt et al., 2001, 2012; Stein et al., 2011). However, a range of confounding factors potentially bias these observational estimates. The handful of existing experimental and quasi-experimental studies, meanwhile, provide a remarkably uneven accounting of the effects of 8th-grade algebra assignment, with experimental analyses from one setting returning positive test score effects of nearly 0.4 standard deviations (Heppen et al., 2012) and quasi-experimental analyses from another setting returning negative test score effects of nearly 0.5 standard deviations (Clotfelter, Ladd, & Vigdor, 2015). Interpreted as reasonably well-identified upper- and lowerbound estimates, this body of research would seem to suggest that the effects of 8th-grade algebra vary substantially across time and place.

Second, we combine a regression discontinuity design with methods developed to measure cross-site variation in multi-site research settings. Much like the North Carolina district that Dougherty et al. (2015, 2017) study, several of California's largest public school districts have course placement policies that instruct schools to place students into 8th-grade algebra if the students scored above a set threshold on the 7th-grade mathematics California Standards Test (CST). Fresno Unified and Long Beach Unified, for example, both mandated that students who scored higher than 325 (halfway between the thresholds for being categorized as "basic" and "proficient" under No Child Left Behind) on the 7th-grade CST be placed in algebra as eighth graders. This approach garnered substantial attention among educators across the state (Marsh, Bush-Mecenas, & Hough, 2017). If implemented with fidelity, such formula-based placement policies provide an opportunity to apply regression discontinuity methods to estimate the effects of advanced course enrollments. Such analyses hinge on the assumption that, in the absence of the formula-based assignment, there would be a continuous relationship between prior CST scores and later outcomes for students across the prior CST distribution. Discontinuities in that relationship at the assignment threshold thus provide a "good as random assignment" (Lee & Lemieux, 2010) signal regarding the effects of 8th-grade algebra assignment on student achievement (Imbens & Lemieux, 2007).

In the typical application of regression discontinuity methods, however, the researcher knows the location of the placement threshold. While we are aware of policies in approximately 37 California schools that use 7th-grade test scores to place students in 8th-grade algebra, there are approximately 1,500 schools serving middle school grades in California in any given year, many of which likely use similar placement strategies. We build on the work of Card, Mas, and Rothstein (2008) to empirically identify settings in which assignment practices facilitate regression discontinuity analyses. We then take advantage of the fact that we are estimating regression discontinuity analyses in multiple settings to explicitly model variation in the effects of 8th-grade algebra across schools (e.g., Raudenbush, Reardon, & Nomi, 2012).

Cross-site effect heterogeneity is a common phenomenon in a policy landscape defined by federalism and local discretion. Prior research documents substantial site-level variation in the effects of multiple policy interventions, including early childhood education (Bloom & Weiland, 2015), charter schools (Angrist, Pathak, & Walters, 2013; Clark Tuttle et al., 2015), and welfare-to-work programs (Bloom, Hill, & Riccio, 2003). There is good reason to expect similar effect heterogeneity in our setting. Approximately one-quarter of California middle schools enrolled virtually all eighth graders in algebra, while a quarter reserved 8th-grade algebra for a small group of high-performing students (Domina et al., 2016). These disparate placement rates reflect differences between educators who believe "it's better to challenge kids" and those who "don't want students to be in a class where they're … not going to be successful" (Rickles, 2011, p. 508). In line with earlier evidence suggesting that high-achieving students benefit more than lower-achieving students from advanced courses (Clotfelter, Ladd, & Vigdor 2015; Domina, 2014; Simzar, Domina, & Tran, 2016), we find that the effects of 8th-grade algebra are most positive in schools that restrict access to the course to high-achieving students. However, as we also find that students who have historically lacked access to advanced mathematics courses benefit the most from 8th-grade algebra placement, our results highlight the tradeoff facing policymakers in relatively low-performing schools.

DATA

Our analyses use data provided by the California Department of Education (CDE) containing information on all sixth through eleventh graders enrolled in California public schools between the 2005/2006 to 2012/2013 school years. From these data, we create a panel of four cohorts of eighth graders who completed eighth grade between the 2007/2008 and 2010/2011 school years, which allows us to follow them from sixth through tenth grade (through eleventh grade for the first three cohorts). In these years, the California Department of Education was culminating a decades-long policy effort aimed at broadening students' access to 8th-grade algebra, a course once reserved for a relatively small proportion of high-achieving students. In 2008, the state declared algebra the "sole course of record" for accountability in 8th-grade mathematics, threatening schools with accountability penalties for enrolling eighth graders in pre-algebra or other less advanced courses. Court actions and the state's 2010 move to the Common Core State Standards prevented the algebra-for-all policy's full implementation. However, these policy efforts induced California middle schools to develop new approaches to middle school mathematics course placements.

Our administrative data include students' 6th- through 11th-grade California Standards Test (CST) subject identifiers and scores, 10th-grade California High School Exit Exam (CAHSEE) scores, as well as basic student-level demographics and school and district identifiers. The CSTs, administered each spring for accountability purposes, are designed to measure student mastery of state academic standards. Students take an end-of-grade ELA CST in grades 3 to 11. By contrast, math CSTs are course-specific. While virtually all California students take the same grade-level CST annually through the seventh grade, eighth graders who enroll in algebra take the algebra CST and eighth graders who enroll in pre-algebra take the 8th-grade general mathematics CST. As such, the test identifier associated with students' 8th-grade math CST provides information on students' 8th-grade math course enrollment.[1] Table 1 (below) provides a descriptive summary of these data.

Since our analyses hinge on the association between 7th-grade CSTs and 8th-grade course placements comparing students in algebra to a general math course, we exclude students who take the algebra CST as seventh graders and students who take end-of-grade tests designed for students with severe learning disabilities (collectively, this is approximately 17 percent of the 8th-grade population).

[1]Although course-enrollment data are not publicly available for all California public school students, analyses of data from one large California public school district indicates that end-of-course tests provide a highly reliable proxy for course content. In this district, approximately 99 percent of eighth graders who enroll in pre-algebra courses take the 8th-grade General Mathematics California Standards Test (CST) (Penner et al., 2015). Similarly, 99 percent of students in algebra I courses enroll in the 8th-grade algebra CST. Analyses of data from another large California public school district point to a similarly high level of correspondence between course enrollment and end-of-course CST completion (Taylor, 2011).

METHODS

Student selection into algebra is likely driven by a number of observed and unobserved factors. In this paper, we implement an augmented regression discontinuity design to estimate the local average treatment effect (LATE) of 8th-grade algebra on students' math and ELA achievement as well as high school math course-taking. Such a design is ideally suited to a scenario in which schools and districts place students into 8th-grade algebra using an explicitly articulated system based on observable factors, such as students' 7th-grade math achievement. However, while California incentivized algebra enrollment over the 1990s and 2000s, the state did not implement a universal enrollment policy, nor did it require schools and districts to report how they enrolled students in 8th-grade algebra. As a result, we observe pronounced heterogeneity in middle school math placement policies and practices across the more than 300 districts and 1,500 schools that serve California middle school students (e.g., Domina et al., 2016). Since several California districts had stated policies of placing students into 8th-grade courses based on a 7th-grade test score-threshold, we search across the state for test score-based assignments. However, even in districts with explicit policies, the implementation of these threshold-based assignment mechanisms varied across schools: some schools followed the district guidelines, others adapted them by moving the cut score, and still others ignored the guidelines altogether.[2] As such, we focus our paper on school-based regression discontinuities.

Identifying Discontinuities in 8th-Grade Algebra Assignments

We implement an algorithm to identify settings in which students' likelihood of 8th-grade algebra placement varies discontinuously based on 7th-grade math CST scores, using data from each of the 1,479 California schools that enrolled at least 50 eighth graders in a given cohort. Separately for each of the school-by-year combinations, we conduct a series of first-stage linear probability OLS regressions:

$$Alg_{it} = \beta_0 + \beta_1 1\left[CST_{i,t-1} \geq x\right] + \beta_2\left(CST_{i,t-1} - x\right) + \beta_3 1\left[CST_{i,t-1} \geq x\right] * \left(CST_{i,t-1} - x\right) + \epsilon_{it}\,. \quad (1)$$

In each run of equation (1), Alg_{it} is a dichotomous variable distinguishing students who enroll in 8th-grade algebra from students who enroll in grade-level general mathematics in year t, and CST is student i's score on the 7th-grade math CST in year $t-1$. Because the CSTs in all subjects and grades are discrete, we prefer a linear-spline functional form for equation (1) and we cluster our standard errors at the school level (Gelman & Imbens, 2014; Lee & Card, 2008).[3] We restrict our search to iterate across potential thresholds x between 295 and 355, a range that includes two key policy-relevant thresholds: "basic" (score of 300)

[2]We do not have detailed information about the reasons schools adapted or ignored guidelines. However, it is likely that schools made adjustments to fill the classes that they planned to offer, and that they faced capacity constraints in the number of algebra teachers available.

[3]The results are more conservative with a quadratic functional form. However, as most quadratic terms in the school specific regressions are not statistically significant, we prefer the linear specification. Results from the quadratic specification are available upon request.

and “proficient” (score of 350). For each potential threshold *x*, we also restrict our analyses to students within 75 points of *x* (roughly one sd on the 7th-grade math CST).[4]

For each iteration, we store: 1) The magnitude of the discontinuity in the rate of algebra placement at the assumed cut point, β_1; 2) the amount of variance explained, R^2, by equation (1); 3) the location of the assumed discontinuity, *x*; 4) the *t*-statistic for the simple test $\hat{\beta}_1 = 0$; and 5) the percent of students in algebra at the right- and left-hand side of *x*, estimated from the model. Hansen (2000) demonstrated that the value of *x*, which maximizes the R^2 from equation (1), identifies a break in the forcing variable. Following prior applied work (Andrews, Imberman, & Lovenheim, 2017; Bertrand, Hanna, & Mullainathan, 2010; Chay, McEwan, & Urquiola, 2005; Goodman, Hurwitz, & Smith, 2015; Pan, 2015; Steinberg, 2014), we use this value of *x*, which represents an estimated structural break in the likelihood of treatment, conditional on a continuous forcing variable, in a traditional fuzzy regression discontinuity (RD) framework.

While we execute the search process and estimate $\widehat{\beta_1}$ across all schools, we cannot use the full sample to estimate the test statistic for $\widehat{\beta_1} = 0$ since doing so could overidentify RD schools (Card, Mas, & Rothstein, 2008; Hansen, 2000; Pan, 2015). To ensure that the thresholds we identify are meaningful, we bootstrap confidence intervals for $\hat{\beta}_1$ at *x* for each school-year combination (Pan, 2015). Specifically, we resample students with replacement within a given school year to create 1,000 bootstrap replicates and estimate equation (1) at the proposed algebra cutoff (i.e., *x*) and store $\hat{\beta}_1$ each time. We then calculate 99 percent confidence intervals from the empirical distribution of the 1,000 $\hat{\beta}_1$ for each school-year setting.[5] We consider a school-year combination in which the 99 percent confidence interval for β_1 does not include zero to be a school in which students’ likelihood of 8th-grade algebra placement varies discontinuously at a threshold *x* in a given year. We use these discontinuities to estimate the effects of 8th-grade algebra assignment in each school-year combination.

Of the 1,479 schools (and 4,469 school-by-year units) in the search sample, we initially identify 972 school-year settings (in 603 unique schools) that use a course placement system in which students’ placement rates vary discontinuously at a threshold on the 7th-grade math test score distribution and pass our bootstrap test. In Table 1, we provide a descriptive comparison of California middle schools in which we find evidence of discontinuous 8th-grade math course assignment based on 7th-grade test scores (RD schools) and our non-RD schools. Table 1 further distinguishes between our initial RD search sample that includes the 972 school-year sites that pass the bootstrap test and our main analytic “trimmed sample” that includes only the 753 school-year sites that also pass a placebo test (discussed shortly). Sixth- and 7th-grade math and ELA scores are approximately 0.15 standard deviations lower

[4]The range of possible CST scores runs from 150 to 600. Under No Child Left Behind, scores were given performance labels: far below basic was 150 to 256, below basic was 257 to 299, basic was 300 to 349, proficient was 350 to 413, and advanced was 414 to 600. Students who scored above 350 were considered to be at grade level. We limit our search to scores between 295 and 355, as the density of the 7th-grade math CST thins out above and below these limits.

[5]To ensure that our results are not sensitive to the specific thresholds we use to determine whether schools are RD schools, we also estimate our models using one- and two-tailed 95 and 99 percent confidence intervals. We find similar results across these groups of schools.

in RD schools than in non-RD schools. Further, RD schools have larger shares of Hispanic students as well as students from a lower socioeconomic level, and fewer White students compared to non-RD schools.

As a first test on the validity of our search process, we pool all of the possible RD schools into a single data set, re-centering each RD around the school-year specific cutoff. We then use this pooled data set to estimate equation (1) to examine the overall magnitude of the pooled first stage, which we report in the first column of panel A in Table 2. On average, there is a 41 percentage point difference in the likelihood of taking algebra in eighth grade for students just above their school-year specific threshold compared to students just below their school-year specific threshold.

In column 2 of panel A (Table 2), we report the results of an adapted McCrary test to see if there is bunching or manipulation of students' test scores around the discontinuity (McCrary, 2008). For each school year, we collapse our data down to the individual CST score. In this case, each cell represents the number of students who received a given score (e.g., 300) in a given school-year combination. We then estimate equation (1) using these cell counts as dependent variables. While statistically significant, the results suggest that the difference in cell size between scores just to the right and left of the cutoff differ only by .282 of a student.[6]

In the rest of the columns in panel A, we report the results of placebo RDs that use students' prior achievement, demographics, and completion of the 10th-grade CAHSEE as dependent variables. Differences in student characteristics at RD thresholds may indicate endogenous placement of students at the margin of either side of the cutoff, or an endogenous selection of where to locate the placement threshold. Potentially most problematic to our analysis, students just above their school-year specific cutoffs score .02 to .05 standard deviations higher on their 6th- and 7th-grade ELA and 6th-grade math CST compared to students just below their school-year specific cutoffs (these test scores are standardized by grade, subject, and year). In this case, however, manipulation of student test scores is unlikely since such manipulation would require educators to alter student scores in administrative record databases or to alter student responses on 7th-grade tests based on a precise awareness of the 7th-grade math threshold and students' 6th-grade math test score (as well as students' 6th- and 7th-grade ELA scores). Similarly, while it is possible that schools could try to pick a 7th-grade math test score for their cutoff such that a handful of students above the threshold did better on 6th-grade math (and do better on their 6th-grade ELA CSTs) than students just below the cutoff, this also seems unlikely.

We address the discontinuity in students' prior achievement by first averaging students' 6th-grade math and ELA CSTs and 7th-grade ELA CST into a single test score. We then rerun equation (1) separately for each of the 972 school-year combinations that passed the bootstrap test, using students' averaged prior achievement as our dependent variable. For each site-specific regression, we store the p-value for the t-test that $\hat{\beta}_1 = 0$. We remove from

[6]We also ran the density test suggested by Cattaneo, Jansson, and Ma (2018) using the Stata program -rddensity- which likewise suggests that bunching is not a substantial concern (p=.53).

the sample schools with a p-value ≤ .2 (i.e., schools that exhibit some evidence of having a statistically significant discontinuity in students' prior achievement at the estimated threshold).[7] We identify 753 school-year settings (in 510 unique schools) that pass this placebo test, which we call the "trimmed sample." In panel B of Table 2, we report the results for the first stage (column 1), the adapted McCrary test (column 2), and the placebo regressions (columns 3 through 13). The discontinuity in students' 6th-grade math CST scores at the school-year specific thresholds has decreased but is still statistically significant while the discontinuities in students' 6th- and 7th-grade ELA scores have disappeared. We do not think the small difference in 6th-grade math scores is due to human manipulation, and the difference does not appear to reflect meaningful unobserved differences between students just above and below the cutoff. In Appendix A, we present our main results using our full sample, including specifications that directly control for students on the 6th-grade math CST.[8]

In Figure 1, we show the pooled first stage for our trimmed sample. The relationship between 7th-grade test scores and algebra placement in eighth grade appears linear with a noticeable jump at the estimated school-year cutoff. In Figure 2, we show the distribution of estimated 7th-grade cutoffs. It is notable that this distribution has sizable spikes at 300 and 350, the state's threshold for labeling a student's mathematics skills "basic" and "proficient." In these schools, students who score 299 on the 7th-grade math CST (and whose mathematics skills are thus rated as "below basic" by state law) are substantially less likely to be placed in 8th-grade algebra than students who score 301 (and whose mathematics skills are thus rated "basic"). The histogram reveals a similar spike at 350, the state's proficiency threshold. In addition, we observe a smaller spike at 325, the threshold that Fresno Unified and Long Beach Unified both articulated in their explicit, district-wide 8th-grade algebra placement policies. Indeed, more than half of the schools that we identify as regression discontinuity settings have placement thresholds at one of these three accountability policy-relevant points in the 7th-grade math CST score distribution. We present a version of our results limiting our search to schools that have a discontinuity point at 300, 325, or 350 in Appendix A.[9]

In Table 3, we present statistics from the RD search algorithm for non-RD schools, the schools that passed the bootstrap test (i.e., the "initial RD sample"), and the trimmed sample of RD schools (the schools that also passed the placebo test). As noted above, in order for a school year to be identified as a regression discontinuity setting, students' rates of 8th-grade mathematics course enrollment must vary discontinuously at a point in the 7th-grade mathematics test score distribution. RD schools have a much larger first stage coefficient (.48 compared to −.004), R^2 (.57 compared to .35), and t-statistics (5.4 compared to −0.08) from equation (1). Each of these comparisons is consistent with the conclusion that our RD

[7]We chose .2 as a conservative p-value given the small sample sizes in some school-year cells. Our main results are similar if we choose a less conservative value (e.g., p.05).

[8]If the placebo results reflected meaningful unobservable differences, we would expect that our models predicting advanced course enrollments in ninth through eleventh grade would vary across our initial RD sample, our trimmed sample, and our analyses that include prior achievement as a control variable. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[9]All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

search algorithm identifies school-year settings that use substantially different approaches to placing students in 8th-grade algebra than the non-RD schools.

Estimating the Effects of 8th-Grade Algebra Assignments

Since our search algorithm identifies many school years in which compliance with treatment is not absolute, we use fuzzy regression discontinuity models to estimate the effects of 8th-grade algebra assignment in these sites (Hahn, Todd, & Van der Klaauw, 2001; Trochim, 1984). These models make three key assumptions: (1) selection into 8th-grade math courses is strongly determined by the placement formula; (2) students and teachers are unable to control students' location on either side of the cutoff; (3) potential outcomes are a continuous function of the assignment variable at the cutoff (such that a student who scored 300 on a 7th-grade math achievement test is not appreciably different from a classmate who scored 299 on the same test). If these assumptions hold, our discontinuity analyses provide internally valid estimates of the causal effects of 8th-grade algebra for students near the threshold in each of these schools (Imbens & Lemiuex, 2007; Lee & Lemiuex, 2010; McCrary, 2008).

A typical fuzzy RD design will predict treatment participation as a function of a forcing variable and an exogenous cutoff, and then use predicted treatment in a second-stage model to estimate the local average treatment effect (LATE) of a policy or program on an outcome of interest. While our analyses follow these general steps, we also want to account for the potential treatment effect heterogeneity across our 753 school-year RD sites. One approach to estimating the effects across sites is to pool cases across these school-year RDs into a single RD analysis. However, as Cattaneo et al. (2016) note, substantial information about effect heterogeneity is lost by simply pooling estimates into a single state-wide (re-centered) regression discontinuity.

We therefore use a method developed by Raudenbush, Reardon, and Nomi (2012) that uses site-specific intercepts (i.e., fixed effects) and random coefficients to account for treatment-effect heterogeneity in multi-site research settings. Their approach has two benefits over simply pooling our data into a single fuzzy RD and ignoring heterogeneity. First, their approach generates a weighted LATE where the weight is a function of both treatment participation compliance and the precision of site-specific LATEs. Second, the method estimates the variance of treatment effects across sites.

The first step in our fuzzy RD method is to estimate equation (1) separately for each school-year RD site and to estimate $\widehat{Alg}_{ist}$.[10] With these predictions in hand, we pool our data centering the forcing variable around school-year specific cutoffs and estimate the following second-stage model:

[10]This is equivalent to estimating equation (1) over our pooled data set with *k* instruments, where *k* is equal to the number of school-year RD sites.

$$Y_{is,t+p} = \delta_0 + \delta_1 \widehat{Alg}_{ist} + \delta_2(CST_{is,t-1} - x) + \delta_3 1[CST_{is,t-1} \geq x] * (CST_{is,t-1} - x) + \alpha_{st} + \eta_{is,t+p}. \quad (2)$$

In equation (2), we estimate the outcome of interest for student i, in school s, at time $t+p$ (where p is the number of years since eighth grade in time t) as a linear function of their predicted algebra participation ($\widehat{Alg}_{ist}$), the forcing variable (i.e., the distance between their 7th-grade math CST and the school's placement threshold, ($CST_{is,t-1} - x$)); an interaction between indicator variable for scoring above the school's cutoff and the forcing variable ($1[CST_{is,t-1} \geq x] * (CST_{is,t-1} - x)$); and a school-year fixed effect (α_{st}). Our coefficient of interest (δ_1) captures the pooled LATE effect of participating in 8th-grade algebra on students' outcomes across all RD sites. Our dependent variables include measures of advanced math course-taking in high school, high school math achievement, and middle and high school ELA achievement. For advanced course-taking, we measure whether students completed geometry in ninth grade, algebra II in tenth grade, and an advanced math course in eleventh grade (e.g., pre-calculus).

Following Raudenbush, Reardon, and Nomi (2012), we estimate equation (2) as a mixed model with site-specific intercepts (our school-year fixed effects α_{st}) and a random coefficient for our coefficient of interest (i.e., $\delta_1 \sim N(\delta_1, \tau_\delta^2)$ where δ_1 is the mean LATE across RD sites and τ_δ^2 is the estimated variance of the site-specific LATEs). equation (2) will produce a consistent estimate of δ_1 if the heterogeneity in cross-site treatment compliance is not correlated with cross-site treatment effects. This bias could arise, for example, if across sites the perceived quality of 8th-grade algebra influenced decisions to comply with treatment. Reardon and co-authors (2014) developed a method to account for "compliance-effect covariance bias" in multi-site research settings. Our results using their bias-corrected estimator are very similar to those in Table 4. [11] We cluster our standard errors at the school-year level. In Appendix B, we present the results of our fuzzy RD analysis using a number of alternative estimation techniques and samples.[12]

RESULTS

Figures 3 and 4 present our reduced form (or intent-to-treat [ITT] analysis) scatter plots for two of our outcomes of interest: 10th-grade math CAHSEE scores (Figure 3) and accelerated mathematics course-taking in eleventh grade (Figure 4). These figures show that 7th-grade math CST scores are positively correlated with students' 10th-grade math CAHSEE achievement and 11th-grade accelerated course-taking, and that these relationships are approximately linear. In both figures, we see evidence of a discontinuity at the threshold, so that students just above the school-year algebra threshold differ in their

[11]Our points estimates using their bias-corrected estimator for our main effects are .0751 for 10th-grade math CAHSEE, .0378 for 10th-grade ELA CAHSEE, .301 for accelerated course-taking in ninth grade, .207 for accelerated course-taking in tenth grade, .153 for accelerated course-taking in eleventh grade, and .033 to 048 for ELA achievement in grades 8 to 11.

[12]All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

10th-grade math CAHSEE achievement and 11th-grade accelerated math course-taking compared to students just below the threshold.

In Table 4, we build on Figures 3 and 4 by presenting our ITT results of the effect of algebra on students' 10th-grade CAHSEE achievement, high school course-taking, and ELA CST scores in panel A, as well as our two-stage fuzzy RD LATE results in panel B. We also present the variance of our LATE estimates (τ_{δ}^2) in panel B. We see in panel B that students just above their school-year specific thresholds who completed algebra in eighth grade outscored their peers just below the threshold who completed general mathematics in eighth grade by .053 sd (math) and .034 sd (ELA) on the CAHSEE tests. We also find that 8th-grade algebra placement increases students' odds of completing advanced math courses in grades 9 through 11 (columns 3 to 6). While these results are perhaps unsurprising given the hierarchical structure of high school mathematics course sequences, it is worth noting that more than half of California students placed into 8th-grade algebra repeat it in ninth grade (Liang, Heckman, & Abedi, 2012). As such, it is reassuring to note that placement in 8th-grade algebra increases students' likelihood of 9th-grade geometry placement by nearly 30 percentage points, 10th-grade algebra II by nearly 20 percentage points, and 11th-grade trigonometry or pre-calculus by 16 percentage points. Finally, we find evidence that taking algebra in eighth grade had a small spillover effect on ELA achievement: We find consistent evidence of an effect of roughly .02 to .03 sd on ELA achievement on CSTs in grades 8 through 11, as well as the 10th-grade ELA CAHSEE. Although our data do not allow us to examine the mechanisms producing these spillover effects, it seems likely that they are driven by peer effects, as prior research suggests that students in algebra are more likely to take their ELA courses with other algebra students as well (e.g., Domina et al., 2019). Appendix B reports results from supplemental analyses showing that these results are robust across multiple samples and alternative estimation methods (e.g., local linear regressions).[13]

While the results in Table 4 provide useful information about the average benefit of 8th-grade algebra for students near a school-year specific placement threshold, they may conceal substantial variation in the effects of 8th-grade algebra across diverse academic settings. The variance around our fuzzy RD estimates suggests wide variation in the school-year specific effects. For example, we find an average LATE of .053 sd for math CAHSEE achievement with a $\tau_{\delta}^2 = .025$ (or a standard deviation of .16), suggesting that 38 percent of the site-specific treatment effects are negative. In Figure 5, we graphically represent the wide distribution of positive and negative effects via a histogram and kernel density plot of empirical Bayes estimates from equation (2) for the 10th-grade math CAHSEE; Figure 6 presents the analogous distribution for 11th-grade math course-taking.

Cross-Site Heterogeneity

We next turn to examining cross-site heterogeneity. One important way in which the effectiveness of 8th-grade algebra may vary across sites has to do with the location of schools' 7th-grade math CST placement threshold. The location of the placement threshold

[13]All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

may affect 8th-grade algebra in a number of ways. For example, schools that use higher test score thresholds are reserving algebra for their most prepared students, while schools with thresholds toward "basic" allow more students to take algebra as well as more students with weaker math backgrounds. If the effects of algebra vary with student readiness or if the quality of algebra instruction varies with school norms about course provisions, the local effects of 8th-grade algebra placement could vary. (See Appendix Table C1 for basic demographic differences among schools with cutoffs at 300, 325, and 350.[14]) Similarly, many schools appear to use an accountability policy-relevant threshold (e.g., 300, 325, or 350), while others used thresholds in between these scores. While the schools that use accountability policy-relevant thresholds have strong face validity, they may conflate both the effect of accountability performance labeling (e.g., Papay, Murnane, & Willett, 2016) and the effect of algebra.

We explore these possibilities graphically in Figures 7 and 8. In these figures, we plot the site-specific treatment effects for 8th-grade algebra on 10th-grade math CAHSEE (Figure 7) and 11th-grade advanced math course-taking (Figure 8) against schools' 7th-grade math CST thresholds, and fit a flexible local linear regression line.[15] If our estimates of the effects of 8th-grade algebra conflate potential accountability effects at thresholds of 300, 325, and 350, we would expect to see noticeable peaks or valleys at these thresholds compared to the points in between. However, we do not see a noticeable pattern between effects at 300, 325, and 350 versus the non-accountability policy-relevant points in either figure. While we are unable to document the school-specific reasons for the use of different 7th-grade math CST thresholds, the lack of a systematic difference between schools using 300, 325, and 350 versus a cutoff in between these points supports the use of all placement thresholds in our evaluation of 8th-grade algebra.

Consistent with our earlier research (Domina, 2014; Domina et al., 2015) as well as work in Chicago (Allensworth et al., 2009) and North Carolina (Clotfelter, Ladd, & Vigdor, 2015), the patterns in Figures 7 and 8 indicate that students benefit more from early algebra assignment when access to the class is restricted to relatively high-achieving students. The relationship between 8th-grade algebra effectiveness and the algebra placement threshold is particularly striking when comparing students' likelihood of remaining on the advanced course-taking track in high school. By eleventh grade, students in the schools that have cutoffs of at least 340 still maintained a 20 to 25 percent point advantage in the likelihood of taking advanced math, but this advantage is closer to five percentage points for students at the margin of algebra in a school with a cutoff near 300. In Appendix A, we present similar figures for the rest of our main outcomes of interest.[16]

[14]All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[15]We use an Epanechniko kernel, local polynomial order of one, and a bandwidth of two CST points.

[16]One noteworthy finding is that the positive relationship between the size of the effect and the location of threshold may only hold for mathematics outcomes. The relationship between the threshold location and 10th-grade ELA CAHSEE scores is negative, and threshold location has a flat-to-negative relationship with 8th- to 11th-grade ELA CST scores. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

In order to ensure that the relationship between algebra placement thresholds and students' high school outcomes is not a byproduct of the difference in student demographics across the thresholds, we estimate simple OLS regressions of site-specific effects of 8th-grade algebra on three site-level demographics: 7th-grade math CST threshold, the share of students who are socioeconomically disadvantaged (SED) (an index created by the CDE that includes students who either qualify for free and reduced-price lunch or whose parents have not received a high school diploma), and the 8th-grade cohorts' average standardized 7th-grade math CST scores. The results presented in Table 5 suggest that the patterns shown in Figures 7 and 8 hold even after controlling for student poverty and prior achievement. For example, going from a cutoff score of 300 to 350 is associated with an increase in the average effect of 8th-grade algebra of .02 sd on the 10th-grade math CAHSEE and 25, 20, and 15 percentage points, respectively, on the likelihood of taking advanced math courses in ninth, tenth, and eleventh grades.

Student-Level Heterogeneity

Up to this point, our analysis has focused on the local effect of 8th-grade algebra on students' 10th-grade CAHSEE achievement, high school math course-taking, and ELA achievement in grades 8 to 11, as well as how these effects vary across our RD sites. However, it is also important to understand how the effect of 8th-grade algebra varies across student subgroups, especially those who are less likely to be exposed to accelerated math curriculum. In our final analysis, we estimate the effects of 8th-grade algebra separately for male, female, Black, Hispanic, White, Asian, socioeconomically disadvantaged (SED), non-SED, English-language learners (ELL), and non-ELL students; we report these results in Table 6.

We find no evidence of a negative average effect of 8th-grade algebra on 10th-grade math and ELA CAHSEE scores, high school math course-taking, and 8th- through 11th-grade ELA CST scores in any of the student subgroups that we examine. Our results suggest that students who often do not get the same access to accelerated curriculum—female, minority, low-income, and ELL students—all benefit from algebra in eighth grade, and often benefit more than other students. The positive effect of 8th-grade algebra on high school mathematics course-taking, for example, is larger for female students who completed algebra in eighth grade than for their male peers. This effect is perhaps explained by previous research demonstrating that girls' mathematics course-taking decisions are highly responsive to their peers' course-taking decisions (Frank et al., 2008; Riegle-Crumb, Farkas, & Muller, 2006), so that initial placement in eighth grade serves in providing girls not only access to an advanced course trajectory, but also to a set of peers who influence later course-taking outcomes. To the degree that curricular choices in RD schools are driven less by student interest, parent pressure, and teacher evaluations, this finding is also congruent with research observing that highly standardized educational systems tend to have smaller gender gaps in mathematics (Ayalon, 2002; Ayalon & Livneh, 2013).

We also find important positive effects for Black students. Not only does 8th-grade algebra have a large positive effect on math CAHSEE scores for Black students (.15 sd), but Black students assigned to 8th-grade algebra also experience large test score gains on the ELA

CAHSEE and the 8th- through 11th-grade ELA CST. On each of these outcomes, Black students thus receive greater benefits from enrolling in 8th-grade algebra than White students. If threshold-based assignment policies also narrow Black/White gaps in exposure to accelerated coursework (Dougherty et al., 2015), these policies may help to narrow Black/White achievement gaps through undermining racial segregation and opportunity hoarding within schools (Lewis & Diamond, 2015). Likewise, the analyses reported in Table 7 indicate that the large benefits that ELL students receive from 8th-grade algebra on their math CAHSEE scores and high school math course-taking do not come at the expense of ELA achievement. In fact, ELL students who complete algebra in eighth grade score .06 to .1 sd higher on the ELA CAHSEE and CST. This underscores that ELL students' effort in advanced math courses does not detract from their mastery of English and performance on ELA tests. Future research should explore whether the effects we observe here last through post-secondary education and into the labor market (e.g., Goodman, 2019; Hemelt, Schwartz, & Dynarski, 2019).

We also estimated the student subgroup models separately by algebra cutoffs of 300, 325, and 350, and report the results in Appendix C.[17] The patterns are largely consistent with the general finding that students do better in 8th-grade algebra when they are exposed to higher-achieving peers (e.g., a cutoff near 350). Our heterogeneity findings highlight both the promise that efforts to enroll students in accelerated coursework holds for students and the challenges that schools face in successfully implementing these efforts. That is, on the one hand, our results suggest schools with more stringent requirements for accelerated curriculum have better student outcomes. However, students of color and students from low-income backgrounds are less likely to enroll in these schools. On the other hand, students of color, female students, and ELL students gain the most from accelerated curriculum. So, although our findings suggest that schools should make a special effort to enroll traditionally underserved students in advanced courses, they also suggest that using lower thresholds to assign students to accelerated courses lowers the benefits of these classes for students. Balancing these two implications is a difficult task.

CONCLUSIONS

Over the past two decades, school systems across the United States have experimented with a number of different approaches to curricular intensification. Our analyses estimate the causal effects of early algebra on students' outcomes, finding evidence of small positive local average effects for achievement and larger positive local average effects on students' access to subsequent advanced math courses. In addition, by documenting a substantial degree of heterogeneity across schools and students in the effects of early algebra, our analyses provide a deeper understanding of the contextual factors related to the success of curricular intensification. Before we highlight our key contributions to the field and policy implications of our findings, it is important to keep in mind our study's limitations.

[17] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

First, while our examination of 8th-grade algebra uses a large data set from a highly populated, diverse state, we lack information on the instructional and curricular mechanisms that might contribute to the effects of 8th-grade algebra assignments and the variation in these effects across schools. Exploratory analyses indicate that the variation in the effects of 8th-grade algebra across schools is not explained by textbook differences. However, we lack data on the extent to which teacher quality, classroom assignment practices, and local status hierarchies vary with 8th-grade algebra assignment across schools. Future research can help clarify the extent to which these and other factors contribute to the variation in the effects of 8th-grade algebra.

Second, there are important questions about the extent to which our findings generalize. We rely on a nonrandom sample of schools that appear to use 7th-grade math CST scores to place students in algebra in eighth grade. These schools are, on average, lower performing and have larger shares of students of color and who are considered SED by the CDE. Although we know of some districts that used explicit placement thresholds (e.g., Fresno Unified and Long Beach Unified School Districts), we are unable to distinguish between schools that *a priori* established a threshold from those whose thresholds were a mechanical byproduct of space constraints in algebra classrooms.

With that said, our paper does extend the field in a number of ways and has implications for future curricular acceleration policies. First, we provide quasi-experimental estimates of the local average treatment effect of 8th-grade algebra enrollments for thousands of students across a diverse set of California middle schools on a wide range of short- and medium-term academic outcomes. Our estimates of the local average treatment effects of early algebra on student achievement are closer to zero than correlational estimates on nationally representative data (e.g., Stein et al., 2011), and are near the middle of the broad distribution of experimental and quasi-experimental estimates. Our analyses suggest that enrolling in 8th-grade algebra boosts students' math performance by approximately 0.05 sd. These estimated effect sizes are more modest than experimental estimates from schools in rural New England (Heppen et al., 2012), but more positive than instrumental variable analyses from North Carolina in the 1990s (Clotfelter, Ladd, & Vigdor, 2015), and roughly equivalent to more recent regression discontinuity estimates from a single school district in North Carolina (Dougherty et al., 2017). Further, we find small, positive effects on students' ELA test scores, suggesting that the benefits to students' academic achievement operate broadly beyond mathematics, perhaps due to peer effects. Finally, we find that enrolling in 8th-grade algebra substantially boosts students' advanced mathematics course-taking rates throughout high school, ultimately increasing students' likelihood of being on track to take calculus in twelfth grade by approximately 16 percentage points.

Our second contribution to the literature on curricular intensification is to document the pronounced heterogeneity in local average effects of early algebra across California middle schools. Prior studies conceptualize early algebra placement as a single treatment across the different schools being studied and focus on its average effect. By contrast, our analyses acknowledge that many key aspects of the early algebra experience vary across school settings. In particular, we focus on the relationship between school-level variation in 8th-grade algebra course placement thresholds and the effects of 8th-grade algebra. In some schools, 8th-grade algebra is reserved for higher-achieving students; in others, the course is open to students with a wider array of pre-algebraic skills. This effect heterogeneity may help to explain the remarkable dispersion among experimental and quasi-experimental estimates of the effects of 8th-grade algebra. In light of the fact that algebra placement has large positive effects in some California middle schools, large negative effects in others, and a range of effects in between, it is perhaps not surprising that well-estimated analyses of the effects of early algebra in different settings yield different results. Treatment effect heterogeneity is a crucial, and crucially underestimated, parameter for policy research. The degree of heterogeneity that we document here may not be unusual in education more broadly in the United States, given that local actors have considerable discretion over whether and how to implement policy directives (Weiss et al., 2017). Modeling that treatment effect heterogeneity is an important first step toward better understanding policy implementation processes and their consequences.

Beyond documenting the heterogeneity in the effects of 8th-grade algebra placement across California middle schools, our analyses provide insights into the sources of this heterogeneity. These analyses are necessarily exploratory, as schools' decisions around issues such as where to locate placement thresholds are not exogenous. Nonetheless, these analyses provide some descriptive evidence about the contexts in which early algebra is and is not effective. We find that the effects of 8th-grade algebra tend to be more positive in schools that restrict access to algebra to students who had higher 7th-grade mathematics test scores.

This variation across contexts has important implications for understanding the capacity of access to early algebra course placement policies to narrow achievement gaps. While these results are necessarily impressionistic, they are consistent with the hypothesis that students need either a high degree of academic preparation (or substantial academic support) to benefit from access to accelerated coursework. For example, Chicago public schools found success in a double-dose algebra curriculum for ninth graders that included a particular focus on instructional strategies for students with below-average prior achievement (e.g., Cortes, Goodman, & Nomi, 2015; Nomi & Allensworth, 2013). In calling attention to the pronounced site-level heterogeneity in the effects of early algebra, our analyses draw attention to the importance of moving beyond one-size-fits-all accounts of curricular intensification.

Third, our results indicate that the effects of 8th-grade algebra are positive in all student subgroups but are particularly evident among groups of students who often have less access to advanced mathematics coursework. We find important and policy-relevant benefits of 8th-grade algebra for female, Black, ELL, and SED students. For the students at the margin of algebra placement in our RD schools, 8th-grade algebra served to help narrow important and persistent achievement and attainment gaps. Future research should focus on whether these benefits persist through post-secondary education and the labor market. However, in light of evidence establishing causal links between high school courses and labor market outcomes (Goodman, 2019), we suspect accessing 8th-grade algebra substantially influences students' life courses.

Finally, our results provide insight into an important policy paradox. Prior work suggests that individual students benefit from being placed into advanced courses, but that policies aimed at placing all students into advanced coursework have negative effects (Domina et al., 2015; Penner et al., 2015). Put differently, the partial equilibrium effect of early algebra (the effect of moving an individual student from pre-algebra to algebra) is positive, but the general equilibrium effect of early algebra at scale (moving all students into algebra) is negative.[18] At first glance, it seems likely that understanding the local average effects is less policy-relevant than understanding what would happen if a policy was adopted at scale. However, our results highlight that the partial equilibrium effect can be extremely relevant for policies concerned with equity. Specifically, we find outsized effects for groups of students that have historically not had access to advanced coursework, suggesting that policies aimed at ensuring access for these students, without universalizing access, could play a powerful role in creating more equitable educational outcomes.

In addition to these empirical contributions to the literature on curricular intensification, our analyses have methodological implications for studies in a wide range of policy settings. The regression discontinuity design (RDD) is rapidly becoming a workhorse methodology for causal estimation in policy research. Regression discontinuity designs are particularly useful in educational research, where they provide opportunities to separate the effects of educational interventions operating at scale from potentially confounding selection processes, while avoiding the expense, logistical challenges, and potential ethical issues surrounding randomized control trials. Traditional RD estimates are typically only possible in settings where assignment to treatment conditions vary discontinuously at a *known* threshold in an observed forcing variable. In practice, this is a major limitation since there are many settings where a treatment threshold is likely but unknown to the researcher. Applying an RD search algorithm to a setting where treatment placement discontinuities are likely to exist in other contexts may create opportunities for rigorous evaluation of the heterogeneous effects of a wide range of policy interventions.

ACKNOWLEDGMENTS

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[18]One reason why research on the general and partial equilibrium effects of early algebra might differ is if prior work looking at the partial equilibrium effects failed to estimate well-identified effects. This study thus helps rule out one reason for this divergence. Our empirical approach may be helpful in other contexts where research suggests a positive partial and negative general equilibrium solution, insofar as estimating a myriad of well-identified local effects and attending to their heterogeneity might help us understand which aspects of scaling up lead to the divergence between the positive partial equilibrium effect and the negative general equilibrium effect.

APPENDIX A

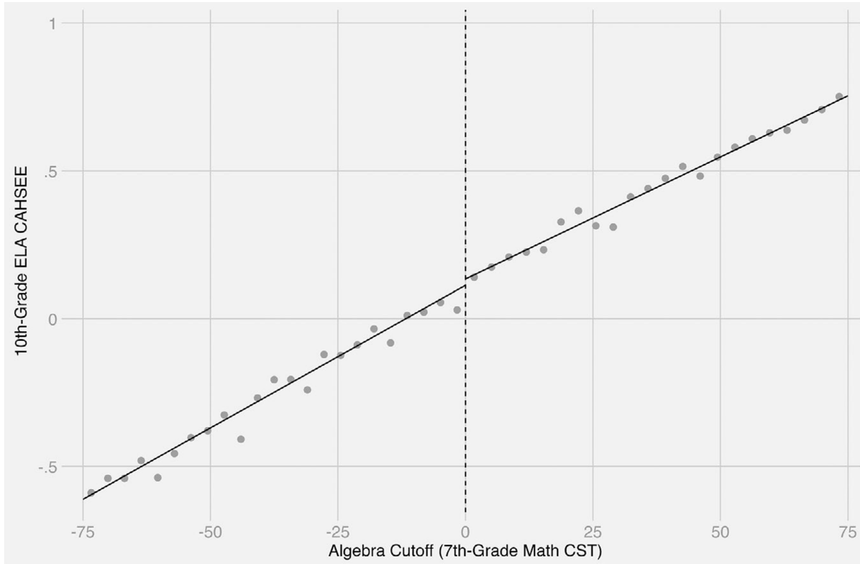

Figure A1.
Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 10th-Grade ELA CAHSEE.

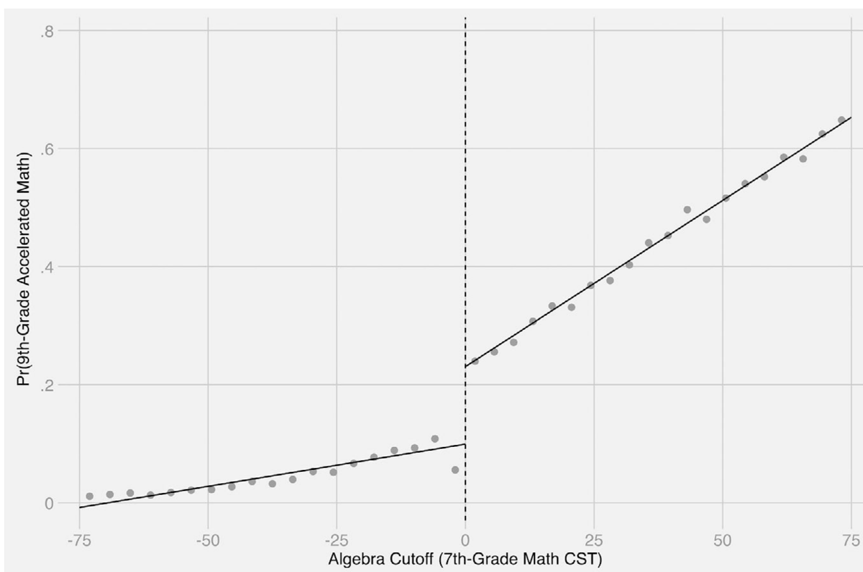

Figure A2.
Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 9th-Grade Accelerated Math Course-Taking.

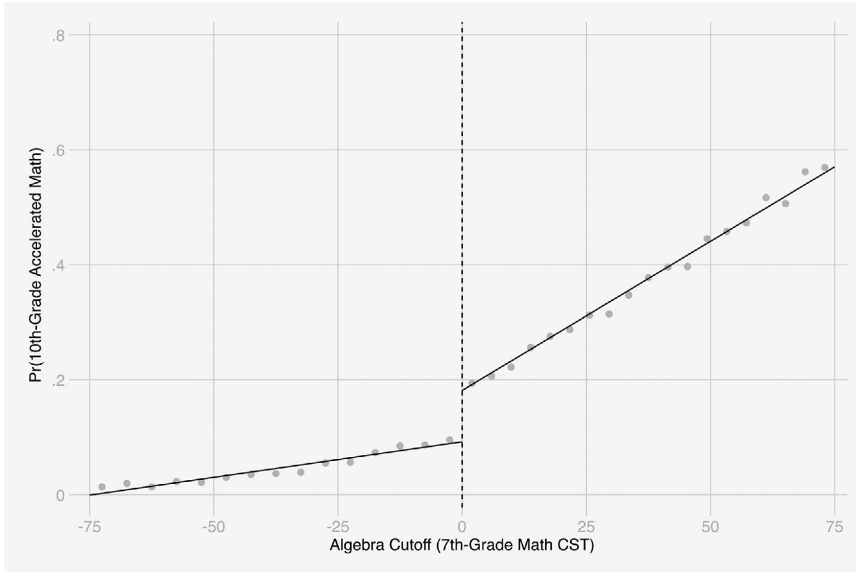

Figure A3.
Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 10th-Grade Accelerated Math Course-Taking.

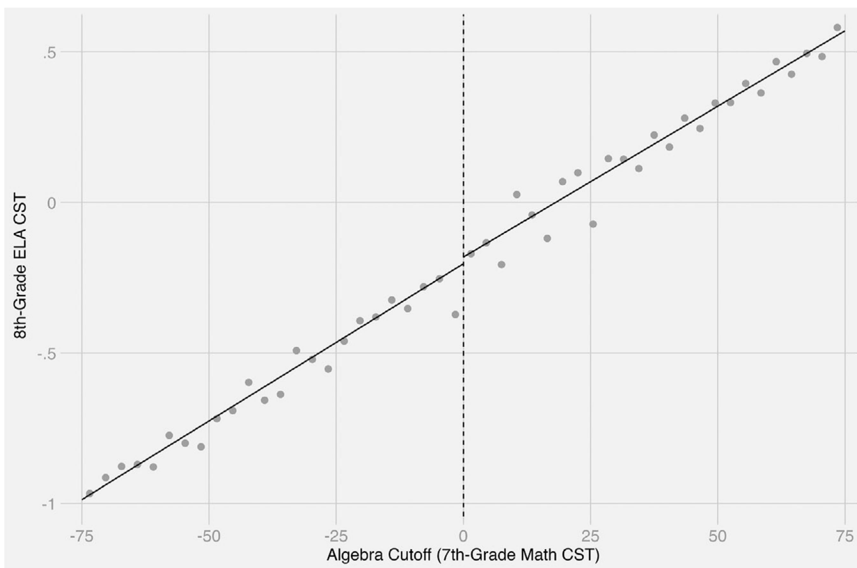

Figure A4.
Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 8th-Grade ELA CST.

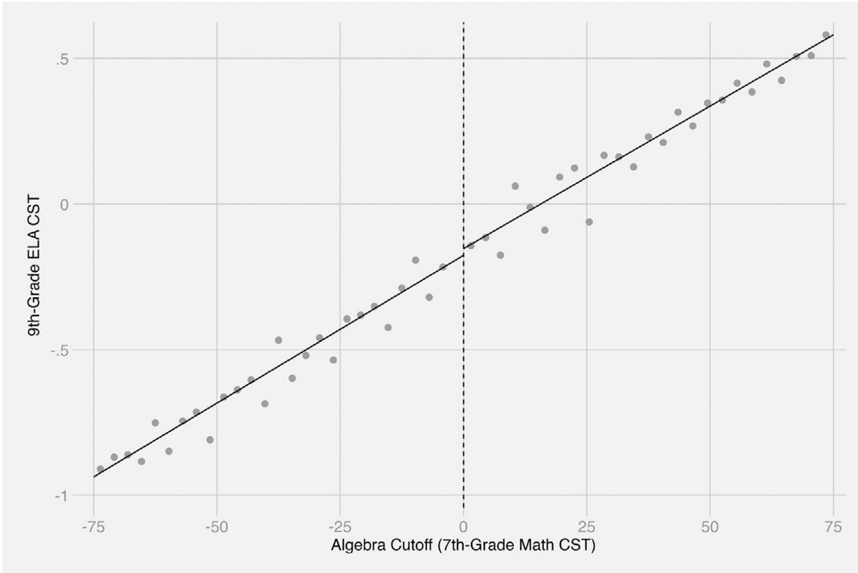

Figure A5.

Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 9th-Grade ELA CST.

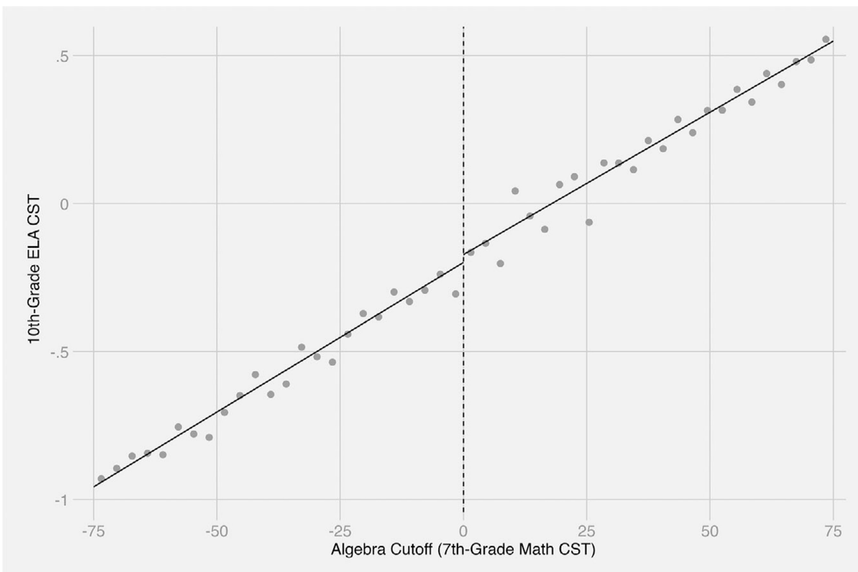

Figure A6.

Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 10th-Grade ELA CST.

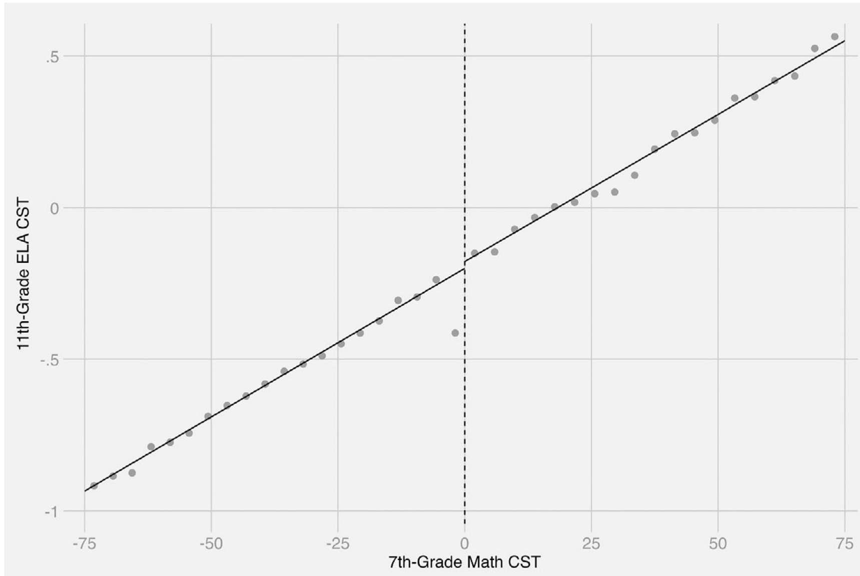

Figure A7.

Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 11th-Grade ELA CST.

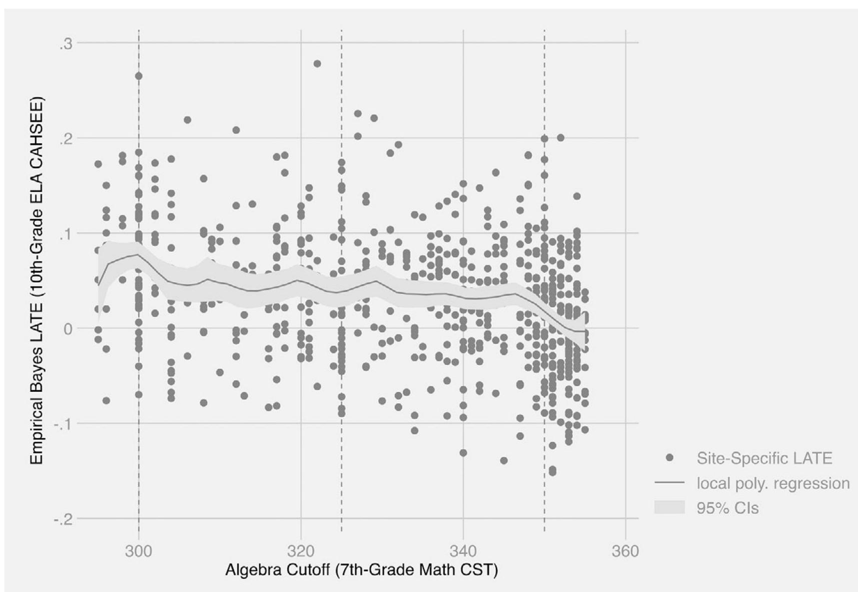

Figure A8.

Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 10th-Grade ELA CAHSEE and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

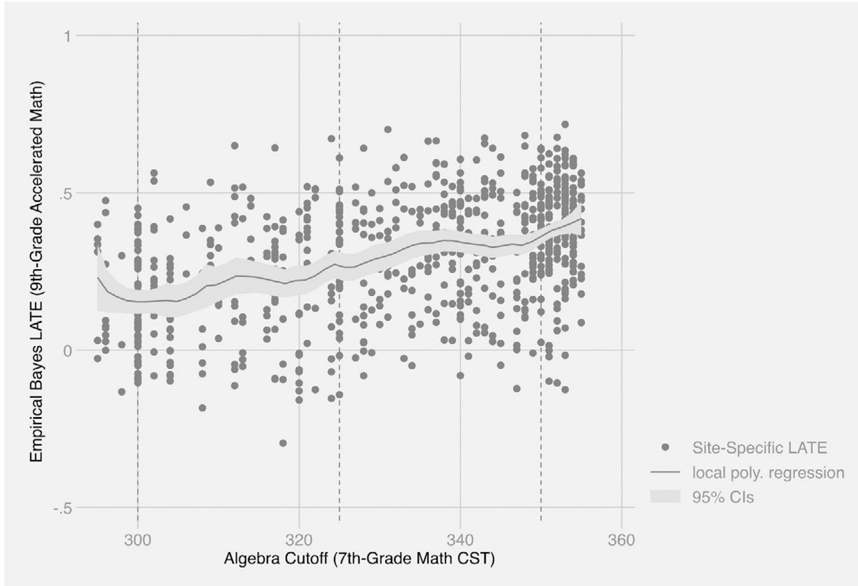

Figure A9.
Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 9th-Grade Advanced Math Course-Taking and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

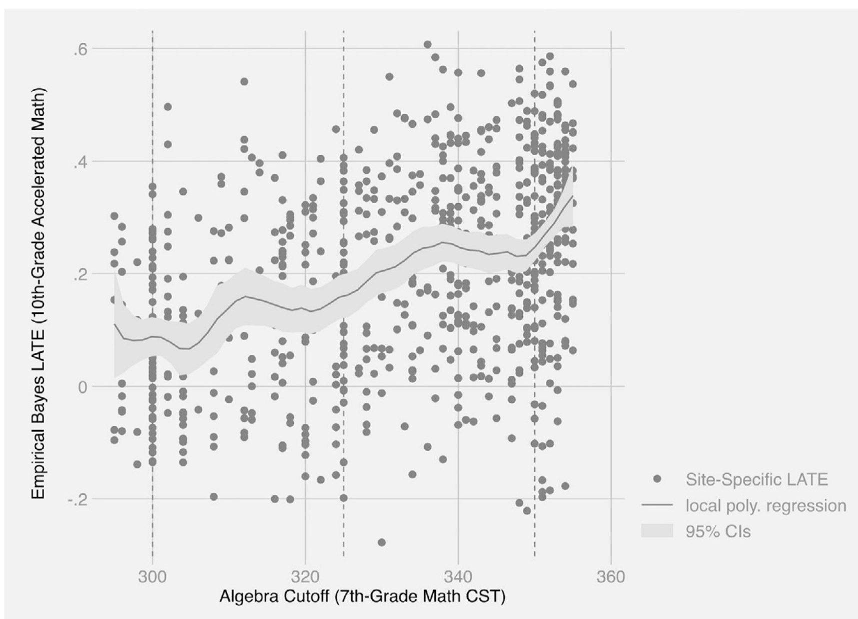

Figure A10.
Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 10th-Grade Advanced Math Course-Taking and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

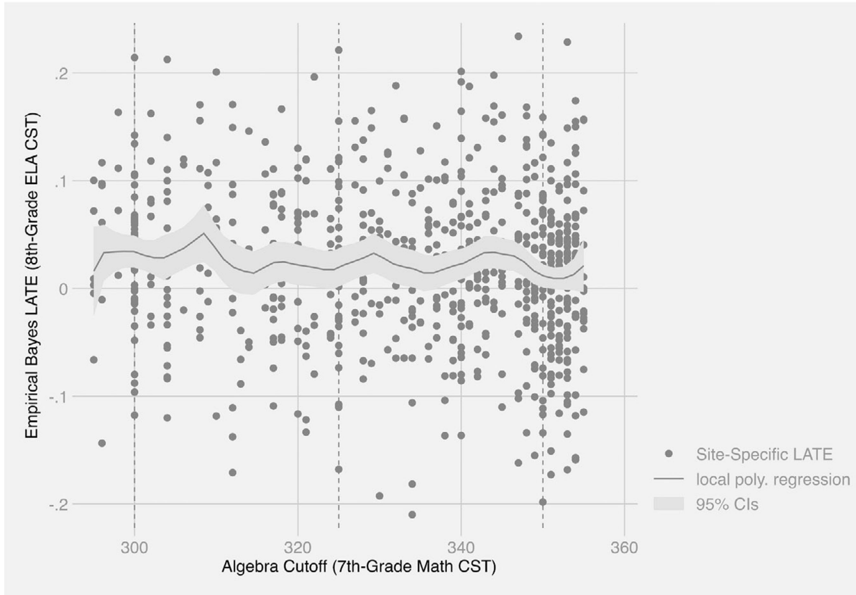

Figure A11.

Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 8th-Grade ELA CST and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

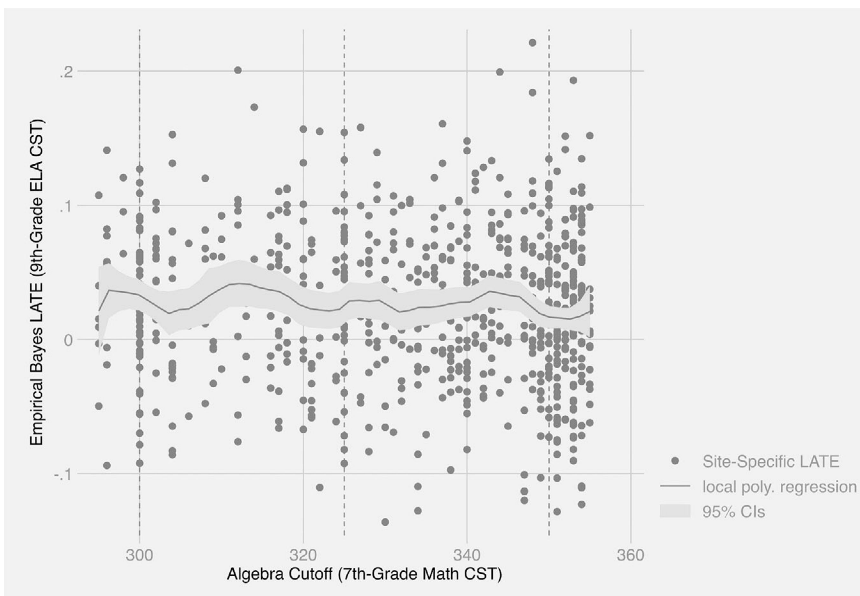

Figure A12.

Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 9th-Grade ELA CST and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

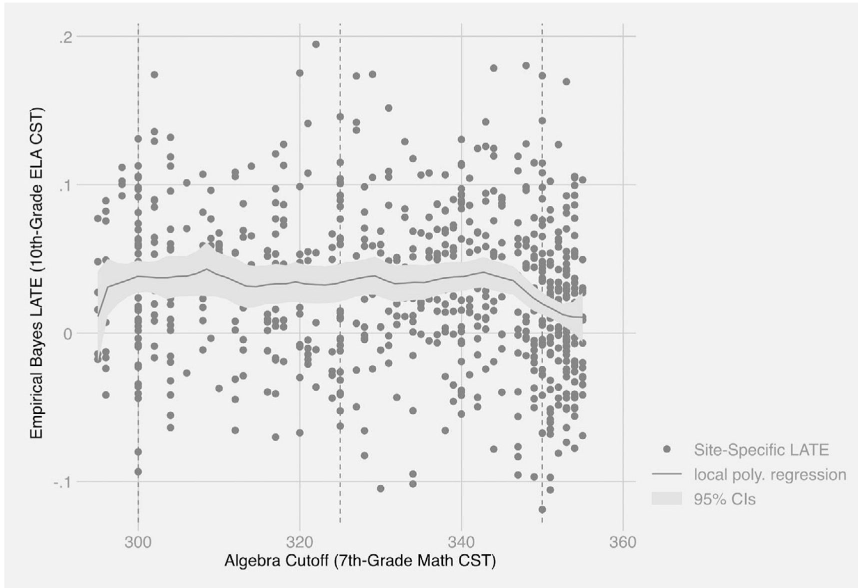

Figure A13.
Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 10th-Grade ELA CST and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

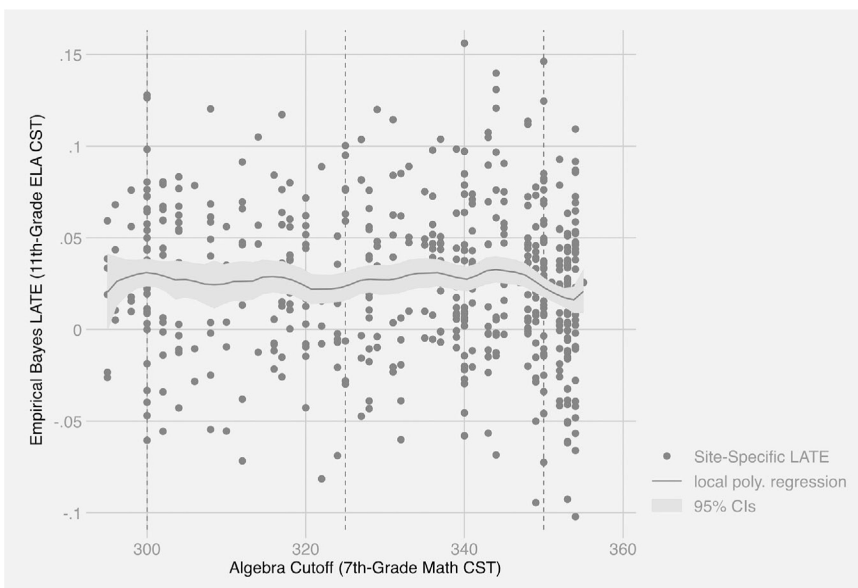

Figure A14.
Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 11th-Grade ELA CST and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

APPENDIX B

In this appendix, we report our main results using a number of different samples, model specifications, and estimation techniques. We start with two main samples. First, we have the full set of 972 school-year observations that passed our bootstrap test that we call the "full sample." Second, we have the trimmed sample used in the analysis in the main paper that includes the 753 school-year observations that not only passed the bootstrap test but also our placebo test using students' 6th- and 7th-grade math and ELA CST scores as a dependent variable in equation (1). We call this sample the "trimmed sample." The key difference between the full and trimmed samples is that the former does not correct for the small discontinuity in prior achievement at the placement thresholds, while the latter does. Therefore, across the specifications reported below, in each one we include results for the full sample that control for students' 6th-grade math CST scores.

We also introduce two new subsamples. The first includes schools that have an algebra placement policy using 7th-grade math CST scores of 300, 325, or 350. We call these "policy-relevant cut scores" since 300 and 350 correspond with the cutoff for the "basic" and "proficient" performance categories—the former considered below grade-level, and the latter considered grade-level. We also include the score of 325 because a number of school districts stated policies using this score. Second, we include a set of schools in districts with known policies that use 7th-grade math CST scores for 8th-grade algebra placement.

Finally, we introduce two new specifications/estimation approaches to the random coefficient model with site fixed effects and site-by-treatment instruments used in the article. The first uses the same pooled data set used in the article but estimates equation (1) with a single instrument and equation (2) without a random coefficient but keeps the rest of the specification including school-year fixed effects. The second also uses the same pooled data set from the manuscript but estimates equations (1) and (2) using a local linear regression with a triangular kernel and a bandwidth estimated following Calonico, Cattaneo, and Titiunik (2014). We use the Stata command -*rdrobust*- to estimate this model (Calonico et al., 2017).

We present the results across Tables B1 to B21. There are a few exceptions where the results deviate slightly from the main paper; however, the qualitative results from our main model in equation (1) hold across these alternative specifications. For example, the results from the local linear specification tend to report larger positive effects of 8th-grade algebra on student outcomes than our random coefficient model in the article. We interpret the collection of our results as students in 8th-grade algebra in our RD sites experiencing positive test score improvements on the math CAHSEE and being more likely to take advanced math courses in high school than students just below the algebra placement threshold who completed a remedial math course in eighth grade.

Table B1.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Full Sample).

	Panel A: ITT Effects		
	10th-Grade CAHSEE	Advanced Math Course-Taking	ELA CST

	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST > = Cutoff]	0.039 ***	0.033 ***	0.133 ***	0.089 ***	0.064 ***	0.031 ***	0.035 ***	0.038 ***	0.033 ***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.065 ***	0.061 ***	0.289 ***	0.198 ***	0.151 ***	0.051 ***	0.060 ***	0.058 ***	0.049 ***
	(0.010)	(0.011)	(0.012)	(0.010)	(0.009)	(0.011)	(0.011)	(0.012)	(0.014)
τ^2	0.022	0.018	0.044	0.036	0.027	0.026	0.022	0.024	0.022
# of Students	186763	186815	201443	201443	150817	201060	189922	181456	129651
# of School Years	972	972	972	972	703	972	972	972	703
# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B2.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Full Sample; conditional on 6th-grade math CST).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.023 ***	0.018 ***	0.129 ***	0.085 ***	0.061 ***	0.015 **	0.019 ***	0.022 ***	0.014 *
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade

Algebra	0.037 ***	0.039 ***	0.281 ***	0.191 ***	0.146 ***	0.023 *	0.035 ***	0.034 **	0.020
	(0.009)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)
τ^2	0.125	0.178	0.249	0.215	0.169	0.000	0.000	0.000	0.000
# of Students	178085	178126	190820	190820	142202	190477	180996	173305	123497
# of School Years	972	972	972	972	703	972	972	972	703
# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also includes a control for students' 6th-grade math CST scores. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B3.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Full Sample; schools with policy cutpoints of 300, 325, or 350 only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.030 ***	0.025 ***	0.133 ***	0.091 ***	0.069 ***	0.025 ***	0.028 ***	0.028 ***	0.021 *
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.046 ***	0.050 ***	0.286 ***	0.201 ***	0.165 ***	0.039 **	0.048 ***	0.037 **	0.033 +
	(0.011)	(0.012)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.017)
τ^2	0.026	0.021	0.044	0.037	0.028	0.028	0.024	0.029	0.025
# of Students	122192	122251	132015	132015	96584	131759	124915	119313	83142
# of School Years	630	630	630	630	443	630	630	630	443
# of Schools	451	451	451	451	357	451	451	451	357

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that have an algebra placement cutoff using 7th-grademath CST scores of 300, 325, or 350. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table B4.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Full Sample; schools in districts with known policies only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.026	0.019	0.243***	0.152***	0 121***	0.005	−0.011	0.008	0.018
	(0.016)	(0.016)	(0.022)	(0.020)	(0.022)	(0.016)	(0.017)	(0.020)	(0.021)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.035	0.031	0.447***	0.279***	0.259***	−0.006	−0.011	0.019	0.001
	(0.028)	(0.029)	(0.034)	(0.032)	(0.041)	(0.036)	(0.035)	(0.039)	(0.045)
τ^2	0.019	0.012	0.044	0.034	0.021	0.027	0.022	0.016	0.019
# of Students	13654	13675	14615	14615	9362	14591	13821	13218	8097
# of School Years	69	69	69	69	42	69	69	69	42
# of Schools	37	37	37	37	27	37	37	37	27

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table B5.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Trimmed Sample; schools with policy cutpoints of 300, 325, or 350 only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST>= Cutoff]	0.023***	0.012+	0.135***	0.094***	0.071***	0.009	0.012+	0.014+	0.013
	(0.007)	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.009)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.034**	0.026*	0.294***	0.206***	0.169***	0.014	0.019	0.015	0.016
	(0.013)	(0.013)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.017)
τ^2	0.029	0.028	0.045	0.037	0.028	0.033	0.032	0.037	0.031
# of Students	95876	95909	103480	103480	76540	103290	97862	93407	65919
# of School Years	492	492	492	492	351	492	492	492	351
# of Schools	376	376	376	376	298	376	376	376	298

Notes: This sample uses the trimmed sample of school-year observations that pass our bootstrap and placebo test and that have an algebra placement cutoff using 7th-grade math CST scores of 300, 325, or 350. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table B6.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a random coefficient model with site fixed effects (Trimmed Sample; schools in districts with known policies only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			

	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST>=Cutoff]	0.014	−0.004	0.237***	0.139***	0.109***	−0.016	−0.023	−0.006	0.009
	(0.019)	(0.014)	(0.025)	(0.022)	(0.026)	(0.015)	(0.016)	(0.019)	(0.020)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.033	0.017	0.441***	0.266***	0.254***	−0.025	−0.011	0.017	−0.010
	(0.031)	(0.028)	(0.041)	(0.035)	(0.052)	(0.030)	(0.031)	(0.031)	(0.037)
τ^2	0.019	0.011	0.047	0.035	0.024	0.025	0.018	0.013	0.016
# of Students	10952	10976	11729	11729	6690	11712	11096	10624	5804
# of School Years	55	55	55	55	30	55	55	55	30
# of Schools	34	34	34	34	21	34	34	34	21

Notes: This sample uses the trimmed sample of school-year observations that pass our bootstrap and placebo test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B7.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Full Sample).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST>=Cutoff]	0.042***	0.035***	0.129***	0.088***	0.060***	0.033***	0.036***	0.039***	0.033***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			

	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.095***	0.079***	0.290***	0.197***	0.139***	0.074***	0.081***	0.088***	0.075***
	(0.011)	(0.012)	(0.011)	(0.009)	(0.009)	(0.012)	(0.012)	(0.014)	(0.016)
# of Students	186763	186815	201443	201443	150817	201060	189922	181456	129651
# of School Years	972	972	972	972	703	972	972	972	703
# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B8.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Full Sample; conditional on 6th-grade math CST).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST>= Cutoff	0.026***	0.020***	0.125***	0.084***	0.058***	0.016**	0.020***	0.024***	0.015*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.059***	0.046***	0.284***	0.191***	0.134***	0.037**	0.045***	0.053***	0.034*
	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)	(0.013)	(0.016)
# of Students	178085	178126	190820	190820	142202	190477	180996	173305	123497
# of School Years	972	972	972	972	703	972	972	972	703
# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also includes a control for students' 6th-grade math CST. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B9.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Full Sample; schools with policy cutpoints of 300, 325, or 350 only).

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST> = Cutoff	0.034 ***	0.027 ***	0.131 ***	0.092 ***	0.066 ***	0.027 ***	0.030 ***	0.030 ***	0.021 *
	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.075 ***	0.060 ***	0.286 ***	0.200 ***	0.150 ***	0.060 ***	0.065 ***	0.065 ***	0.046 *
	(0.013)	(0.014)	(0.013)	(0.012)	(0.012)	(0.015)	(0.015)	(0.016)	(0.020)
# of Students	122192	122251	132015	132015	96584	131759	124915	119313	83142
# of School Years	630	630	630	630	443	630	630	630	443
# of Schools	451	451	451	451	357	451	451	451	357

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that have an algebra placement cutoff using 7th-grade math CST scores of 300, 325, or 350. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B10.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Full Sample; schools in districts with known policies only).

Panel A: ITT Effects

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST> = Cutoff	0.031 *	0.021	0.248 ***	0.155 ***	0.117 ***	0.006	−0.011	0.010	0.018
	(0.014)	(0.017)	(0.017)	(0.015)	(0.018)	(0.017)	(0.016)	(0.019)	(0.021)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.058 *	0.039	0.466 ***	0.292 ***	0.248 ***	0.012	−0.020	0.018	0.038
	(0.028)	(0.031)	(0.029)	(0.027)	(0.035)	(0.032)	(0.031)	(0.035)	(0.044)
# of Students	18538	18559	19858	19858	13323	19825	18757	17918	11417
# of School Years	69	69	69	69	42	69	69	69	42
# of Schools	37	37	37	37	27	37	37	37	27

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B11.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Trimmed Sample).

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Panel A: ITT Effects								
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST> = Cutoff	0.035 ***	0.019 ***	0.131 ***	0.090 ***	0.063 ***	0.015 **	0.017 **	0.023 ***	0.021 **
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			

	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.079***	0.042***	0.295***	0.202***	0.145***	0.034**	0.037**	0.052***	0.047**
	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.017)
# of Students	144351	144363	155513	155513	117755	155241	146910	140405	101441
# of School Years	753	753	753	753	550	753	753	753	550
# of Schools	510	510	510	510	424	510	510	510	424

Notes: This sample uses the trimmed sample of school-year observations that pass our bootstrap and placebo test. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B12.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Trimmed Sample; schools with policy cutpoints of 300, 325, or 350 only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST>= Cutoff	0.029***	0.015*	0.131***	0.092***	0.065***	0.012+	0.013*	0.017*	0.014
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.063***	0.033*	0.287***	0.201***	0.149***	0.025+	0.029*	0.037*	0.031
	(0.015)	(0.015)	(0.015)	(0.013)	(0.014)	(0.014)	(0.015)	(0.017)	(0.021)
# of Students	95876	95909	103480	103480	76540	103290	97862	93407	65919
# of School Years	492	492	492	492	351	492	492	492	351
# of Schools	376	376	376	376	298	376	376	376	298

Notes: This sample uses the trimmed sample of school-year observations that pass our bootstrap and placebo test and that have an algebra placement cutoff using 7th-grade math CST scores of 300, 325, or 350. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B13.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a pooled model with site fixed effects (Trimmed Sample; schools in districts with known policies only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	Panel A: ITT Estimates of Taking 8th Grade Algebra								
1[CST>= Cutoff	0.021	−0.002	0.242***	0.143***	0.107***	−0.014	−0.022	−0.004	0.010
	(0.017)	(0.017)	(0.019)	(0.017)	(0.021)	(0.016)	(0.016)	(0.018)	(0.020)
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.038	−0.004	0.451***	0.265***	0.226***	−0.026	−0.040	−0.008	0.020
	(0.032)	(0.032)	(0.032)	(0.030)	(0.041)	(0.029)	(0.030)	(0.033)	(0.042)
# of Students	15146	15166	16223	16223	10578	16198	15327	14637	9058
# of School Years	55	55	55	55	30	55	55	55	30
# of Schools	34	34	34	34	21	34	34	34	21

Notes: This sample uses the trimmed sample of school-year observations that pass our bootstrap and placebo test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are from a pooled model with school-year fixed effects and a single instrument. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B14.

First-stage estimates from a local linear regression specification.

	First Stage	Density Test	6th-Grade Math CST	6th-Grade ELA CST	7th-Grade ELA CST	Male Student	SED Student	Asian Student	Black Student	Hispanic Student	ELL Student	Has 10th-grade Math CAHSEE	Has 10th-Grade ELA CAHSEE
Panel A: Initial RD Search Sample													
1[CST> = Cutoff]	0.369*** (0.013)	−0.071 (0.290)	0.05** (0.017)	0.035+ (0.018)	0.032+ (0.019)	−0.008 (0.008)	−0.001 (0.013)	0.016** (0.005)	−0.003 (0.006)	−0.016 (0.014)	−0.019+ (0.010)	0.002 (0.004)	0.003 (0.004)
Bandwidth	17.766	25.897	28.516	35.058	31.029	25.065	39.563	31.585	30.908	34.955	23.324	27.966	29.427
# of Students	201443	201443	190820	190918	201215	201443	201406	201013	201013	201013	201341	201443	201443
# of School Years	972	972	972	972	972	972	972	972	972	972	972	972	972
Panel B: Trimmed Sample													
1[CST> = Cutoff]	0.373*** (0.014)	0.072 (0.323)	0.039* (0.019)	0.007 (0.020)	0.002 (0.022)	−0.008 (0.009)	0.001 (0.015)	0.022*** (0.006)	−0.004 (0.007)	−0.017 (0.017)	−0.005 (0.011)	−0.001 (0.005)	0.001 (0.005)
Bandwidth	19.183	21.904	25.955	31.366	29.177	24.912	34.019	23.708	22.785	28.776	23.512	23.31	25.22
# of Students	155513	155513	147088	147149	155330	155513	155481	155159	155159	155159	155432	155513	155513
# of School Years	753	753	753	753	753	753	753	753	753	753	753	753	753

Notes: The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table B15.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Full Sample).

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Panel A: ITT Effects									
1[CST> = Cutoff]	0.048**	0.068***	0.114***	0.085***	0.062***	0.056**	0.054**	0.052**	0.047*
	(0.017)	(0.018)	(0.009)	(0.008)	(0.008)	(0.020)	(0.019)	(0.018)	(0.020)
Bandwidth	29.007	20.771	20.546	24.484	20.08	25.775	26.989	27.409	30.148
Panel B: Fuzzy RD Effects									

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.129**	0.188***	0.304***	0 224***	0 128***	0.142**	0.141**	0.14**	0.134*
	(0.047)	(0.051)	(0.020)	(0.019)	(0.015)	(0.053)	(0.051)	(0.050)	(0.058)
Bandwidth	29.28	19.625	28.287	30.942	26.179	29.074	27.973	26.465	26.431
# of Students	186763	186815	201443	201443	150817	201060	189922	181456	129651
# of School Years	972	972	972	972	703	972	972	972	703
# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B16.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Full Sample; condition on 6th-grade math CST).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.025*	0.042**	0.108***	0.078***	0.058***	0.032*	0.028*	0.024+	0.015
	(0.013)	(0.014)	(0.009)	(0.008)	(0.008)	(0.015)	(0.014)	(0.015)	(0.018)
Bandwidth	27.76	19.554	20.843	24.539	21.913	21.913	24.105	23.224	20.921
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.079*	0.118**	0.296***	0.213***	0.164***	0.085+	0.081+	0.063	0.049
	(0.039)	(0.043)	(0.021)	(0.020)	(0.021)	(0.043)	(0.040)	(0.041)	(0.048)
Bandwidth	19.803	16.789	23.709	25.746	19.535	20.228	21.804	21.868	22.201
# of Students	186763	186815	201443	201443	142202	201060	189922	181456	129651
# of School Years	972	972	972	972	703	972	972	972	703

# of Schools	603	603	603	603	508	603	603	603	508

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014). Model also controls for students' 6th-grade math CST.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B17.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Full Sample; schools with policy cutpoints of 300, 325, or 350 only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.037	0.047 *	0.113 ***	0.085 ***	0.065 ***	0.047 +	0.047 +	0.039 +	0.021
	(0.023)	(0.022)	(0.011)	(0.009)	(0.009)	(0.026)	(0.025)	(0.024)	(0.028)
Bandwidth	25.411	26.866	20.069	22.693	21.516	27.676	27.726	31.513	28.555
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.102	0.142 *	0.303 ***	0.238 ***	0.182 ***	0.148 +	0.123 +	0.096	0.046
	(0.063)	(0.067)	(0.027)	(0.027)	(0.026)	(0.076)	(0.072)	(0.071)	(0.097)
Bandwidth	26.22	19.147	19.685	17.098	20.474	17.987	20.988	18.875	15.584
# of Students	122192	122251	132015	132015	96584	131759	124915	119313	83142
# of School Years	630	630	630	630	443	630	630	630	443
# of Schools	451	451	451	451	357	451	451	451	357

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that have an algebra placement cutoff using 7th-grademath CST scores of 300, 325, or 350. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B18. Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Full Sample; schools in districts with known policies only).

Table B18.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Full Sample; schools in districts with known policies only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.048	0.086	0.186 ***	0.120 ***	0.086 **	0.052	0.032	0.061	0.075
	(0.049)	(0.060)	(0.030)	(0.026)	(0.031)	(0.065)	(0.063)	(0.067)	(0.078)
Bandwidth	30.091	23.023	22.837	20.855	22.070	24.356	23.664	20.413	34.292
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.125	0.215	0.448 ***	0.293 ***	0.245 **	0.150	0.076	0.179	0.291
	(0.126)	(0.148)	(0.064)	(0.055)	(0.074)	(0.163)	(0.151)	(0.178)	(0.249)
Bandwidth	24.033	22.879	23.253	23.797	24.647	21.389	23.706	18.274	22.672
# of Students	13654	13675	14615	14615	13323	14591	13821	13218	8097
# of School Years	69	69	69	69	42	69	69	69	42
# of Schools	37	37	37	37	27	37	37	37	27

Notes: This sample uses all 972 initial school-year observations that passed the bootstrap test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B19.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Trimmed Sample).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.051 *	0.067 **	0.120 ***	0.087 ***	0.069 ***	0.038 +	0.028	0.036 +	0.041 +

	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
	(0.021)	(0.022)	(0.010)	(0.009)	(0.008)	(0.022)	(0.021)	(0.021)	(0.023)
Bandwidth	19.913	17.785	22.277	24.764	26.630	24.007	25.721	26.569	31.078
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.130^{**}	0.163^{**}	0.313^{***}	0.236^{***}	0.189^{***}	0.099^{+}	0.078	0.091^{+}	0.109^{+}
	(0.053)	(0.057)	(0.023)	(0.023)	(0.022)	(0.059)	(0.057)	(0.055)	(0.062)
Bandwidth	25.293	19.642	28.295	23.005	24.362	27.166	26.986	28.863	30.888
# of Students	144351	144363	155513	155513	117755	155241	146910	140405	101441
# of School Years	753	753	753	753	550	753	753	753	550
# of Schools	510	510	510	510	424	510	510	510	424

Notes: This sample uses the trimmed sample of school-year observations that passed the bootstrap and placebo test. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

$^{+}$ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table B20.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Trimmed Sample; schools with policy cutpoints of 300, 325, or 350 only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.042	0.046^{+}	0.116^{***}	0.086^{***}	0.066^{***}	0.036	0.033	0.026	0.022
	(0.027)	(0.026)	(0.012)	(0.011)	(0.010)	(0.029)	(0.028)	(0.027)	(0.030)
Bandwidth	23.826	24.815	23.988	24.679	25.835	28.04	30.003	31.684	36.034
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.106	0.148^{*}	0.304^{***}	0.225^{***}	0.185^{***}	0.097	0.089	0.068	0.051
	(0.071)	(0.073)	(0.028)	(0.027)	(0.029)	(0.079)	(0.076)	(0.078)	(0.097)
Bandwidth	25.281	21.317	27.117	25.656	23.533	25.637	25.468	20.668	18.87

# of Students	95876	95909	103480	103480	76540	103290	97862	93407	65919
# of School Years	492	492	492	492	351	492	492	492	351
# of Schools	376	376	376	376	298	376	376	376	298

Notes: This sample uses the trimmed sample of school-year observations that passed the bootstrap and placebo test and that have an algebra placement cutoff using 7th-grade math CST scores of 300, 325, or 350. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's –rdrobust-command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table B21.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes using a local linear regression (Trimmed Sample; schools in districts with known policies only).

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.038	0.064	0.192***	0.115***	0.085*	0.029	0.015	0.042	0.097
	(0.054)	(0.065)	(0.032)	(0.028)	(0.035)	(0.069)	(0.065)	(0.068)	(0.091)
Bandwidth	31.939	24.4	26.844	25.275	25.844	25.535	26.58	22.826	27.951
	Panel B: Fuzzy RD Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.091	0.162	0.439***	0.26***	0.238*	0.065	0.041	0.079	0.391
	(0.128)	(0.157)	(0.065)	(0.056)	(0.076)	(0.158)	(0.157)	(0.145)	(0.291)
Bandwidth	26.437	22.691	26.993	27.197	32.917	25.276	23.058	27.638	20.215
# of Students	10952	10976	11729	11729	10578	11712	11096	10624	5804
# of School Years	55	55	55	55	30	55	55	55	30
# of Schools	34	34	34	34	21	34	34	34	21

Notes: This sample uses the trimmed sample of school-year observations that passed the bootstrap and placebo test and that are in districts with known placement policies using 7th-grade math CST scores. The coefficients are estimated using a local linear regression with a triangular kernel using Stata's -rdrobust- command. Bandwidths are estimated using the method outlined in Calonico, Cattaneo, and Titiunik (2014).

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

APPENDIX C

Table C1.

Student demographics and achievement by algebra policy cutoff (300, 325, or 350).

	Algebra Cutoff = 300			Algebra Cutoff = 325			Algebra Cutoff = 350		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Share of 8th graders in algebra	0.626	0.484	24338	0.518	0.5	22853	0.437	0.496	56289
7th-grade CST math (std.)	−0.493	0.563	24338	−0.287	0.599	22853	0.049	0.612	56289
7th-grade CST ELA (std.)	−0.485	0.744	24304	−0.332	0.769	22808	0.02	0.756	56249
Black	0.086		24324	0.071		22807	0.064		56128
White	0.122		24324	0.132		22807	0.273		56128
Hispanic	0.720		24324	0.671		22807	0.544		56128
SED	0.777		24334	0.768		22852	0.594		56283

Table C2.

Student demographics and achievement by 8th-grade math course and algebra policy cutoff (300, 325, or 350).

	Algebra Cutoff = 300						Algebra Cutoff = 325						Algebra Cutoff = 350					
	Not Algebra			Algebra			Not Algebra			Algebra			Not Algebra			Algebra		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Within School Decile 7th-Grade CST Math	2.93	1.90	9095	6.76	2.32	15243	3.33	2.06	11014	7.21	2.15	11839	3.65	2.20	31682	7.49	2.05	24607
7th-Grade CST Math (std.)	−0.98	0.41	9095	−0.20	0.43	15243	−0.72	0.43	11014	0.11	0.43	11839	−0.32	0.45	31682	0.52	0.45	24607
Within-School Decile 7th-Grade CST ELA	3.67	2.40	9073	6.40	2.63	15231	3.98	2.52	10984	6.67	2.55	11824	4.21	2.55	31655	6.86	2.52	24594
7th-Grade CST ELA (std.)	−0.93	0.65	9073	−0.22	0.67	15231	−0.71	0.68	10984	0.02	0.68	11824	−0.29	0.68	31655	0.42	0.65	24594
Black	0.11		9090	0.07		15234	0.08		10994	0.06		11813	0.07		31603	0.05		24525
White	0.09		9090	0.14		15234	0.11		10994	0.16		11813	0.23		31603	0.33		24525
Hispanic	0.76		9090	0.70		15234	0.73		10994	0.62		11813	0.61		31603	0.46		24525
SED	0.82		9093	0.75		15241	0.82		11014	0.72		11838	0.66		31677	0.51		24606

Table C3.

Fuzzy RD effects of 8th-grade algebra on 10th-grade math CAHSEE by student subgroup and school policy cutoff.

	10th-Grade CAHSEE					
	Math			ELA		
	c = 300	c = 325	c = 350	c = 300	c = 325	c = 350
Male	0.088**	0.055	0.045+	0.085*	0.022	0.048+
	(0.029)	(0.040)	(0.025)	(0.039)	(0.034)	(0.026)
Female	0.035	0.068+	0.070**	0.117***	0.047	0.033
	(0.032)	(0.035)	(0.023)	(0.035)	(0.037)	(0.025)
Black	0.070	0.193**	0.181***	0.082	0.166*	0.104+
	(0.068)	(0.062)	(0.039)	(0.071)	(0.074)	(0.060)
Hispanic	0.049+	0.024	0.058*	0.077**	0.007	0.073**
	(0.026)	(0.034)	(0.023)	(0.024)	(0.031)	(0.024)
White	0.035	0.213**	0.095***	0.145*	0.192*	0.078*
	(0.062)	(0.065)	(0.028)	(0.068)	(0.083)	(0.037)
Asian	0.107	0.141+	0.089+	−(0.139)	0.071	0.023
	(0.109)	(0.072)	(0.047)	0.012	(0.061)	(0.051)
SED	0.052+	0.062+	0.057*	0.085**	0.020	0.081**
	(0.027)	(0.033)	(0.024)	(0.027)	(0.029)	(0.025)
Non-SED	0.014	0.146**	0.103***	0.066	0.062	0.033
	(0.053)	(0.054)	(0.027)	(0.054)	(0.048)	(0.027)
ELL	0.144**	0.074+	0.197***	0.073+	0.027	0.084+
	(0.045)	(0.041)	(0.042)	(0.041)	(0.041)	(0.043)
Non-ELL	−0.004	0.073*	0.046*	0.053+	0.023	0.031
	(0.026)	(0.032)	(0.019)	(0.031)	(0.033)	(0.020)

Notes: We first partition the data by student subgroup and school policy cutoff. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level. SED = Socioeconomically disadvantaged, and ELL = English Language Learner.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table C4.

Fuzzy RD effects of 8th-grade algebra on 11th-grade accelerated math course-taking by student subgroup and school policy cutoff.

	Advanced Course Taking								
	9th-Grade			**10th-Grade**			**11th-Grade**		
	c = 300	**c = 325**	**c = 350**	**c = 300**	**c = 325**	**c = 350**	**c = 300**	**c = 325**	**c = 350**
Male	0.077***	0.205***	0.335***	0.039*	0.117***	0.258***	0.025	0.088**	0.204***
	(0.020)	(0.029)	(0.025)	(0.017)	(0.024)	(0.023)	(0.018)	(0.032)	(0.023)
Female	0.123***	0.299***	0.452***	0.060*	0.187***	0.342***	0.018	0.119***	0.288***
	(0.028)	(0.032)	(0.024)	(0.026)	(0.028)	(0.024)	(0.021)	(0.034)	(0.022)
Black	0.070+	0.234***	0.450***	0.066+	0.101**	0.316***	0.070*	0.088*	0.255***
	(0.039)	(0.043)	(0.038)	(0.034)	(0.037)	(0.038)	(0.032)	(0.042)	(0.043)
Flispanic	0.110***	0.223***	0.388***	0.049*	0 122***	0.300***	0.014	0.065*	0.258***
	(0.022)	(0.032)	(0.026)	(0.021)	(0.025)	(0.023)	(0.020)	(0.033)	(0.022)
White	0.092*	0.194***	0.358***	0.063+	0.114**	0.282***	0.037	0.038	0.203***
	(0.042)	(0.041)	(0.028)	(0.034)	(0.039)	(0.027)	(0.036)	(0.041)	(0.027)
Asian	0.185**	Q 424***	0.519***	0.114+	0.374***	0.391***	0.128	0.300***	0.340***
	(0.068)	(0.062)	(0.037)	(0.063)	(0.059)	(0.042)	(0.085)	(0.078)	(0.043)
SED	0.110***	0.258***	0.395***	0.056**	0.154***	0.292***	0.025	0.114***	0.243***
	(0.022)	(0.030)	(0.026)	(0.020)	(0.023)	(0.024)	(0.019)	(0.028)	(0.022)
Non-SED	0.082*	0.238***	0.393***	0.037	0.155***	0.315***	0.007	0.101*	0.257***
	(0.032)	(0.036)	(0.027)	(0.025)	(0.034)	(0.025)	(0.025)	(0.048)	(0.025)
ELL	0.120***	0.284***	0.416***	0.077**	0.178***	0.320***	0.043+	0.150***	0.335***
	(0.029)	(0.035)	(0.036)	(0.024)	(0.033)	(0.036)	(0.023)	(0.035)	(0.038)
Non-ELL	0.101***	0.241***	0.406***	0.041+	0.143***	0.311***	0.012	0.085**	0.254***
	(0.025)	(0.030)	(0.023)	(0.023)	(0.025)	(0.022)	(0.019)	(0.032)	(0.020)

Notes: We first partition the data by student subgroup and school policy cutoff. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level. SED = Socioeconomically disadvantaged, and ELL = English Language Learner.

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table C5.

Fuzzy RD effects of 8th-grade algebra on 9th- to 11th-grade ELA CST by student subgroup and school policy cutoff.

	ELA CST											
	8th-Grade			9th-Grade			10th-Grade			11th-Grade		
	c = 300	c = 325	c = 350	c = 300	c = 325	c = 350	c = 300	c = 325	c = 350	c = 300	c = 325	c = 350
Male	0.041	0.002	0.065*	0.054	0.049	0.041	−0.002	0.046	0.064*	0.023	−0.037	0.054
	(0.038)	(0.036)	(0.026)	(0.043)	(0.039)	(0.026)	(0.045)	(0.046)	(0.029)	(0.051)	(0.069)	(0.034)
Female	0.056^{+}	0.058	−0.006	0.063*	0.050	0.027	0.085*	0.080*	0.005	0.072*	0.095^{+}	0.017
	(0.029)	(0.036)	(0.025)	(0.031)	(0.031)	(0.025)	(0.034)	(0.036)	(0.027)	(0.034)	(0.053)	(0.034)
Black	0.135^{+}	0.081	0.105^{+}	0.115	0.133*	0.147**	0.063	0.154^{+}	0.124*	0.080	0.080	0.183*
	(0.073)	(0.080)	(0.055)	(0.072)	(0.062)	(0.055)	(0.090)	(0.088)	(0.059)	(0.093)	(0.099)	(0.090)
Flispanic	0.054*	0.039	0.073**	0.067*	0.026	0.062**	0.041	0.077^{+}	0.079**	0.038	0.005	0.091**
	(0.024)	(0.029)	(0.023)	(0.028)	(0.033)	(0.024)	(0.031)	(0.040)	(0.024)	(0.034)	(0.053)	(0.031)
White	0.111	0.133^{+}	0.056	−0.05	0.182*	0.075*	0.012	0.258**	0.053	−0.045	0.318**	0.061
	(0.071)	(0.079)	(0.037)	(0.074)	(0.078)	(0.036)	(0.080)	(0.091)	(0.039)	(0.100)	(0.099)	(0.045)
Asian	−0.055	−0.022	0.030	−0.124	−0.024	0.064	0.063	0.008	0.041	0.147	0.150	0.068
	(0.098)	(0.084)	(0.059)	(0.117)	(0.072)	(0.053)	(0.092)	(0.091)	(0.059)	(0.117)	(0.097)	(0.062)
SED	0.060*	0.021	0.056*	0.076*	0.029	0.056*	0.055^{+}	0.048	0.062*	0.052	−0.011	0.075*
	(0.028)	(0.028)	(0.024)	(0.030)	(0.031)	(0.024)	(0.032)	(0.038)	(0.026)	(0.037)	(0.050)	(0.032)
Non-SED	−0.029	−0.004	0.062*	−0.031	0.051	0.067*	−0.021	0.065	0.019	−0.024	0.153^{+}	0.056
	(0.054)	(0.053)	(0.031)	(0.058)	(0.055)	(0.028)	(0.063)	(0.053)	(0.030)	(0.065)	(0.078)	(0.037)
ELL	0.064	0.029	0.058	0.070^{+}	0.040	0.098*	0.028	0.030	0.168***	0.005	0.008	0.127*
	(0.044)	(0.037)	(0.040)	(0.036)	(0.044)	(0.047)	(0.047)	(0.045)	(0.048)	(0.061)	(0.052)	(0.055)
Non-ELL	0.008	−0.006	0.034^{+}	0.010	0.052^{+}	0.029	−0.007	0.055	0.011	0.031	0.010	0.025
	(0.026)	(0.031)	(0.021)	(0.030)	(0.031)	(0.019)	(0.034)	(0.037)	(0.020)	(0.036)	(0.047)	(0.027)

Notes: We first partition the data by student subgroup and school policy cutoff. The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level. SED = Socioeconomically disadvantaged, and ELL = English Language Learner.

$^{+}$ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

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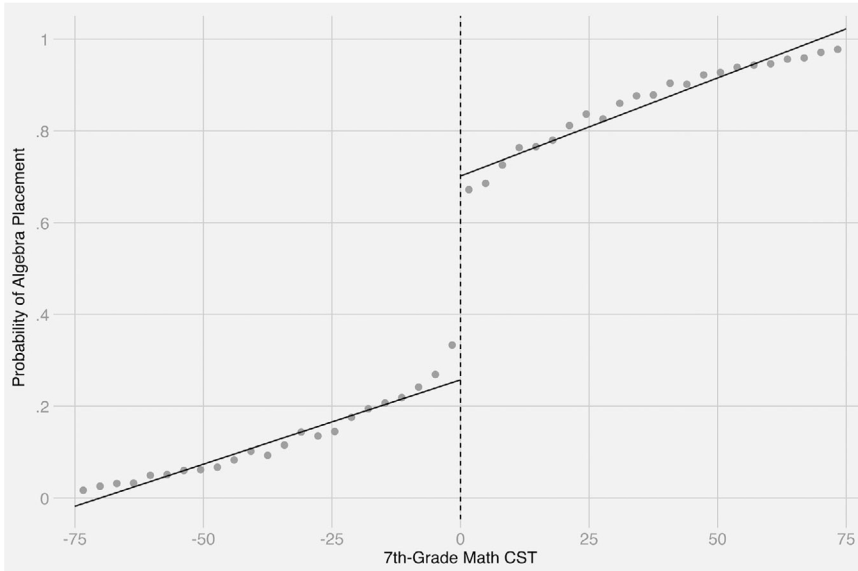

Figure 1.
Scatter Plot of the Pooled First Stages for RD Schools.

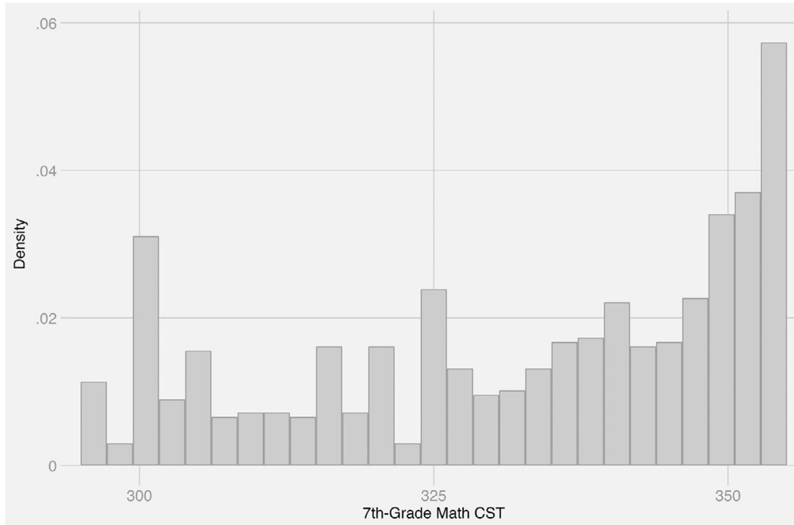

Figure 2.
Location of Discontinuity Points for RD Schools.

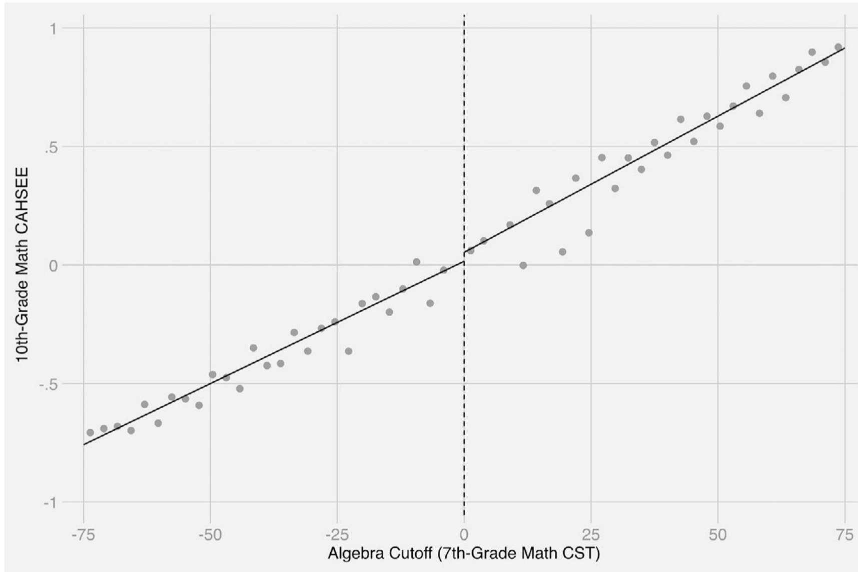

Figure 3.
Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 10th-Grade Math CAHSEE.

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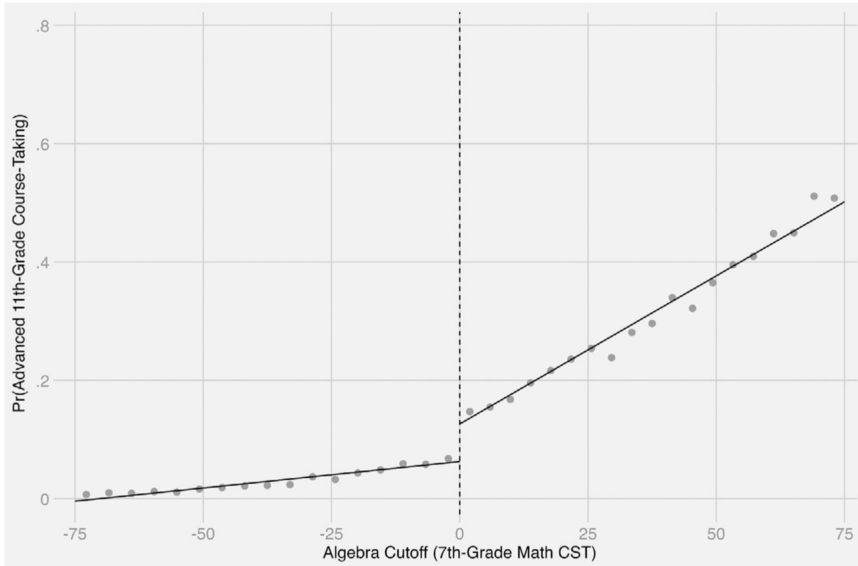

Figure 4.

Scatter Plot of the Intent-to-Treat Effect of 8th-Grade Algebra on 11th-Grade Advanced Math Course-Taking.

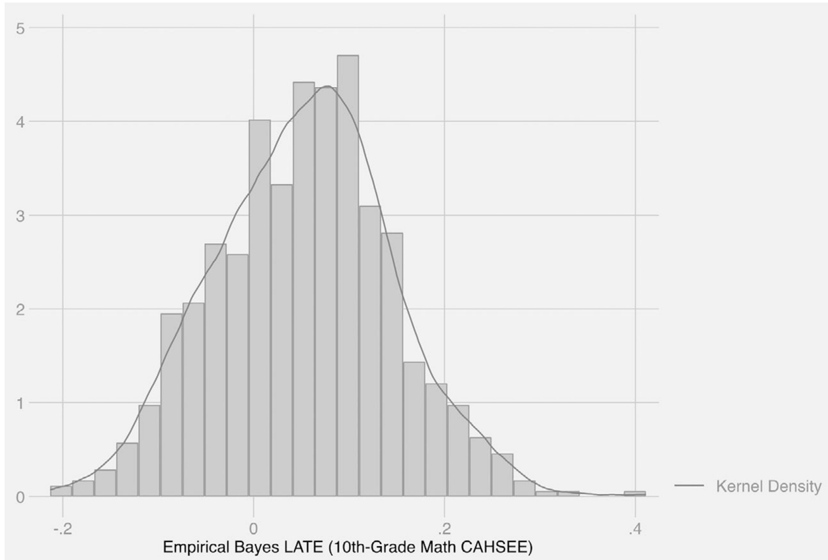

Figure 5.
Distribution of the Site-Specific Fuzzy RD Estimates of 8th-Grade Algebra on 10th-Grade Math CAHSEE.

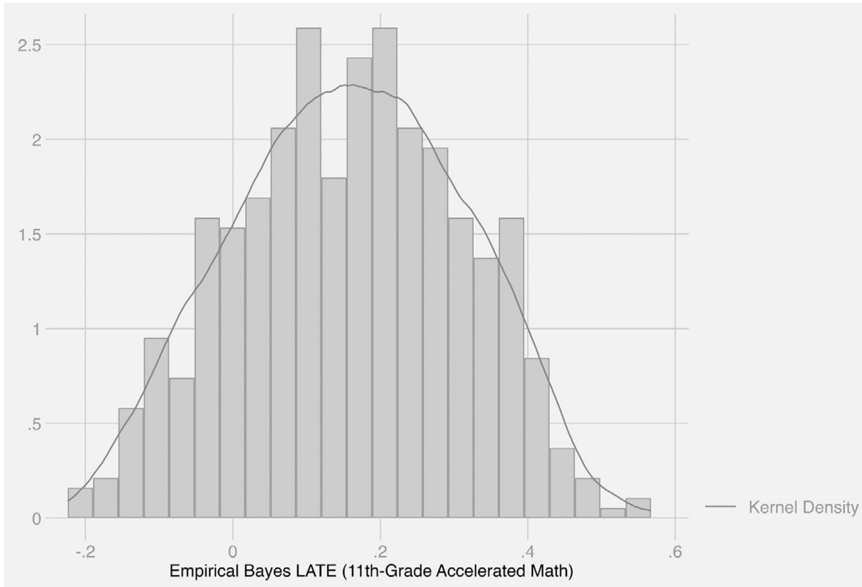

Figure 6.
Distribution of the Site-Specific Fuzzy RD Estimates of 8th-Grade Algebra on 11th-Grade Advanced Math Course-Taking.

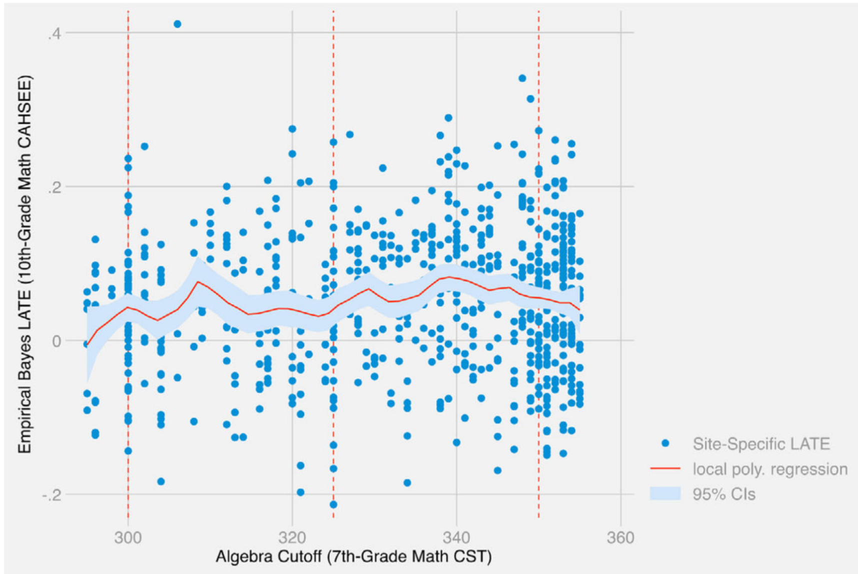

Figure 7.

Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 10th-Grade Math CAHSEE and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

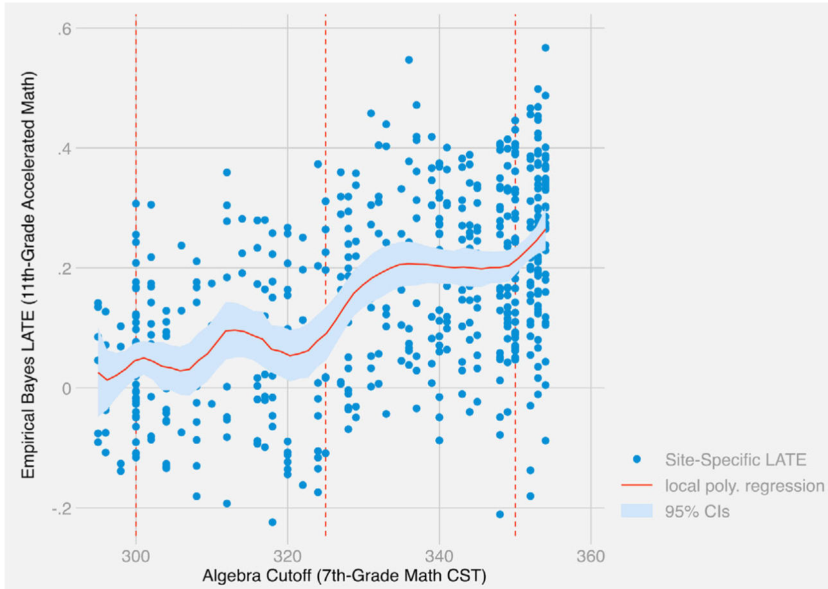

Figure 8.

Scatter Plot of Site-Specific Effects of 8th-Grade Algebra on 11th-Grade Advanced Math Course-Taking and the Location of the 7th-Grade Math CST Algebra Placement Cutoff.

Table 1.

Descriptive statistics for our analytic sample by RD school status.

	Non-RD Schools			Initial RD Search Sample			Trimmed RD Search Sample		
Student Dependent Variables	Mean	SD	N	Mean	SD	N	Mean	SD	N
10th-Grade Math CAHSEE	0.148	0.743	452093	0.057	0.735	186763	0.069	0.734	144351
10th-Grade ELA CAHSEE	0.221	0.755	452166	0.102	0.747	186815	0.111	0.747	144363
9th-Grade Accelerated Math	0.238	0.426	488642	0.236	0.425	201443	0.240	0.427	155513
10th-Grade Accelerated Math	0.216	0.412	488642	0.204	0.403	201443	0.207	0.405	155513
11th-Grade Accelerated Math	0.131	0.338	488642	0.119	0.324	201443	0.124	0.329	155513
8th-Grade ELA CST	−0.075	0.813	487945	−0.211	0.795	201060	−0.195	0.796	155241
9th-Grade ELA CST	−0.029	0.810	458967	−0.173	0.788	189922	−0.162	0.791	146910
10th-Grade ELA CST	−0.058	0.821	439094	−0.188	0.809	181456	−0.179	0.811	140405
11th-Grade ELA CST	−0.075	0.842	332211	−0.188	0.822	129651	−0.178	0.822	101441
Student Independent Variables	Mean	SD	N	Mean	SD	N	Mean	SD	N
6th-Grade Math CST	−0.129	0.705	462062	−0.229	0.681	190820	−0.212	0.684	147088
7th-Grade Math CST	−0.094	0.649	488642	−0.179	0.633	201443	−0.165	0.633	155513
6th-Grade ELA CST	−0.041	0.805	462346	−0.178	0.780	190918	−0.161	0.781	147149
7th-Grade ELA CST	−0.054	0.801	488172	−0.200	0.783	201215	−0.181	0.784	155330
Male Student	0.477	0.499	488642	0.478	0.500	201443	0.478	0.500	155513
SED Student	0.555	0.497	488548	0.688	0.463	201406	0.679	0.467	155481
Asian Student	0.062	0.241	486584	0.062	0.241	201013	0.066	0.248	155159
Black Student	0.069	0.254	486584	0.069	0.254	201013	0.069	0.254	155159
Hispanic Student	0.518	0.500	486584	0.628	0.483	201013	0.617	0.486	155159
ELL Student	0.158	0.365	488328	0.199	0.399	201341	0.197	0.398	155432
Took 10th-Grade Math CAHSEE	0.925	0.263	488642	0.927	0.260	201443	0.928	0.258	155513
Took 10th-Grade ELA CAHSEE	0.925	0.263	488642	0.927	0.260	201443	0.928	0.258	155513

Notes: SED = socioeconomically disadvantaged. ELL = English Language Learner.

Table 2.

First stage and placebo regression analysis of 8th-grade algebra course assignment.

	First Stage	Density Test	6th-Grade Math CST	6th-Grade ELA CST	7th-Grade ELA CST	Male Student	SED Student	Asian Student	Black Student	Hispanic Student	ELL Student	Has 10th-Grade Math CAHSEE	Has 10th-Grade ELA CAHSEE
Panel A: Initial RD Search Sample													
1[CST> = Cutoff]	0.412 *** (0.007)	−0.282 * (0.112)	0.046 *** (0.004)	0.032 *** (0.005)	0.020 *** (0.005)	0.005 (0.004)	−0.002 (0.003)	0.006 ** (0.002)	−0.001 (0.002)	−0.010 ** (0.003)	−0.015 *** (0.004)	0.002 (0.002)	0.001 (0.002)
# of Students	201443	201443	190820	190918	201215	201443	201406	201013	201013	201013	201341	201443	201443
# of School Years	972	972	972	972	972	972	972	972	972	972	972	972	972
Panel B: Trimmed Sample													
	First Stage	Density Test	6th-Grade Math CST	6th-Grade ELA CST	7th-Grade ELA CST	Male Student	SED Student	Asian Student	Black Student	Hispanic Student	ELL Student	Has 10th-Grade Math CAHSEE	Has 10th-Grade ELA CAHSEE
1[CST> = Cutoff]	0.410 *** (0.008)	−0.142 (0.121)	0.034 *** (0.004)	0.009 + (0.005)	−0.006 (0.005)	0.010 * (0.005)	0.001 (0.004)	0.007 ** (0.002)	−0.003 (0.002)	−0.008 + (0.004)	−0.002 (0.004)	0.001 (0.003)	0.002 (0.003)
# of Students	155513	155513	147088	147149	155330	155513	155481	155159	155159	155159	155432	155513	155513
# of School Years	753	753	753	753	753	753	753	753	753	753	753	753	753

Notes: The results presented in this table use a pooled dataset of all 972 RD sites centered around their school-year-specific algebra cutoff (e.g., a 7th-grade math CST score of 325). Column 2, the adapted McCary Density Test, uses data aggregated to the discrete CST math score level instead of student-level data. The coefficients in the table are from a pooled reduced-form linear spline with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. SED = socioeconomically disadvantaged. The model also includes school-year fixed effects, and standard errors are clustered at the school-year level.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table 3.

Descriptive statistics for the RD search process.

	Non-RD Schools			Initial RD Search Sample			Trimmed RD Search Sample		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
First Stage Magnitude	−0.004	0.197	2720	0.484	0.168	972	0.481	0.169	753
First Stage Location	333.513	18.451	2720	331.061	19.038	972	332.158	18.645	753
First Stage R2	0.348	0.134	2720	0.571	0.139	972	0.571	0.14	753
First Stage T-Stat	−0.080	1.473	2720	5.420	3.533	972	5.436	3.752	753
First Stage Left-hand Limit	0.489	0.355	2720	0.238	0.161	972	0.237	0.162	753
First Stage Right-hand Limit	0.486	0.339	2720	0.722	0.181	972	0.718	0.182	753
Number of 8th graders	179.648	109	2720	207.246	99.823	972	206.525	97.322	753

Table 4.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes.

	Panel A: ITT Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
1[CST> = Cutoff]	0.031***	0.016**	0.135***	0.092***	0.067***	0.013*	0.015**	0.022***	0.021**
	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
	Panel B: Fuzzy RD LATE Effects								
	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th Grade	10th Grade	11th Grade	8th Grade	9th Grade	10th Grade	11th Grade
Algebra	0.053***	0.034**	0.297***	0.203***	0.158***	0.021*	0.025*	0.030*	0.026+
	(0.011)	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.015)
τ^2	0.025	0.024	0.044	0.036	0.026	0.031	0.030	0.033	0.029
# of Students	144351	144363	155513	155513	117755	155241	146910	140405	101441
# of School Years	753	753	753	753	550	753	753	753	550
# of Schools	510	510	510	510	424	510	510	510	424

Notes: The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra). The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level.

+ $p<0.10$

* $p<0.05$

** $p<0.01$

*** $p<0.001$.

Table 5.

Site-level OLS regressions of site-specific effects of 8th-grade algebra on school demographics.

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th-Grade	10th-Grade	11th-Grade	8th-Grade	9th-Grade	10th-Grade	11th-Grade
Algebra Placement Threshold	0.001 * (0.000)	−0.001 *** (0.000)	0.005 *** (0.001)	0.004 *** (0.001)	0.003 *** (0.000)	0.000 (0.000)	−0.000 ** (0.000)	0.000 (0.000)	0.000 (0.000)
% Socioeconomically Disadvantaged	0.009 (0.016)	−0.002 (0.012)	0.048 (0.031)	−0.023 (0.031)	−0.030 (0.024)	−0.088 *** (0.013)	−0.054 *** (0.010)	−0.041 *** (0.009)	−0.039 *** (0.006)
Avg. 7th-Grade Math CST	−0.028 (0.025)	−0.008 (0.016)	−0.011 (0.046)	−0.010 (0.045)	−0.013 (0.034)	−0.045 * (0.018)	0.006 (0.014)	−0.025 + (0.013)	−0.024 ** (0.009)
Adjusted R2	0.008	0.085	0.175	0.152	0.176	0.064	0.064	0.037	0.049
# of School Years	753	753	753	753	753	753	753	753	753

Notes: The coefficients are from an RD site-level OLS regression of the various effects of 8th-grade algebra on site-level characteristics. The site-level effects are empirical Bayes estimates from equation (2). Robust standard errors are in parenthesis.

+ p<0.10

* p<0.05

** p<0.01

*** p<0.001.

Table 6.

Fuzzy RD estimates of 8th-grade algebra course assignment on educational outcomes by student subgroup.

	10th-Grade CAHSEE		Advanced Math Course-Taking			ELA CST			
	Math	ELA	9th-Grade	10th-Grade	11th-Grade	8th-Grade	9th-Grade	10th-Grade	11th-Grade
Male	0.068***	0.058**	0.253***	0.169***	0.129***	0.034*	0.037*	0.039*	0.017
	(0.015)	(0.016)	(0.013)	(0.012)	(0.012)	(0.017)	(0.016)	(0.017)	(0.022)
Female	0.062***	0.042**	0.331***	0.231***	0.175***	0.024+	0.025+	0.040**	0.052**
	(0.013)	(0.014)	(0.016)	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)	(0.018)
Black	0.151***	0.130***	0.287***	0.193***	0.158***	0.117***	0.168***	0.149***	0.159***
	(0.027)	(0.032)	(0.022)	(0.019)	(0.020)	(0.033)	(0.030)	(0.035)	(0.045)
Hispanic	0.051***	0.060***	0 277***	0.186***	0.145***	0.054***	0.048***	0.066***	0.055**
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.018)
White	0.113***	0.083***	0.269***	0.194***	0.130***	0.061*	0.031	0.056*	0.068*
	(0.021)	(0.023)	(0.019)	(0.017)	(0.017)	(0.024)	(0.024)	(0.026)	(0.033)
Asian	0.077*	0.050	0.446***	0.348***	0.286***	0.066+	0.043	0.045	0.094*
	(0.031)	(0.033)	(0.026)	(0.027)	(0.029)	(0.036)	(0.033)	(0.036)	(0.038)
SED	0.065***	0.058***	0.291***	0.196***	0.151***	0.038**	0.049***	0.060***	0.054**
	(0.013)	(0.013)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.018)
Non-SED	0.086***	0.048**	0.286***	0.209***	0.158***	0.038+	0.039*	0.031	0.049+
	(0.018)	(0.018)	(0.017)	(0.015)	(0.015)	(0.020)	(0.019)	(0.021)	(0.025)
ELL	0.135***	0.097***	0.308***	0.225***	0.200***	0.061**	0.068***	0.110***	0.081**
	(0.020)	(0.020)	(0.018)	(0.016)	(0.017)	(0.021)	(0.020)	(0.022)	(0.028)
Non-ELL	0.046***	0.033**	0.296***	0.202***	0.154***	0.017	0.025*	0.021	0.023
	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.016)

Notes: The coefficients are from a two-stage model with treatment-by-site instruments, school-year fixed effects, and a random coefficient for the treatment (8th-grade algebra) run separately by student subgroup. The model also uses a linear spline specification with an indicator for whether students' 7th-grade CST scores are above the school-specific policy threshold, a linear control for students' 7th-grade CST scores, and an interaction between the indicator variable and the linear control for students' 7th-grade CST scores. Standard errors are clustered at the school-year level. SED = Socioeconomically disadvantaged, and ELL = English Language Learner.

+ p<0.10

* $p<0.05$

** $p<0.01$

*** $p<0.001$.