Evaluating the Transition to College Mathematics Course in Texas High Schools: Findings from the First Year of Implementation

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Abstract

Texas House Bill 5 introduced requirements that school districts partner with institutions of higher education to provide college preparatory courses in mathematics and English for high school seniors who are not yet college ready. As districts and college partners begin to respond to these provisions, there is a need for empirical research on the effects of different approaches to implementing the college preparatory courses. Drawing on principles from their Mathematics Pathways Project, the Charles A. Dana Center has developed a model college preparatory mathematics course, Transition to College Mathematics Course (TCMC), which has been adopted by dozens of school districts across Texas over the past two school years. In this paper, we examine the effects of TCMC on students' progress into post-secondary education by comparing students who partipated in TCMC during the 2016-17 school year (the first year of implementation) to observationally similar students, either from a previous cohort that did not have access to TCMC or from the same cohort but who did not enroll in the course. We find that, although students who took TCMC graduated at slightly higher rates than comparison students, they had lower rates of enrollment in post-secondary education, driven by lower rates of enrollment in 4-year colleges or universities. We find that students who took TCMC were also less likely than students in the comparison group to pass college-level math courses by the end of their first semester after high school. However, these results must be interpreted cautiously because we were unable to fully assess and account for students' college-readiness status at the start of their senior year.

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Introduction

Post-secondary education has become a gateway for economic and social mobility in U.S. society. While both federal and state policy has sought to broaden access to higher education, there remain substantial obstacles to expanding the more crucial objective of student degree completion. One challenge is that many students exit high school under-prepared for college-level work—particularly in mathematics. Bailey, Jeong, and Cho (2010) found that, across a large sample of community colleges from across the U.S., over half of entering students were deemed to be unprepared for college-level course-work in mathematics, while one third of students were deemed unprepared for college-level reading.

Students who are under-prepared for college-level course work are referred for or required to complete developmental courses in areas of deficit. Developmental courses are meant to help under-prepared students learn skills necessary to do well in college-level work, and large numbers of students begin such courses. For example, as of 2003-04, 59% of students entering public 2-year institutions and 33% of students entering public 4-year institutions took remedial mathematics (Chen, 2016). Moreover, low-income students and minority students are disproportionately likely to take developmental coursework (Chen, 2016).

Although developmental courses are intended to help students succeed, they may have the effect of raising barriers to success in college, hindering credit and degree completion. Attewell, Lavin, Domina, and Levey (2006) found that only 30% of students who take developmental mathematics courses pass all of the classes. Some scholars have posited that assignment to developmental courses has the effect of discouraging student persistence or diverting lower ability students into separate courses from better-prepared students (Levin & Calcagno, 2008; Scott-Clayton & Rodriguez, 2015). Evidence from a range of settings—including 2- and 4-year public institutions in Texas—indicates that participation in

conventional developmental coursework does little to improve student persistence and credit completion, relative to immediately beginning college-level coursework (Calcagno & Long, 2008; Martorell & McFarlin, 2011; Scott-Clayton & Rodriguez, 2015; Xu, 2016).

State-level policy makers and institutions of higher education are adopting a variety of policy responses to address under-preparation of students for college-level course-work (Couturier & Cullinane, 2015). Potential lines of intervention include offering developmental courses as co-requisites to college-level work (Logue, Watanabe-Rose, & Douglas, 2016); improving assessment and placement practices (Hodara, Jaggars, & Karp, 2012); or differentiating course content to better fit students' intended areas of study (Ruschow, Diamond, & Serna-Wallender, 2015). Another response focuses on the transition from high school to higher education, aiming to provide high school coursework that better aligns with the design and sequence of work at the post-secondary level. In this paper, we consider implementation of one such policy in Texas.

Texas House Bill 5

Texas House Bill 5 (HB5), introduced in the 2013 legislative session, made a number of substantial changes to state high school curriculum and graduation requirements. Among its provisions, HB5 requires school districts to offer a college preparatory mathematics course for students not meeting college readiness standards in mathematics by the end of their third year of high school. It further requires that the course be offered through a partnership with an institution of higher education—typically a community college—and that successful completion of the course must satisfy the partner institution's requirements for enrollment in college-level coursework.

As a form of early college coursework, the college preparatory math course requirement introduced by HB5 could benefit students by allowing them to bypass developmental courses and immediately begin college level work. Evidence indicates that participating in early college coursework positively impacts post-secondary persistence and degree completion (An,

2013; Giani, Alexander, & Reyes, 2014; Karp, Calcagno, Hughes, Jeong, & Bailey, 2007) and might be particularly beneficial for lower-income students (An, 2013). On the other hand, the college preparatory math course targets a different sub-group of students and has somewhat different aims than typical early college coursework. Further, if high schools and community college partners implement the course following the pattern of a conventional developmental education course (i.e., a remedial Algebra II course), then one might expect that it will have similarly weak effects. In short, the design and content of the college math preparatory course must also be considered.

Transition to College Mathematics

The Transition to College Mathematics Course (TCMC) was developed by the Charles A. Dana Center as a model college preparatory math course, aligned with the goals and requirements of the HB5. Drawing on a framework of learning objectives for the college preparatory math course developed by a statewide task force, Dana Center researchers created TCMC by melding previously developed secondary-level course materials with strategies they had used to build college-level developmental courses.

TCMC differs from conventional remedial math courses in several important respects. First, the course content aligns with the Mathematics Pathways framework (Charles A. Dana Center, 2016) adopted by many Texas higher education institutions, which recognizes the broad range of mathematical and quantitative reasoning skills needed across different fields of study and professions. Thus, the course provides a coherent sequence of work across the transition from high school to higher education. Second, the course involves novel material and instructional strategies, rather than repetition of content that students have already encountered. Third, the course incorporates evidence-based pedagogical approaches including putting greater emphasis on richly contextualized applications, developing students' self-regulated learning strategies and productive persistence, and varying instructional activities. Taken together, these differences provide reason to expect that student

participation in TCMC could have immediate and longer-term impacts on student outcomes.

TCMC was offered at high schools in nine districts across central Texas during the 2016-17 school year. The following year, offerings were expanded to over thirty districts. However, as of yet there is no empirical evidence on the effects of TCMC on post-secondary outcomes.

Aim and Research Questions

In this report, we aim to evaluate the impacts of TCMC in its first year of implementation. Our guiding research question is: relative to taking typical high school coursework, what are the effects of participating in TCMC on high school graduation, post-secondary enrollment, and progress in college-level mathematics for 12th grade students enrolled in TCMC?

Methods

Within high schools that offered the course during 2016-17, enrollment in TCMC was at the discretion of students and school staff. Most students who enrolled in the course were in 12th grade. Beyond that, however, schools did not follow any consistent rule for determining which students should take the course, and advising practices differed from school to school. Our identification strategy is therefore to construct comparison groups of students who did not enroll in TCMC, but who are observationally similar to the group of students who did enroll in the course. We aim to create groups that are closely matched on confounders—that is, background characteristics that may have influenced students to enroll in the course and that may be associated with later student outcomes—so that differences between the groups in later outcomes provide estimates of the impact of enrolling in TCMC. Further, we aim to estimate the effects of participating in TCMC *for students who chose to participate in it*—that is, an average effect of treatment for those who received treatment.

The primary assumption that must hold for our approach to identify the causal impacts of participating in the course is known as *strong ignorability* (Rosenbaum & Rubin,

1983). The assumption has two parts. The first part requires that there are no unobserved confounding variables beyond those that we account for. Our analysis therefore includes prior math course-taking patterns and a standardized measure of math achievement. Students who had not taken adequate classes earlier in high school and students who performed poorly in math may be more likely to participate in TCMC in 12th grade and may be less likely to graduate and enroll in college. We also incorporate relevant demographic variables that could influence both enrollment in TCMC and later outcomes. One potential omitted confounder is performance on Texas Success Initiative (TSI) or other standardized test that would designate students as college-ready. The second part of the strong ignorability assumption requires that propensity score distributions of the TCMC and comparison groups overlap. We provide a detailed assessment of this part of the assumption in the results section.

We considered multiple approaches for defining a comparison group. One source is the set of 12th grade students from the same school and same class year as the students who enrolled in TCMC during 2016-17, but who did not enroll in the course. The advantage of using this source is that comparison students are contemporaries of the students who enrolled in TCMC, so that background characteristics and later outcome variables can be assessed at the same points in time, using consistent definitions and data sources. The primary drawback of this approach is that these comparison students have all elected *not* to enroll in the course, and thus might differ from students who participated in TCMC in ways beyond what we can measure.

An alternative source for a comparison group is students from the same school, who were in 12th grade during the 2015-16 school year—the year *prior* to when the course was first offered. To the extent that student cohorts are similar from year to year, the set of students from the prior year might provide a better point of comparison because a subset of them likely would have enrolled in TCMC, had it been available. Consequently, there may be fewer or smaller unobserved differences between students who enrolled in the course in 2016-17 and those from the prior year who did not have access to the course. However, this

approach has the disadvantage that year-to-year changes in economic conditions, state education policy, or assessment methods could produce differences in outcomes between students who enrolled in TCMC and comparable students from the prior year.

Given that these two approaches have complementary advantages and drawbacks, we used *both* in order to more robustly assess the effects of participating in TCMC. We used propensity score weighting methods (Hirano & Imbens, 2001; Schafer & Kang, 2008) to construct comparison groups from each source and weighted least squares regression to estimate average treatment effects across the set of schools that offered TCMC for the 2016-17 school year. In the remainder of this section, we describe the implementation of TCMC during the 2016-17 school year, explain our data sources, and provide further details about our analytic strategy.

TCMC Implementation

In the initial year of implementing TCMC, the Dana Center worked with higher education partners to recruit high schools interested in offering the course and participating in evaluation activities. Colleges who were partnering with the Dana Center in implementing their Mathematics Pathways framework assisted with recruitment. Eighteen high schools in nine districts agreed to participate for the 2016-17 school year. To satisfy the college readiness course requirements of HB5, participating districts partnered with several different community colleges, including Austin Community College, Lone Star College, and Lee College.

Participating high schools received free curriculum materials and professional development, as well as ongoing technical support during the first year of implementation. Professional development consisted of a two-day, in-person training during the summer of 2016 and a further, one-day training during winter of 2017. In return, participating schools agreed to assist with evaluation activities by administering surveys to and providing further administrative data on students enrolled in the course.

Data Sources

We used statewide longitudinal data collected by the Texas Education Agency (TEA), and Texas Higher Education Coordinating Board (THECB). We accessed the data through the Education Research Center at The University of Texas at Austin. The data include student demographics, course enrollment and completion in elementary, secondary and higher secondary schools, performance on State of Texas Assessments of Academic Readiness (STAAR) assessments, high school graduation, matriculation into college, and performance in college-level courses during Fall of 2017, the first semester following students' senior year of high school.

Analytic Samples. Using the TEA course completion data, we identified students enrolled in classes labeled as College Preparatory Mathematics or Independent Study in Math in participating districts. To identify sections of TCMC, we compared class name, class identification, class period, teacher identification number, and the number of sections to separate evaluation data provided to us by the Dana Center. We were unable to identify any sections of TCMC in one district. Our final sample therefore included students from seventeen high schools in eight districts.

To define the treatment group, we identified 12th grade students enrolled in sections of TCMC in the eight focal districts. We excluded a small number of students who appeared to be enrolled in sections of TCMC but were not actually enrolled in the focal campuses according to the TEA attendance data.

We created two comparison groups. The first group (contemporaneous comparison) included 12th grade students who were enrolled at the focal campuses during the 2016-17 school year but not enrolled in TCMC. The second group (previous year comparison) included 12th grade students who were enrolled at the focal campuses the previous year (the 2015-16 school year). The samples of comparison students were determined from records in the TEA attendance data, which includes information as of the end of the school year. For students who were enrolled at multiple campuses during a single year (i.e., because they

switched schools mid-year), we retained the record from the school with the maximum number of eligible days.

Outcomes. We assessed the impacts of TCMC on outcomes related to students' post-secondary success. The main goal of the TCMC program was to improve student preparedness for college-level math. Thus, the primary outcomes of interest are enrollment and passage rates for college-level math courses. For completeness, we also examine enrollment and passage rates for developmental math courses at the post-secondary level. In order to affect post-secondary performance outcomes, however, students must first graduate and enroll in post-secondary education. Therefore, we also examine impacts on high school graduation and college enrollment rates as intermediate outcomes. We further dis-aggregate college enrollment rates by sector, distinguishing between community college and four-year colleges or universities. Finally, we examine rates of enrollment in the specific community colleges who partnered with each district to provide TCMC. Due to data availability constraints, college enrollment, course enrollment, and course passing rates were limited to the first (Fall) semester of the 2017-18 school year.

Table 1 provides definitions of the outcomes and lists the data sources from which they were obtained. We obtained data on high school graduation from TEA graduation datasets. We obtained college enrollment and course-taking data from THECB enrollment and course datasets. We excluded non-degree seeking students and dual-credit students from our analyses. It is important to emphasize that our analysis of post-secondary outcomes is limited to students who enrolled in institutions of higher education within the state of Texas, as recorded in THECB data.

Table 1
Outcome definitions and sources

Outcome	Definition	Source
High School Graduation	Graduating high school by the end of the 12th grade year (2016-17 for the TCMC group and the contemporaneous comparison group, 2015-16 for the previous year comparison group).	p_graduate
College Enrollment	Enrollment in community college, public university independent college or health programs. For all analyses of college enrollment below, we excluded non-degree seeking students and dual-credit students. For all the analyses of college enrollment and performance in math courses, we examined the data for the Fall semester the year after the students' 12th grade year (only the Fall semester data are available for the contemporaneous comparison groups).	cbm_001
College Enrollment: Community	Enrollment in community colleges.	cbm_001
College Enrollment: Four Year	Enrollment in four-year colleges.	cbm_001
College Enrollment: Partner	Enrollment in community colleges that partnered with the focal districts to offer TCMC.	cbm_001
College Math Course Enrollment: Non-Developmental	Enrollment in non-developmental college math courses. For all the outcomes below based on cbm_00s, we excluded students who took courses for dual credit. We excluded lab, co-op, internship, clinical and practicum courses.	cbm_00s
College Math Course Enrollment: Developmental	Enrollment in developmental college math courses.	cbm_00s
College Math Course Passing: Non-Developmental	Passing non-developmental college math courses. For duplicated records, we kept the passing grade.	cbm_00s
College Math Course Passing: Developmental	Passing developmental college math courses. For duplicated records, we kept the passing grade.	cbm_00s

Covariates. Our ability to identify the effects of enrolling in TCMC hinges on controlling for student characteristics that could be confounders. We therefore identified an extensive set of background characteristics for use in developing propensity score weights and estimating impacts. Our main covariates included current demographic status and history, program and service enrollment history, prior math course enrollments, and prior math performance. Because TCMC is designed for students who are under-prepared for college-level math courses, it is highly likely that prior math course-taking and achievement influence whether students are advised or required to take TCMC and also related to later student outcomes. With respect to student socio-economic background, Michelmore and Dynarski (2017) demonstrated that the effects of economic disadvantage on educational outcomes can be better captured by using longitudinal measures of income that estimate duration of disadvantage than by using a contemporaneous measure alone. We therefore included longitudinal measures of economic disadvantage as well as immigrant status, history of special education enrollment, gifted enrollment, and drop-out at-risk status.

We assembled the following covariates:

(1) Current demographic and program enrollment status: Sex, race/ethnicity categories, immigrant status, economic disadvantage status[1], gifted program enrollment, special education program enrollment, and dropout at-risk status. These variables were drawn from the attendance and enrollment data from the 12th grade year.

(2) Demographic and program enrollment history: The number of years of available data; the number of years that a student was indicated as being in any of the categories for economic disadvantage and the number of years that the student was indicated as being in special education program, in gifted program, an immigrant, and at risk for dropping out; the proportion of years (the number of years the student was in the

[1] Economic disadvantage categories include: eligibility for free lunch as part of the National School Lunch And Child Nutrition Program (NSLP), eligibility for reduced-price lunch under NSLP, and other economic disadvantage. Other economic disadvantage is determined from sources other than NSLP eligibility, including having annual income below the federal poverty line or being eligible for public assistance such as through Temporary Assistance to Needy Families.

category divided by the number of years of record available) for the economic disadvantage categories; and whether the student was ever indicated as enrolled in a special education program, enrolled in a gifted program, an immigrant, and at risk. For the contemporaneous comparison, we traced the history from 2016 to 2008 for both groups. For the previous year comparison, we traced the TCMC group's history from 2016 to 2009 and the comparison group's history from 2015 to 2008.

(3) Math course-taking history: For both contemporaneous and previous comparisons, we gathered data on whether students took (and passed or failed or did not complete) 8th grade math (four years prior), Algebra I (three and four years prior), Geometry (two and three years prior), Algebra II (one and two years prior), and Precalculus (one year prior).

(4) STAAR scores: Score on Algebra I end-of-course exam. We retained the earliest score if a student took the test multiple times. For the contemporaneous comparison, we traced scores from 2016 to 2012. For the previous year comparison, we traced the TCMC group's scores from 2016 to 2013, and the comparison group's scores from 2015 to 2012.

Full definitions of these variables and data sources from which they were obtained are in Table 2. For categorical variables with missing data, we created an additional category indicating missingness. For continuous variables, missing data were imputed with the mean of the variable in the TCMC group within the given high school. For the continuous variables, we also created additional variables indicating missing values (Rosenbaum & Rubin, 1984).

Table 2
Covariate definitions and sources

Variable	Definition	Source
Sex	Sex- male/female.	p_attend_demog
Race/Ethnicity	Race/ethnicity- Asian American, African American, Hispanic, American Indian, Pacific Islander, Multiracial, and White.	p_attend_demog
Economic disadvantage	Indicates economic disadvantage status: free lunch status, reduced lunch status, no disadvantage or other disadvantage. We dummy coded the variable and took the average of the data from the attend and enroll datasets for the 12th grade year.	p_attend_demog & p_enroll_demog
At risk for dropping out	Indicates whether a student was at risk for dropping out of school according to state-defined criteria as of the beginning of the 12th grade year .	p_enroll_demog
Giftedness	Indicates whether a student participated in state-approved gifted and talented program. We took the average of the data from the attend and enroll datasets for the 12th grade year.	p_attend_demog & p_enroll_demog
Immigrant status	Indicates whether a student was identified as an immigrant according to the definition in Title III of No Child Left Behind Act of 2001- individuals who are aged 3 through 21, were not born in any state, and have not been attending one or more schools in any one or more states for more than three full academic years. The data is from the beginning of the 12th grade year.	p_enroll_demog
Special education status	Indicates whether a student participated in special education instructional and related services program or general education program using special education services, supplementary aids, or other special arrangements. We took the average of the data from the attend and enroll datasets for the 12th grade year.	p_attend_demog & p_enroll_demog
Limited English proficiency	Indicates whether a student was limited English proficient as determined by Language Proficiency Assessment Committee (LPAC) as of the end of the 12th grade year.	p_attend_demog
Prior math course-taking	Indicates whether a student took Grade 8 Mathematics (four years prior), Algebra I (three and four years prior), Geometry (two and three years prior), Algebra II (one and two years prior) and Pre-calculus (one year prior). Variables for these courses indicated if the student passed, failed, or did not take the class in the given year.	p_course_complete
Prior math performance	STAAR end-of-course exam score for Algebra I. For the comtemporaneous comparison, we traced the data from 2016 to 2012. For the previous comparison, we traced the data from from 2016 to 2013 for the TCMC group and from 2015 to 2012 for the comparison group. For duplicate scores (i.e., if the students took the test in multiple years), we kept the earliest score.	staareoca1
History of economic disadvantage, at-risk for dropping out, giftedness, immigrant status, and special education status	For the contemporaneous comparison, we tracked these variables from 2016 to 2008. For the previous comparison, we tracked back from 2016 to 2009 for the TCMC group and 2015 to 2008 for the comparison group. Variables include (1) the number of years of available tracked data; (2) the number of years that a student was indicated as being in any of the categories for economic disadvantage and the number of years that the student was indicated as being in special education program, in gifted program, an immigrant, and at risk; (3) the proportion of years (the number of years the student was in the category divided by the number of years of record available) for the economic disadvantages categories; and, (4) if the student was ever indicated as being in special education program, in gifted program, an immigrant, and at risk.	p_enroll_demog. (p_attend did not have data earlier than 2010 for economic, and does not contain at-risk or immigrant)

Tables 3 through 8 show the distribution of the covariates in the TCMC and the two comparison groups. The TCMC group had higher percentages of African American and Hispanic students while the contemporaneous comparison group had a higher percentage of white students. Relative to the contemporaneous comparison group, the TCMC group had a higher percentage of students receiving free lunch, higher percentages of students who were at risk for dropping out and were ever at risk, lower percentages of students who were in gifted programs and ever in gifted programs, and lower percentages of students currently in special education programs and ever in these programs. The TCMC group also had higher average number and proportion of years of receiving free lunch and having other disadvantage, lower average number and proportion of years of receiving reduced-price lunch and being not economically disadvantaged, higher average number of years of being at risk for graduation, and lower average number of years of being in gifted programs and being in special education programs.

In terms of academics, the TCMC group had lower average Algebra I STAAR scores. A higher percentage of the contemporaneous comparison group took Algebra I, Geometry, Algebra II and Precalculus a year prior to when they would normally be required to take the courses. The comparison group also had higher passing rates for these courses. For students who took Algebra I, Geometry and Algebra II in the year required, those in the TCMC group had higher passing rates than those in the comparison group.

Imbalances between the previous year comparison group and the TCMC group were similar to those in the contemporaneous comparison, except that the percentages of African American students were the same across the TCMC and comparison group. The TCMC group also had a higher percentage of students receiving reduced-price lunch and lower percentage of students classified as other economic disadvantage, whereas these percentages did not differ much between the TCMC and contemporaneous comparison groups.

Table 3
Distribution of Covariates: Contemporaneous Comparison

Variable	TCMC	Comparison
N	1090	6777
Sex		
Female	49%	49%
Male	51%	51%
Race or Ethnicity		
Asian American	<1%	2%
African American	17%	15%
Hispanic	62%	54%
American Indian	<1%	<1%
Pacific Islander	<1%	<1%
Multiracial	2%	<2%
White	18%	26%
Economic Disadvantage		
Free Lunch	52%	45%
Reduced Lunch	9%	8%
Not Disadvantaged	37%	44%
Other Disadvantage	2%	2%
Limited English Proficiency		
Limited English Proficiency	8%	7%
At Risk for Graduation		
At Risk	68%	54%
At Risk Ever	84%	73%
Giftedness		
Giftedness	2%	10%
Gifted Ever	6%	14%
Immigrant		
Immigrant	<3%	2%
Immigrant Ever	7%	6%
Special Education		
Special Education	2%	10%
Special Education Ever	6%	14%
Missingness Indicators		
Algebra 1 End of Course STAAR Scores	7%	14%
Demographic Tracked Data	1%	2%
Enrollment Data	<1%	2%

Analytic Models

We used propensity score analysis and weighted outcome regression to estimate the average causal effect of participating in TCMC compared to taking typical high school coursework. All analyses were conducted in R (version 3.3.1; R Core Team, 2016).

To construct comparison groups, we used a recently developed algorithm called the

Table 4
Distribution of Covariates: Previous Year Comparison

Variable	TCMC	Comparison
N	1090	7614
Sex		
Female	49%	49%
Male	51%	51%
Race or Ethnicity		
Asian American	<1%	2%
African American	17%	17%
Hispanic	62%	53%
American Indian	<1%	<1%
Pacific Islander	<1%	<1%
Multiracial	2%	<2%
White	18%	26%
Economic Disadvantage		
Free Lunch	52%	26%
Reduced	9%	4%
Not Disadvantaged	37%	42%
Other Disadvantage	2%	27%
Limited English Proficiency		
Limited English Proficiency	8%	6%
At Risk for Graduation		
At Risk	68%	52%
At Risk Ever	81%	72%
Giftedness		
Giftedness	2%	10%
Gifted Ever	6%	13%
Immigrant		
Immigrant	<3%	1%
Immigrant Ever	6%	5%
Special Education		
Special Education	2%	9%
Special Education Ever	5%	12%
Missingness Indicators		
Algebra 1 End of Course STAAR Scores	7%	12%
Demographic Tracked Data	1%	2%
Enrollment Data	<1%	2%

generalized boosted regression model (GBRM; McCaffrey, Ridgeway, & Morral, 2004), an extension of propensity score methods introduced by Rosenbaum and Rubin (1983). A student's propensity scores represent the probability that they participate in the program (i.e., enroll in TCMC) as a function of their observed characteristics. Traditionally, propensity scores have been estimated using logistic regression of treatment status on the set

Table 5
Distribution of Covariates: Contemporaneous

	TCMC		Comparison	
Variable	M	SD	M	SD
Demographic Tracking Number of Years	8.09	2.13	7.97	2.25
Economic Disadvantage History				
Free Proportion of Years	0.49	0.37	0.45	0.38
Free Number of Years	4.20	3.28	3.78	3.38
Reduced Proportion of Years	0.06	0.13	0.07	0.15
Reduced Number of Years	0.54	1.16	0.60	1.27
Not Disadvantaged Proportion of Years	0.32	0.39	0.40	0.42
Not Disadvantaged Number of Years	2.60	3.30	3.15	3.53
Other Disadvantage Proportion of Years	0.12	0.20	0.08	0.17
Other Disadvantage Number of Years	0.85	1.16	0.58	1.01
At Risk History				
At Risk Number of Years	4.38	3.19	3.77	3.32
Giftedness History				
Gifted Number of Years	0.33	1.40	0.84	2.31
Immigrant History				
Immigrant Number of Years	0.14	0.56	0.12	0.53
Special Education History				
Special Education Number of Years	0.26	1.22	0.86	2.40
STAAR Scores				
Algebra 1 End of Course STAAR Scores	3867.09	291.36	3971.51	417.39

of covariates. GBRM differs from standard methods in that it is a non-parametric model, which does not impose strong assumptions about the functional form of the relationship between the propensity score and the covariates. Furthermore, rather than estimating the model by optimizing predictive fit, GBRM directly optimizes a measure of comparability between treated and untreated units. Thus, GBRM is particularly well-suited for estimating propensity scores based on a large set of covariates, as we use here (Lee, Lessler, & Stuart, 2009; McCaffrey et al., 2004).

We estimated propensity scores via GBRM with the twang package (version 1.4-9.5; Ridgeway, McCaffrey, Morral, Griffin, & Burgette, 2016). Following the recommendations of the package authors, we specified number of trees to be 5000, interaction depth of 3, and shrinkage of .01. We specified the estimand to be Average Treatment Effect for the Treated (ATT). We included in the propensity score model all of the covariates listed in Table 2. Due

Table 6
Distribution of Covariates: Previous

	TCMC		Comparison	
Variable	M	SD	M	SD
Demographic Tracking Number of Years	7.26	1.82	7.19	1.93
Economic Disadvantage History				
Free Proportion of Years	0.49	0.37	0.47	0.39
Free Number of Years	3.72	2.93	3.55	3.07
Reduced Proportion of Years	0.06	0.13	0.08	0.16
Reduced Number of Years	0.46	1.04	0.60	1.25
Not Disadvantaged Proportion of Years	0.32	0.39	0.39	0.42
Not Disadvantaged Number of Years	2.33	2.96	2.84	3.17
Other Disadvantage Proportion of Years	0.13	0.20	0.06	0.13
Other Disadvantage Number of Years	0.82	1.09	0.35	0.74
At Risk History				
At Risk Number of Years	3.84	2.91	3.48	3.04
Giftedness History				
Gifted Number of Years	0.29	1.28	0.74	2.11
Immigrant History				
Immigrant Number of Years	0.13	0.53	0.11	0.51
Special Education History				
Special Education Number of Years	0.22	1.10	0.69	2.07
STAAR Scores				
Algebra 1 End of Course STAAR Scores	3867.09	291.36	3915.10	386.91

to small sample size in the TCMC group within each school, we did not estimate propensity scores separately for each school. Rather, we included schools and districts as additional covariates in the propensity score model, which has the effect of allowing the GBRM algorithm to discover school-by-covariate interactions that improve balance.

Based on the propensity score model estimated using GBRM, ATT weights were calculated as

$$w_{ij} = D_{ij} + (1 - D_{ij}) \left(\frac{\hat{p}_{ij}}{1 - \hat{p}_{ij}} \right) \tag{1}$$

Here, w_{ij} is the ATT weight for student i from school j, D_{ij} is an indicator term equal to one if the student was enrolled in TCMC, and $\hat{p}_{ij}$ is the estimated propensity score for the student. Weights were standardized to sum to one within the TCMC and comparison groups.

To estimate the average effect of enrolling in TCMC for students who participated in the course, we regressed each outcome on the covariates, indicators for each school,

Table 7
Math Course Taking History: Contemporaneous

Course	Group	Pass	Fail	Incomplete	Did not take	Missing
8th Grade Math						
Math Grade 8 4 Yrs	TCMC	18%	<2%	<1%	72%	9%
Math Grade 8 4 Yrs	Comparison	13%	<1%	<1%	76%	9%
Math Grade 8 A 4 Yrs	TCMC	62%	<3%	<1%	26%	9%
Math Grade 8 A 4 Yrs	Comparison	48%	<2%	<1%	40%	9%
Algebra I						
Algebra I 4 Yrs	TCMC	<6%	<1%	<1%	86%	9%
Algebra I 4 Yrs	Comparison	20%	<1%	<1%	70%	<10%
Algerba I 3 Yrs	TCMC	80%	7%	<1%	8%	<5%
Algerba I 3 Yrs	Comparison	56%	8%	<1%	31%	<6%
Geometry						
Geometry 3 Yrs	TCMC	<5%	<1%	<1%	89%	5%
Geometry 3 Yrs	Comparison	20%	<1%	<1%	73%	6%
Geometry 2 Yrs	TCMC	81%	7%	<1%	9%	<3%
Geometry 2 Yrs	Comparison	56%	9%	<1%	31%	<4%
Algebra II						
Algebra II 2 Yrs	TCMC	5%	<1%	<1%	91%	<4%
Algebra II 2 Yrs	Comparison	20%	<2%	<1%	75%	4%
Algebra II 1 Yr	TCMC	72%	16%	<1%	10%	<2%
Algebra II 1 Yr	Comparison	39%	5%	<1%	54%	<2%
Pre-Calculus						
Precalculus 1 Yr	TCMC	3%	<1%	<1%	95%	<2%
Precalculus 1 Yr	Comparison	19%	<2%	<1%	78%	2%

Note: The percentages reflect performance in second semester of two semester courses. 8th Grade Math A refers to a year long non-high school course. Yrs or Yr indicates the number of years before 12th grade when the students took the course.

covariate-by-treatment interactions, and school-by-treatment interactions. We used the following analytic model:

$$Y_{ij} = \alpha_j + \beta_j D_{ij} + \boldsymbol{\gamma} X_{ij} + \boldsymbol{\delta} X_{ij} D_{ij} + e_{ij} \tag{2}$$

Here, Y_{ij} is the outcome of student i in school j, α_j is an indicator for the school in which the student is enrolled, D_{ij} is an indicator equal to one if the student was enrolled in TCMC and equal to zero if the student was in the comparison group, and X_{ij} is a set of covariates encoding student background characteristics. The set of covariates included all the variables listed in Table 2. Treatment was allowed to interact with each of the covariates, with $\boldsymbol{\delta}$ representing the vector of interactions. Treatment was also allowed to interact with school,

Table 8
Math Course Taking History: Previous

Course	Group	Pass	Fail	Incomplete	Did not take	Missing
8th Grade Math						
Math Grade 8 4 Yrs	TCMC	18%	<2%	<1%	72%	9%
Math Grade 8 4 Yrs	Comparison	14%	<1%	<1%	76%	<9%
Math Grade 8 A 4 Yrs	TCMC	62%	<3%	<1%	26%	9%
Math Grade 8 A 4 Yrs	Comparison	49%	<2%	<1%	40%	8%
Algebra I						
Algebra I 4 Yrs	TCMC	<6%	<1%	<1%	86%	9%
Algebra I 4 Yrs	Comparison	18%	<1%	<1%	72%	<9%
Algerba I 3 Yrs	TCMC	80%	7%	<1%	8%	<5%
Algerba I 3 Yrs	Comparison	60%	8%	<1%	26%	<6%
Geometry						
Geometry 3 Yrs	TCMC	<5%	<1%	<1%	89%	5%
Geometry 3 Yrs	Comparison	18%	<2%	<1%	75%	6%
Geometry 2 Yrs	TCMC	81%	7%	<1%	9%	<3%
Geometry 2 Yrs	Comparison	54%	10%	<1%	32%	<4%
Algebra II						
Algebra II 2 Yrs	TCMC	5%	<1%	<1%	91%	<4%
Algebra II 2 Yrs	Comparison	19%	<2%	<1%	75%	4%
Algebra II 1 Yr	TCMC	72%	16%	<1%	10%	<2%
Algebra II 1 Yr	Comparison	41%	7%	<1%	50%	<2%
Pre-Calculus						
Precalculus 1 Yr	TCMC	3%	<1%	<1%	95%	<2%
Precalculus 1 Yr	Comparison	17%	<1%	<1%	80%	2%

Note: The percentages reflect performance in second semester of two semester courses. 8th Grade Math A refers to a year long non-high school course. Yrs or Yr indicates the number of years before 12th grade when the students took the course.

thereby allowing that the effects of participating in TCMC could vary by school. Categorical covariates were dummy coded. Each covariate was centered at its unweighted mean in the treated group within each school. Because the covariates were centered in this way, β_j term represents the school-specific ATT and α_j represents the expected school-specific average outcome if the students in the TCMC group had not taken the course.

To estimate an overall average effect for students who took TCMC (β), we calculated a weighted average of the school-specific estimates, with weights based on the size of the TCMC group in each school. Let N_{1j} denote the number of students enrolled in TCMC in school j and N_1 denote the total number of students enrolled in TCMC across schools. We

then calculated the overall average treatment effect as:

$$\beta = \sum_{j=1}^{J} \left(\frac{N_{1j}}{N_1} \right) \beta_j \tag{3}$$

To calculate the overall standard error of the estimate, we first calculated standard errors for the school-specific estimates using HC2-type standard errors (Zeileis, 2004, version 2.3–4), which are robust to heteroskedasticty in the regression errors of Equation (2). Let V_j be the estimated sampling variance of β_j. The variance of the overall average treatment effect was then calculated as:

$$V^{\beta} = \sum_{j=1}^{J} \left(\frac{N_{1j}}{N_1} \right)^2 V_j. \tag{4}$$

We conducted hypothesis tests and calculated 95% confidence intervals for the average effect based on large-sample normal approximations.

Results

Propensity Score Distribution: Common Support

Figures 1 and 2 show the distribution of logit of propensity scores for TCMC and comparison groups for the contemporaneous comparison and previous year comparison. We can see that both the TCMC and comparison groups have students with extreme non-overlapping scores for both comparisons. To satisfy the strong ignorability assumption, we excluded students with extreme propensity scores from our analyses (right). This led to small differences in the set of students included in the TCMC group for the contemporaneous comparison versus the previous year comparison.

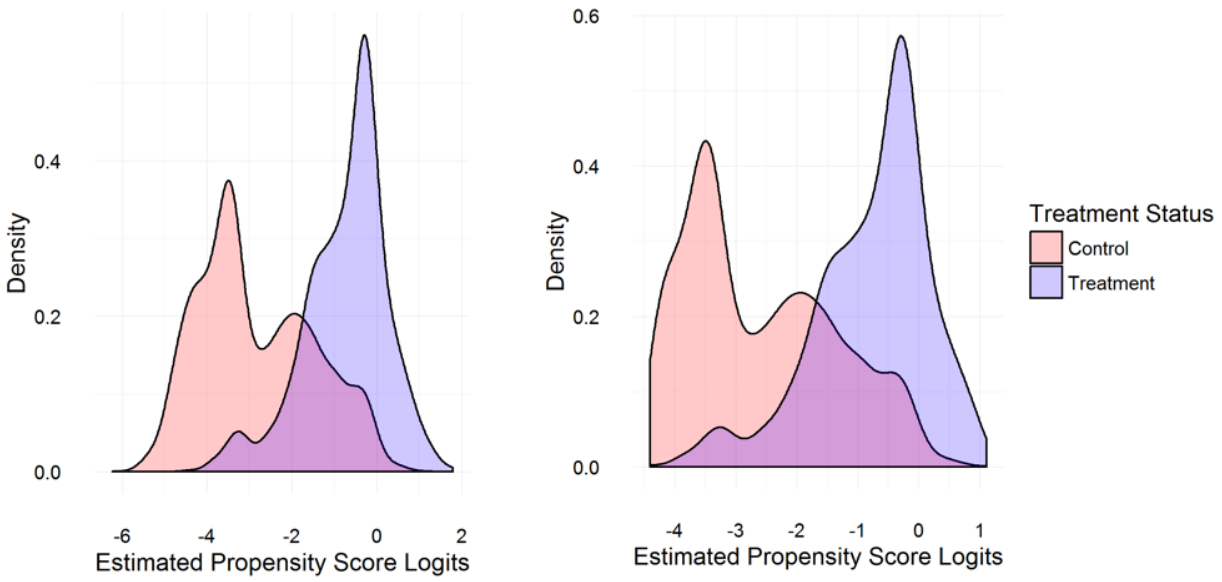

Figure 1. Propensity score support before cutting extreme scores (left) and after cutting extreme scores (right): Contemporaneous comparison

Figure 2. Propensity score support before cutting extreme scores (left) and after cutting extreme scores (right): Previous year comparison

Table 9 reports sample sizes and effective sample sizes in each group for the contemporaneous comparison and the previous-year comparison, after excluding students with extreme propensity scores. In the table, N refers to the unweighted sample size. ESS

Table 9
Sample sizes for contemporaneous and previous-year comparisons

Comparison	Quantity	TCMC	Comparison
Contemporaneous	N	1074	5981
	ESS	1074	2466
Previous	N	940	5459
	ESS	940	1587

refers to the effective sample size, which indicates the number of observations from an unweighted sample that would yield the same level of precision as a weighted sample (Ridgeway et al., 2016).

Covariate Balance

We assessed balance on all of the covariates that were included in the propensity score model. Balance assessments were conducted with the cobalt package (version 1.2.0; Greifer, 2016). Figures 3 and 4 show results of the balance assessment for the contemporaneous and previous year comparison respectively. For continuous covariates, standardized mean differences were calculated, standardized by the standard deviation of the covariate in the TCMC group from the unadjusted sample (i.e., the sample before weights are applied). For binary covariates, raw differences in proportions were calculated. Standardized mean differences and differences in proportions were calculated before (Unadjusted) and after (Adjusted) propensity score weighting. The dashed line in the figures below represent threshold values of -.1 and .1, as recommended by Stuart (2008); mean differences within the dashed lines indicate acceptable levels of imbalance.

After weighting based on propensity scores, mean differences on the covariates were close to zero for all the covariates for both the contemporaneous and previous year comparison groups. In the contemporaneous comparison, covariates that were not fully balanced after propensity score weighting included: giftedness, number and proportion of years of receiving reduced-price lunch, number and proportion of years of being not economically disadvantaged, and Algebra I STAAR scores. These differences, however, were

still very close to zero. In the previous year comparison, covariates with remaining imbalance included: being in special education program, giftedness, receiving reduced-price lunch, and being not economically disadvantaged. These imbalances were within the .1 threshold, but closer to the .1 line than to zero. Covariates with smaller remaining imbalance include: number of years of special education, Hispanic ethnicity, at risk for graduation, proportion of years of being not economically disadvantaged, and Algebra I STAAR scores.

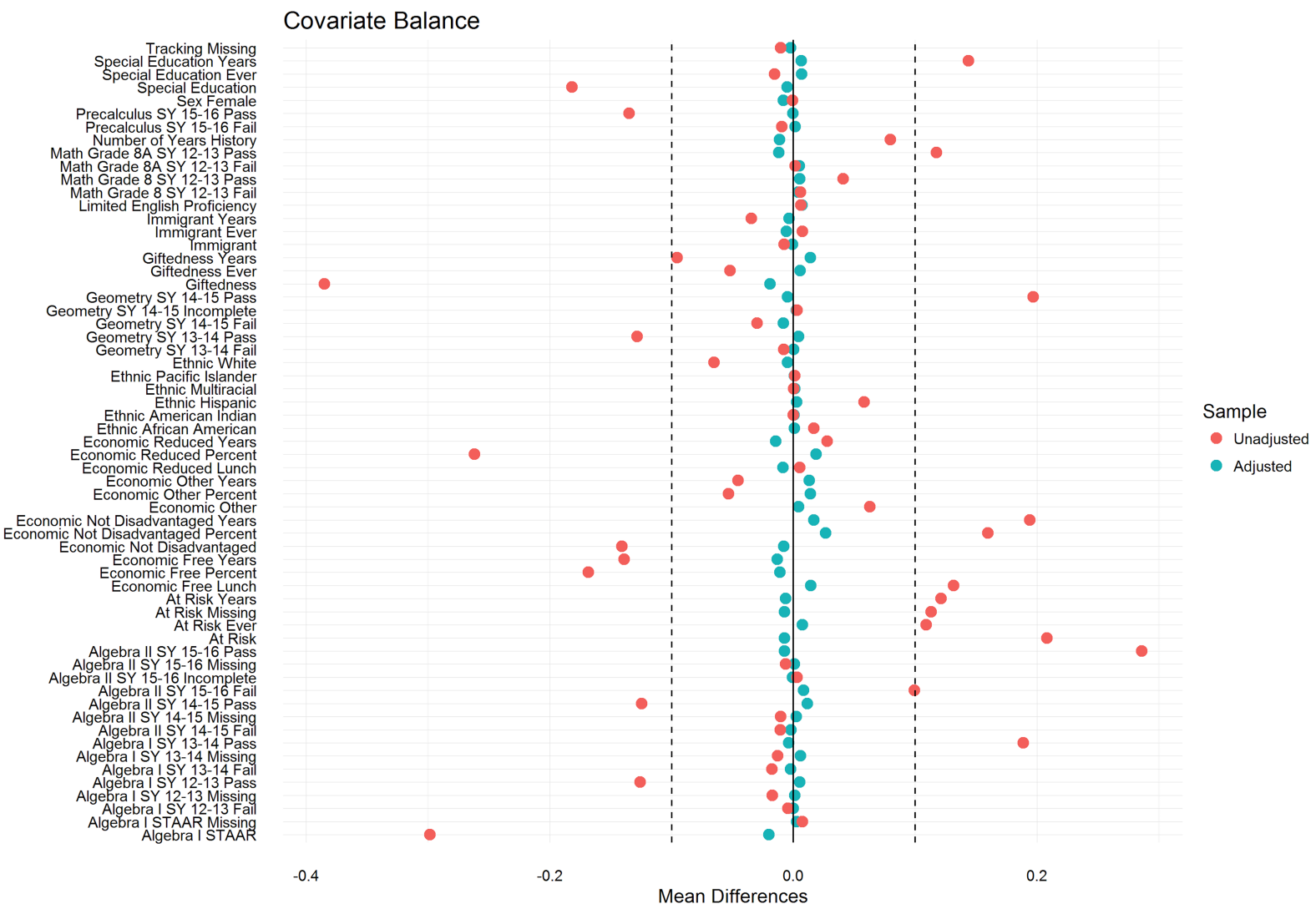

Figure 3. Balance results: Contemporaneous comparison

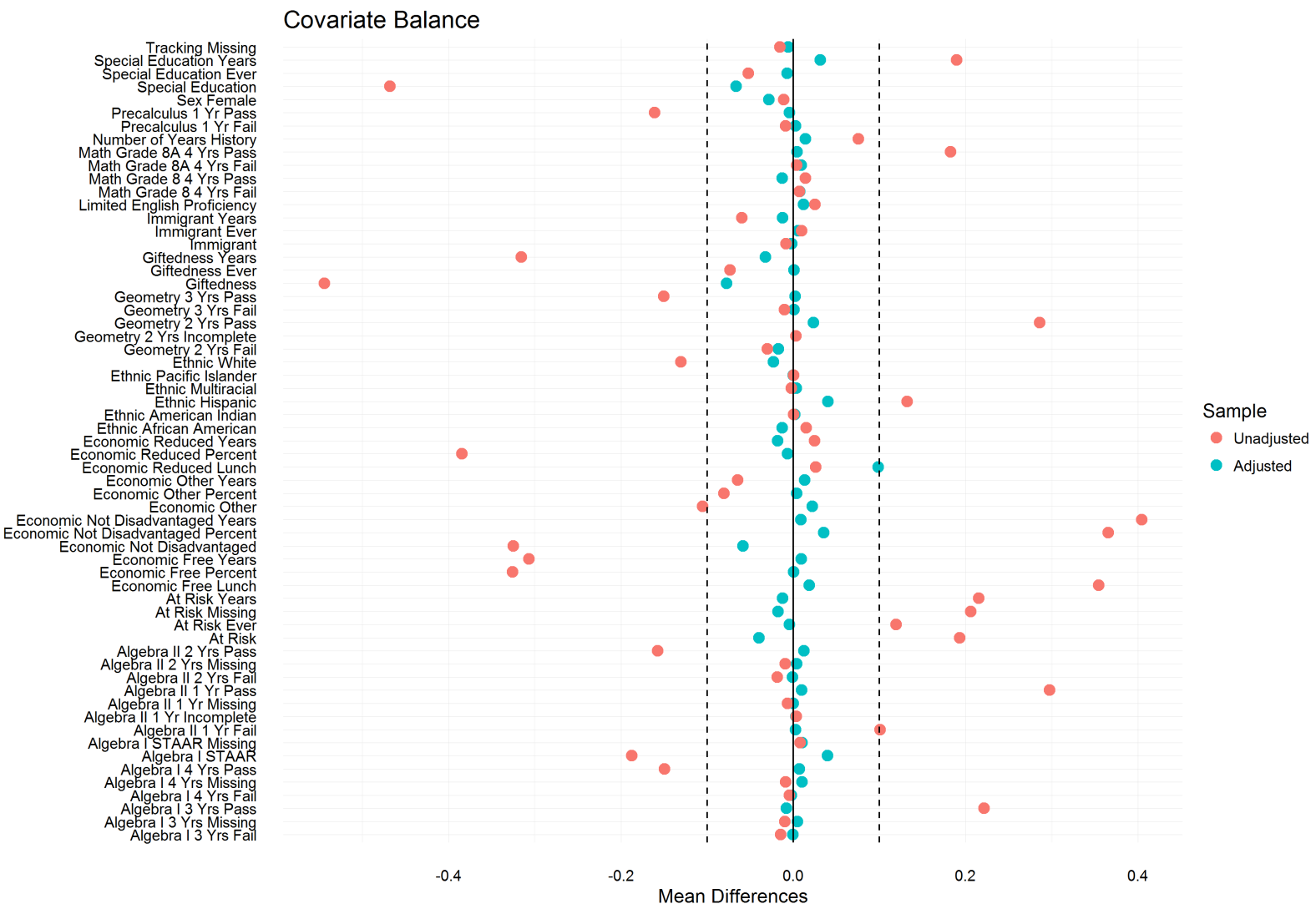

Figure 4. Balance results: Previous year comparison

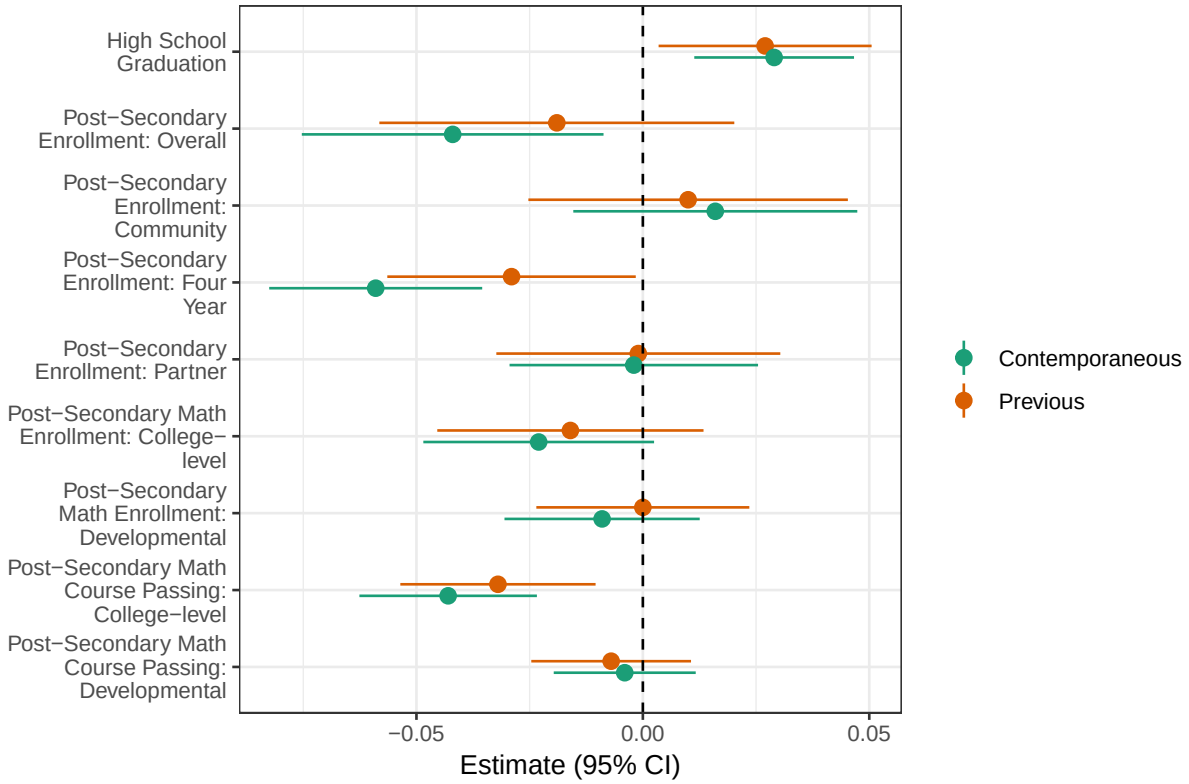

Figure 5. Overall average effects of taking TCMC based on contemporaneous and previous year comparison groups.

Impact Estimates

Figure 5 and Table 10 report impact estimates for the full set of outcomes that we examined. Figure 5 depicts the estimated effects of taking TCMC averaged across schools, along with the 95% confidence interval bands, for the contemporaneous and previous year comparisons. The dashed line on zero indicates no effect; interval bands that cross the dashed line represent estimates that are not statistically distinguishable from zero.

Table 10 presents estimated rates of the outcomes for the TCMC and the two Comparison groups. The rates for the comparison groups can be considered as the baseline rates of the outcomes. The columns labeled "Difference" are the estimated difference between the TCMC group and the comparison groups, represent our estimates of the effects of taking TCMC. Table 10 also reports standard errors (SE) and p-values (p) associated with

Table 10
Estimated average effects of TCMC

Outcome	Group	TCMC	Comparison	Difference	SE	p
High School Graduation						
On-time	Contemporaneous	95.3	92.4	2.9	0.9	0.002
	Previous	95.3	92.6	2.7	1.2	0.020
Post-Secondary Enrollment						
Overall	Contemporaneous	33.1	37.3	-4.2	1.7	0.015
	Previous	34.3	36.1	-1.9	2.0	0.351
Community	Contemporaneous	21.6	20.0	1.6	1.6	0.296
	Previous	21.8	20.8	1.0	1.8	0.572
Four Year	Contemporaneous	11.7	17.6	-5.9	1.2	0.000
	Previous	12.6	15.5	-2.9	1.4	0.033
Partner	Contemporaneous	16.5	16.7	-0.2	1.4	0.871
	Previous	16.6	16.7	-0.1	1.6	0.941
Post-Secondary Math Enrollment						
College-level	Contemporaneous	13.6	15.9	-2.3	1.3	0.085
	Previous	13.9	15.6	-1.6	1.5	0.276
Developmental	Contemporaneous	7.7	8.7	-0.9	1.1	0.377
	Previous	7.6	7.5	0.0	1.2	0.974
Post-Secondary Math Course Passing						
College-level	Contemporaneous	7.2	11.5	-4.3	1.0	0.000
	Previous	7.6	10.7	-3.2	1.1	0.005
Developmental	Contemporaneous	3.7	4.2	-0.4	0.8	0.550
	Previous	3.7	4.4	-0.7	0.9	0.426

the impact estimates. We discuss significance results based on a conventional α value of 0.05. However, we also note cases when significant results become non-significant after applying Bonferroni correction for multiple hypothesis tests, treating all 9 outcomes as a single family.

We found that participating in TCMC resulted in a small, statistically significant increase in high school graduation rates, from a rate of about 92% in the contemporaneous comparison group (92.6% in the previous year comparison group) to a rate of 95% among students who took TCMC.[2]

In contrast to the estimated average effect on high school graduation, we estimated that participating in TCMC resulted in a *reduction* in overall college enrollment. The decrease was larger and statistically significant for the contemporaneous comparison—around

[2] The effect is not statistically distinguishable from zero after accounting for multiple testing.

4 percentage points against a baseline of 37%—whereas the estimate based on the previous year comparison was around 2 percentage points against a baseline of 36%.[3]

The reduction in college enrollment rates appears to have been driven by reductions in enrollment in four-year colleges. With each of the comparison groups, we estimated that course participation resulted in a decrease in four-year college enrollment rates, with an estimated effect of 6 percentage points against a baseline of around 18% in the contemporaneous comparison group and 3 percentage points against a baseline of around 16% in the previous year comparison group.[4] The effect of participating in TCMC on the enrollment rate in community colleges was positive but small and not statistically distinguishable from zero. Similarly, the effect of taking the course on enrollment in partner community colleges was very small and non-significant.

Turning to the primary outcomes of math course enrollment and passing, we estimated that taking TCMC resulted in small decreases in enrollment rates for both college-level and developmental math courses, which are not statistically distinguishable from zero. The magnitude of the effects on college-level math enrollment was slightly smaller for the previous year comparison (-1.6 percentage points) than for the contemporaneous comparison (-2.3 percentage points). Based on our estimates from both comparison groups, taking the course resulted in a significant decrease in passing rate for college-level math courses. For the contemporaneous comparison, the passing rate decreased by around 4 percentage points, from a baseline of 12% in the comparison group. For the previous year comparison, the passing rate decreased by approximately 3 percentage points, from a baseline of 11%. The estimated effects on passing rates for developmental math courses were very small and not statistically distinguishable from zero, based on both contemporaneous and previous year comparisons.

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[3] For the contemporaneous comparison, the effect on college enrollment rates is not distinguishable from zero after accounting for multiple testing.

[4] Accounting for multiple testing, the effect is no longer be significant for the previous year comparison.

Discussion

To evaluate the effects of taking TCMC, we have compared the outcomes of students enrolled in the course during the 2016-17 school year to outcomes of two distinct groups of observationally similar students. Relative to observationally similar students who did not participate in the course, we found that students who took TCMC graduated from high school at slightly higher rates but had lower rates of enrollment in post-secondary education, driven by lower rates of enrollment in 4-year colleges or universities. Further, we found that students who took TCMC were less likely to pass a college-level math course by the end of the first semester after their senior year. The effects were generally larger in magnitude for the contemporaneous comparison than for the previous year comparison.

These findings raise the possibility that placement and participation in TCMC may lead to some unanticipated effects on student trajectories, discouraging some students from pursuing post-secondary education at four-year institutions. The magnitude of these effects is small in absolute terms, yet the overall fraction of students who enter four-year colleges and universities immediately after high school is also small (17.6% of students in the contemporaneous comparison group, 15.5% of students in the previous year comparison group). Given that the focus of the TCM course is to prepare students for post-secondary math with a community college partner, and that the intended outcome of the course is eligibility for college-level math at the partner community college, we would not have anticipated effects on enrollment in four-year colleges. We must, however, be cautious in interpreting the observed differences in enrollment as causal impacts of the program.

We think the most plausible explanation for these observed differences is bias stemming from our inability to fully adjust for initial differences in college readiness, as well as other potential confounders such as college aspirations, at the start of students' senior year. Notably, the magnitude of the estimated effect on four-year college enrollment based on the previous-year comparison is only half the size of the effect estimated from the contemporaneous comparison. If the contemporaneous comparison is more likely than the

previous year comparison to be subject to problems of omitted confounders, the sensitivity of the effect estimate across the two comparison groups suggests that there may be remaining bias at work.

Apart from bias, an alternative explanation for this pattern of findings is that participating in the course may have led students to become more informed about the challenges of remediation, potentially increasing the salience of attaining college readiness. If participation in the course raises students' awareness of the developmental education system—and the hurdles it presents to completing college-level courses—this could have the effect of dampening students' aspirations and discouraging some from pursuing college. A further possibility is that the course increased students' awareness of partner community colleges as the main pathway available to them for pursuing post-secondary education. These possibilities could be probed further in several ways. One is by further examining the information and processes that participating school used to advise students about senior year math courses. A second is by examining variation in the effects of the course across the schools where it is implemented, to determine whether advising practices, aspects of the agreements between high schools and community college partners, or other features moderate the effects of participating in TCM. A third route, which could let us better adjudicate between the alternative explanations that we have described, is to examine rates of student application and acceptance into four-year colleges. We intend to pursue several of these directions in follow-up work.

We must emphasize that there are several important limitations to interpreting these findings as evidence of the causal effects of TCMC. A first, critical limitation of our propensity model and outcome analysis is that we were unable to fully account for students' college readiness status as of the start of their senior year. Schools determine college readiness based on one or more of several possible pieces of data, including performance on end-of-course exams, SAT or ACT scores, and performance on the Texas Success Initiative Assessment (TSIA). We have controlled for Algebra I end-of-course STAAR scores as well as

detailed course-taking patterns through students' junior year of high school, but we were unable to access SAT, ACT, or TSIA scores for the study sample. As a result, it may be that some students in the comparison groups had already achieved college-readiness status by the start of their senior year, and this status may in turn have increased the likelihood that they pursue post-secondary education, including post-secondary math coursework.

Across outcomes, estimated effects tended to be smaller in magnitude in the previous year comparison than in the contemporaneous comparison. This pattern of estimates is consistent with the possibility that college-readiness status may be confounding the effect estimates. Relative to the contemporaneous comparison groups, we would expect that a smaller proportion of students in the previous year comparison group would have attained college readiness status by the start of their senior year. Thus, college readiness may be a weaker confounder in the previous year comparison group, leading to relatively smaller impact estimates.

A second limitation of our findings is that we have assessed post-secondary course-taking and course passage outcomes only for the first semester following students' senior year in high school. Students are not obligated to enroll in math courses during their first semester of college, and the college preparatory course requirements of HB5 are structured to allow exemption from developmental coursework for up to two years following high school graduation. As further post-secondary data become available, we will be able to assess impacts over a longer time-frame that is more closely aligned with the aims of TCMC.

A third limitation is that, because our analysis is limited to administrative data from TEA and THECB, we were unable to assess fidelity of implementation in the high schools where TCMC was offered. If fidelity was low, then the small impact estimates that we observed here might have less to do with the TCMC curriculum than with the training, resources, advising processes, and implementation strategy used in the initial year of the program. A further limitation is that all of the participating schools were implementing the curriculum for the first time. Effective instruction using novel curricular materials might

require sustained use over more than a single year.

Finally, our analysis was limited to estimating the effects of taking TCMC for the set of students who enrolled in the course during the 2016-17 school year, who were drawn from 17 schools in 8 districts. We have not sought to generalize our findings beyond this sample, nor have we examined variability in the effects across participating schools. During the 2016-17 school year, TCMC did not count towards graduation requirements, which likely affected how schools advised students about taking the course. For the 2017-18 school year, TCMC and other college preparatory math courses became credit-bearing courses that counted towards state graduation requirements. Consequently, cohorts of students who enrolled in TCMC during 2017-18 (and future cohorts) might differ from the sample that we have examined, and the effect of the program for these cohorts might differ from the effect of the program on the sample we have examined.

In on-going work, we plan to examine the effects of taking TCMC for an expanded cohort of students, who enrolled in the course during the 2017-18 school year. This further evaluation will allow us to address several of the limitations of our initial findings. The new cohort will include students from thirty or more districts, including 13 schools from 7 districts who offered TCMC for a second year. The sample will thus allow us to assess whether effects change as teachers learn to use the curriculum. Furthermore, the expanded 2017-18 cohort will provide a better basis for assessing variability in the effects of TCMC across participating schools. Finally, we will update our analysis of the 2016-17 cohort by estimating impacts on course enrollment and passing rates beyond the first semester of college. As these further data become available, we will be able to provide a more complete picture of the effects of TCMC for students who enrolled in the course.

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