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Supporting the Early Academic Momentum of Community College Students: Examining the Impact of Transitional Math Course Taken in High School

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Introduction

Research shows that early academic momentum, including taking and passing key gateway courses during the first year of college, is associated with higher rates of degree completion (Attewell, Heil, & Reisel, 2012; Wang, 2017). Yet more than two-thirds of community college students are required to take at least one developmental education[1] (DevEd) course before enrolling in gateway math and English, and many never complete these courses (Chen, 2016). To explain this, some point to inadequate academic preparation at the secondary level (Bettinger et al., 2013; Scott-Clayton, 2021), while others focus on course placement policies that limit direct access to college-level course work (Belfield & Crosta, 2012). The nation's history of racial and economic segregation, along with unequal funding of secondary and postsecondary education, means that these barriers disproportionately affect Black and Latino students, as well as students from low-income households, thereby widening the gap in degree attainment.

To address the main barriers hindering early academic momentum, several states have implemented transitional courses in an effort to bridge the learning gap between high school and college expectations. These courses, taken during high school, aim to build the academic proficiencies necessary for students at risk of being placed into developmental courses, thereby enhancing their readiness for college-level math and English classes. Students who meet specific performance metrics in these transitional courses are then directly placed into credit-bearing gateway courses upon enrollment in college, facilitating their progress towards degree completion.

[1] Developmental education, also referred to as remedial education, refers to “courses [that are] designed to develop reading, writing, or math skills of students who are deemed underprepared for college-level courses” (Ganga et al., 2018). For the purposes of our work, we avoid the term remedial.

In this study, we present results from a rigorous examination of a transitional math (TM) program implemented in Chicago Public Schools (CPS). As part of the Postsecondary and Workforce Readiness Act 2016, the Illinois TM program is an important component of a comprehensive model that supports a smooth transition from secondary education to postsecondary education and the workforce. Its objective is to bolster college readiness for underprepared high-school seniors before graduation and enable them to receive guaranteed placement into credit-bearing math courses at all Illinois community colleges and accepting universities. To achieve this, the program's instruction emphasizes real-world applications using contextualized content to promote problem-solving skills, helping students meet their college and career goals.

This study aims to evaluate the effects of the Illinois TM policy on several short-term high school and college outcomes. We utilize the math PSAT and SAT cutoff scores, which serve as one of the benchmarks to assess projected college-level math readiness and inform placement into the TM coursework, to isolate the effect of the TM course. In particular, students with PSAT and SAT math scores of 530 and below are more likely to enroll in transitional math than those with scores above 530. Because the same 530 threshold is also used to determine dual credit math and DevEd placement at the City Colleges of Chicago (CCC), we employ a difference-in-regression discontinuity design to isolate the effect of TM from these confounding policies.

Our results show no evidence that an offer of TM improves students' high school general and math credit accumulation, overall GPA or math GPA, or on-time graduation. Regarding college outcomes, our findings suggest limited evidence of significant impacts of TM on college enrollment or enrollment in math courses at CCC. Additionally, we observed no significant increase in the likelihood of students taking and successfully passing gateway math courses. These null results may be partially driven by low participation rates and imperfect record transfer for students who completed TM. It's also worth noting that our study period coincides with the COVID-19 pandemic, during which many TM courses were conducted online. The pandemic had substantial consequences across secondary and post-secondary education nationwide that could have affected the efficacy of TM coursework and made cross-system collaboration more difficult. However, our analytic sample indicates that the gateway math pass rate is slightly higher for students who passed TM, enrolled in CCC, and took gateway math compared to the average gateway pass rate for non-TM takers. This suggests that students who access gateway coursework through TM can be successful, although an increase in the number of students accessing gateway course work through this pathway would be needed for the program to be effective overall.

In the next section, we situate this study in the broader literature and the policy landscape by summarizing key features of similar college-readiness programs adopted by several states and the efficacies of these programs. We then describe the Illinois Transitional Math program in detail. Next, we provide an overview of the data, followed by an outline of the identification strategy and the empirical approach. Finally, we present our findings and discuss their policy implications.

Literature Review

Early academic momentum is typically defined by the number of credit-bearing courses students take and pass during their first year of college. Adelman (1999; 2006) was the first to highlight the importance of early momentum, not only in accruing the number of requisite credits to graduate "on time" but also in setting the stage for future academic success. He identified four main components of academic momentum that lead to degree completion: pre-collegiate course taking, immediate enrollment into a higher education institution, high credit attainment during the first academic year, and enrollment in summer courses. Subsequent work has confirmed that this early momentum is a critical predictor of degree attainment at both four- and two-year colleges (Attewell et al., 2012; Wang, 2017; Clovis & Chang, 2021).

Two primary explanations are offered as barriers to establishing early academic momentum and thus degree attainment: academic preparedness and barriers to direct enrollment into college-level courses. From an early age, students from low-income backgrounds face systemic barriers that often limit their opportunity to prepare for academic success in college. Key differences in school quality and educational experiences affect their likelihood of earning a college degree in myriad ways. For example, as a result of racial and economic segregation, students from wealthier backgrounds often attend well-resourced schools with higher expenditures per pupil, smaller student-to-counselor ratios, and a rich array of courses designed to prepare students for the academic demands of college, giving them a strong advantage (Charles, 2003; Kozol, 1991; Lareau & Goyette, 2014; Vigdor & Ludwig, 2007). Without access to these resources to help build an academic foundation for college success, many students from low-income backgrounds arrive on campus underprepared for the rigors of college coursework (Duncan & Murnane, 2011).

Many educators and researchers worry that the design of DevEd can also act as a barrier to early academic momentum. DevEd is intended as a tool to support students in becoming prepared for college-level coursework (Cullinan et al., 2018). It takes many forms, including co-requisites where students simultaneously enroll in college-level math and English with some support, exclusively developmental classes that must be completed before taking college-level classes, and foundational studies courses that are taken before developmental classes.

The importance of appropriate placement in the DevEd sequence cannot be understated, as these classes can impact students' likelihood of securing a degree in important ways. For example, if students are placed into advanced coursework before they are ready, they may become discouraged, earn poor grades, and choose to unenroll (Burdman, 2012). On the other hand, because DevEd courses do not earn degree credits but still incur tuition and must be completed to gain access to gateway courses, students who are unnecessarily placed into the developmental sequence experience prolonged time to degree and higher costs, both of which may also lead to unenrolling (Lichtenberger & Wilson, 2019a & b).

Historically, to identify the appropriate level of coursework, schools use standardized tests, such as the SAT/ACT, along with specialized developmental assessments. Research, however, suggests that one-time assessments are not the best predictor of students' success in college-level coursework, especially for students from diverse backgrounds, whose skills, abilities, and potential contributions are not always accurately measured by standardized tests (Bahr, 2016; Bracco et al., 2014). Importantly, the evidence suggests that these assessments tend to under place rather than over place students. Put differently, students may lose access to courses in which they may have been successful (Belfield & Crosta, 2012; Scott-Clayton, 2021).

High School Math Developmental Coursework Programs

Recognizing these limitations, educators and policymakers have sought alternative strategies to better prepare students for higher education. To ensure that students arrive on college campuses ready to succeed, several states have begun to offer developmental coursework while students are still in high school. Although these programs vary from state to state, they typically include screening students for college readiness (often using the same assessment employed for DevEd course placement), providing access to developmental coursework during high school, and administering an exit assessment. Passing this exit assessment can sometimes ensure students' direct placement into gateway English and math courses (Fay et al., 2017). The idea behind these programs is that by aligning the high school course content with the skills needed to succeed in gateway courses, transition interventions can save both students and the public time and money while fostering early academic momentum.

As shown in Table 1, states have differed in how they implement transition interventions, and studies of their effectiveness have found similarly mixed results. One of the most consequential differences in program design seems to be whether the curriculum is focused on test preparation or math skill building. Even when looking at the proximal outcome of passing the placement test for entry into gateway courses, programs focused on skill building tend to see larger effects (Pheatt et al., 2016; Mokher et al., 2018; Kane et al., 2019; Xu et al., 2021).

Likewise, what a student would be doing if they were not enrolled in a transition intervention matters. In the case of the West Virginia, Florida, and Tennessee programs, the transitional math instruction supplanted other (frequently more rigorous) math instruction (Pheatt et al., 2016; Mokher et al., 2018; Kane et al., 2019), and the impact of these interventions was more muted. In contrast, in the Kentucky program, which had the most substantive effects across all three outcomes of interest (placing into, taking, and passing gateway math), a substantial share of program participants received programming outside of the regular school day, resulting in an average of 100 minutes of additional instruction a week (Xu et al., 2021). Not surprisingly, the program that required students to be automatically placed into gateway coursework upon successful course completion (Tennessee SAILS) found the largest effects on placement into college-level coursework.

Table 1. *Summary of Existing Literature on Math Transition Interventions*

Program	Automatic Exemption	Curricular Focus	Additional Math Instruction	Findings
West Virginia Transition Mathematics (Pheatt et al., 20216)	No	Test Prep	No	Null effects on placement into college-level coursework and negative effects on gateway course performance
Florida FCCRI (Mokher et al., 2018	No	Test Prep	No	Null effects of placement, enrollment, and performance in gateway courses
Tennessee SAILS (Kane et al., 2019)	Yes	Skill Building (self-paced)	No	Large increases in college-level placement, small gains in gateway enrollment, and null effects on passing gateway courses
Kentucky TI (Xu et al., 2021)	No	Skill Building	Yes	Substantial increases in placement, enrollment, and performance in gateway courses
Illinois Transitional Math (this study)	Yes	Skill Building	Potentially	Focus of current study

Illinois Transitional Math Program

Building on these varied approaches and outcomes, Illinois introduced its own initiative in 2016: the TM program introduced through the Postsecondary and Workforce Readiness Act. TM is an alternative math class for high school seniors who intend to go to college but have not yet tested as college-ready in math. The course content and assessments were developed by teacher workgroups, including high school, community college, and university math instructors. The state created competencies for three TM pathways: STEM, Quantitative Literacy and Statistics, and Technical Math. Each pathway develops students' conceptual and problem-solving skills to increase college readiness. While each pathway is designed to meet specific student needs and goals, successfully completing any pathway will allow students to directly enroll in college-level, credit-bearing courses at all Illinois community colleges and accepting universities in the state (Illinois State Board of Education, 2018).

To ensure the successful implementation of the TM program, high school math teachers receive extensive training in the curriculum and are provided with scope and sequence charts, sample lessons, and assessments. TM courses are reviewed regularly by a panel representing the Illinois State Board of Education to ensure consistency with these standards. The Illinois Community College Board, and the Illinois Board of Higher Education. If students earn a C or higher in an approved TM class, they are placed directly into college-level math, an agreement honored by all two-year colleges in Illinois – including CCC – and, increasingly, some four-year universities.

In alignment with the statewide initiative, CPS piloted TM in five high schools in the 2017 – 2018 school year. Subsequently, the program was expanded to 10 schools in the 2018 – 2019 school year, 35 schools in 2020 – 2021, and 50 schools in 2020 – 2021. Schools were given discretion in determining which students to encourage to participate in TM. Given the program's focus on supporting students who do not initially qualify for credit-bearing math courses, enrollment tends to be higher among students with math PSAT and SAT scores of 530 or lower.

This threshold also corresponds to the score CCC employs for automatic placement into DevEd courses and dual math courses.

We leverage the staggered roll-out within CPS high schools to estimate the effects of TM by comparing outcomes between students just above and below the 530-cutoff score. Given that the threshold serves a dual purpose of signifying college readiness in math and determining TM eligibility, we compare the difference between students above and below the cut score in high schools where TM was implemented in a given school year to the same difference in CPS high schools that were not implementing TM during the same period. This difference-in-regression discontinuity approach allows us to isolate the impact of TM from the two confounding programs offered to students based upon their college readiness in math, namely DevEd for students who matriculate at CCC and the opportunity to enroll in dual credit math courses while still in high school.

Analytic Approach

Data Sources

We draw on administrative data from the Chicago Public School and the City Colleges of Chicago to measure the effect of transitional math on several high school and college outcomes. The CPS data contain information on student demographics and academic characteristics including overall GPA and PSAT or SAT scores. In addition, CPS data allows us to track all the courses students have taken along with their course grades in 11th and 12th grades. Using the course-level dataset, we combine the average course credit per class (0.5 credit), the total credits attempted, and the final grade for each math course to calculate math yearly GPA. We also leverage this dataset to identify enrollment in TM and other types of math courses including IB/AP, dual credits, and other regular non-TM courses.

Data on college enrollment come from the National Student Clearinghouse (NSC). NSC data provides enrollment data for over 90 percent of institutions of higher education in the United States and over 99 percent of four-year public universities (Dynarski et al., 2015). CPS contracts with NSC to receive data on all district graduates. The NSC data do not have information on enrollment terms but provide details on enrollment start and end dates. We examine the distribution of the enrollment start dates, with some consideration of end dates, to construct term boundaries. For observations that fall close to the boundaries, we consult with the institutions' academic calendars and made term adjustments as needed. We define a student as having enrolled in a given year if they appear to have ever enrolled in one of the three terms during that year. Our analysis focused on college enrollment within 18 months of high school graduation to align with TM guaranteed placement period.

The CCC administrative data contains detailed information at both class and term levels. From the datasets, we track enrollment and calculate the total number of credits attempted and credits earned for a variety of courses each semester. Specifically, we examine what courses in the DevEd math sequence students enroll in and how they do in those courses. By studying the data on credits earned and final grades, we can ascertain whether a student has enrolled and passed a gateway math course within 18 months of completing their TM courses. We then compare the list of shared student identification numbers between CPS and CCC to identify those who attend both institutions using a CPS-CCC student ID crosswalk. Altogether, the merged student records enable us to track student progress from their senior year in high school through their postsecondary periods to measure college enrollment and subsequently track student course-level data at CCC within 18 months after completing TM if they enrolled in CCC.

Although TM was first introduced in five high schools in 2018, the course was only offered in the spring semester, as course competencies, policies, and supports (including the competency rubrics) were concurrently being finalized. As such, we exclude 2018 data from the analytic sample. Furthermore, our data suggests that about 10 percent of students who took TM were in 11th grade, and less than 1 percent were in 10th grade. Our analysis focuses on 12th grade students as that is the intended audience for the TM program. Our analytic sample includes 49,866 seniors in the 2019-2021 academic years. We selected students based on several criteria, namely: (1) having either PSAT or SAT scores recorded in the prior year; (2) not having taken TM in the prior school year; (3) attending at least one day in a given school year; and (4) not enrolling in a charter, contract, or special education school.[2] We categorize a school as a TM school in a given school year if TM was offered to seniors in that school year. Non-TM schools are defined as schools that do not offer TM throughout the whole period of study. We only include transferred TM-school students in our analytic sample if the annualized school (the school in which students enroll most of an academic year) is the same as the TM school. Imposing these restrictions results in a sample of 16,462 seniors from 50 TM schools and 33,404 seniors from 149 non-TM schools from 2019 to 2021.

Table 2 shows the summary statistics for the full sample of students who attended TM and non-TM schools. Students who attend TM schools are less likely to be white (8 percent compared to 14.9 percent) and more likely to be Hispanic (57.4 percent compared to 44.5 percent). They are also more likely to have free and reduced lunch status than those who attend non-TM schools. In terms of academic performance, TM school students score lower on the SAT/PSAT. Specifically, 80.7 percent of TM school students score below the 530 threshold,

[2] TM was not offered in these high school types during the period of study. Therefore, we excluded them from the non-TM school lists to construct a more comparable sample.

while this figure is only 56.2 percent among non-TM school students. On average, TM school students have 0.2-points lower overall GPA and math GPA compared to non-TM-school students.

Table 2. *Summary Statistics for Students in TM and Non-TM schools*

	TM school	**Non-TM school**
Female	0.513	0.542
Male	0.487	0.458
Age	17.603	17.591
White	0.080	0.149
Asian	0.049	0.066
Black	0.282	0.316
Hispanic	0.574	0.445
Other races	0.016	0.021
Grade repeater, prior year	0.021	0.027
Free/reduced lunch, prior year	0.831	0.715
Special education, prior year	0.128	0.093
ESL, prior year	0.117	0.065
Homeless, prior year	0.030	0.038
504, prior year	0.055	0.066
Math score (SAT/PSAT), prior year	448	510
Below 530 threshold, prior year	0.807	0.562
GPA overall, prior year	2.534	2.785
GPA math, prior year	2.377	2.584
Credits attempted, prior year	7.022	6.990
Credits earned, prior year	6.746	6.743
Math credits attempted, prior year	1.025	1.044
Math credits earned, prior year	0.970	0.994
Observations	**13,994**	**29,015**

Empirical Model

To estimate the effects of TM on various high school and college outcomes, we leveraged one of the eligibility criteria used to determine if an 11th grade student is projected to be ready for college-level math. Specifically, students scoring below 530 on Math SAT or PSAT are more likely to be recommended to take TM. However, this feature of the program is not suitable for a simple regression-discontinuity design because the 530 threshold is also used to determine access to two other related programs, namely, (1) students who are above the cutoff are qualified to take CCC math courses while in high school and receive both high school and college credit (Dual

Credit Math), and (2) students who enroll in CCC and who are below the cutoff are required to take a math placement test (the ALEKS) and enroll in Math DevEd courses unless they score a 46 or higher on the ALEKS assessment. To isolate the effect of the TM program from the two confounding policies, we use a difference-in-regression discontinuity design by estimating the following model where the observed outcome is expressed as:

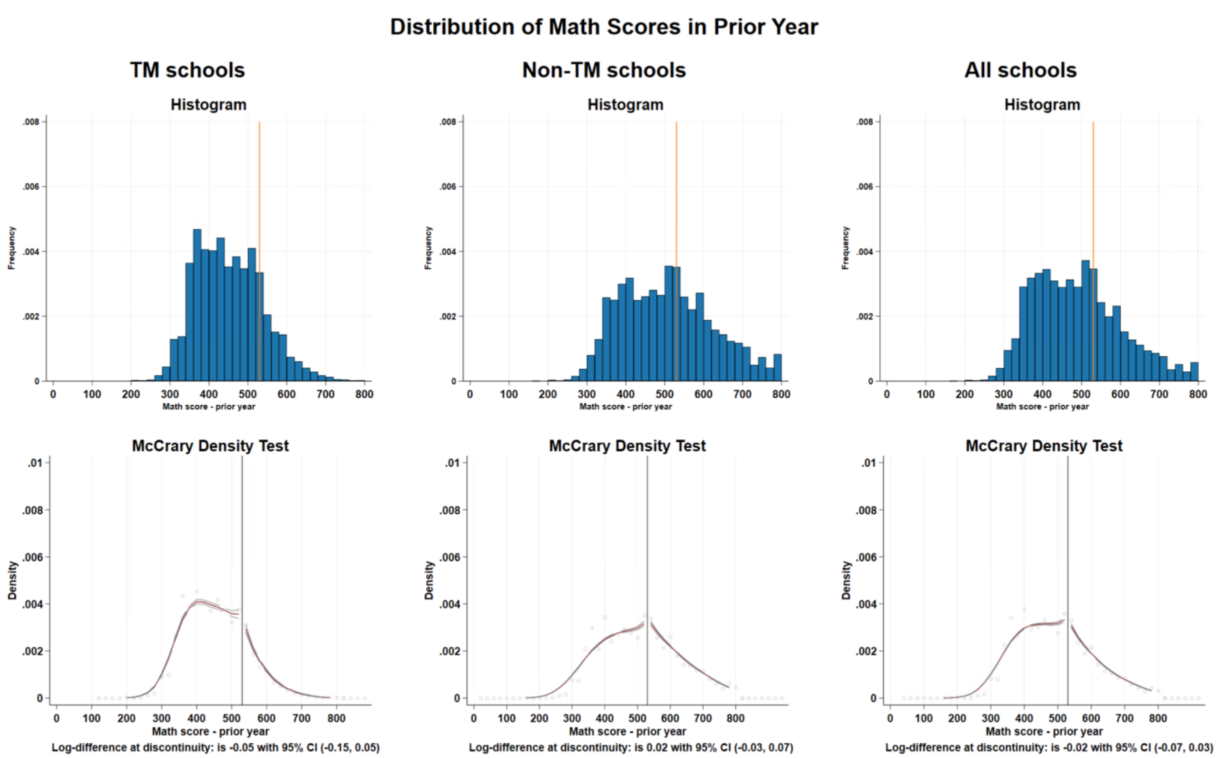
$$Y_{isct} = \gamma_0 + \gamma_1 B_{isc} + \gamma_2 f(S_{isc}) + \gamma_3 TMS_{st} + \gamma_4 B_{isc} f(S_{isc}) + \gamma_5 TMS_{st} f(S_{isc}) + \gamma_6 TMS_{st} B_{isc} + \gamma_7 D_{isc} TMS_{st} f(S_{isc}) + X_i + \mu_{sc} + \epsilon_{isc} \quad (1)$$

In this model, Y_{isct} represents the outcome of interest for a student *i* in cohort *c* who attends school *s* in time *t*. B_{isc} is an indicator equaling to 1 if student *i* scores below 530 on the math SAT the prior year. $f(S_{ic})$ is the functional form of the normalized math PSAT/SAT score centered at 0 in prior year. TMS_{sc} is an indicator equaling to 1 if the student attends a TM school (as defined above) at time *t*, X_i represents a vector of student *i*'s demographic and academic characteristics. μ_s are school fixed effects and θ_c are cohort fixed effects. The inclusion of the fixed effects accounts for any unobserved mean differences across schools and across cohorts. ϵ_{isc} is the idiosyncratic error term and is clustered at school level. The coefficient of interest, γ_6, represents the intent-to-treat effects of TM program on high school and college outcomes.

To assess the robustness of our results, we use a 50-, 100-, and 150-point bandwidth and model the running variable using both a linear and quadratic functional form. We present results associated with the 100-point bandwidth and a quadratic fit, our preferred specification below. This specification was selected based on visual inspection to optimize the tradeoff between bias and precision. A 50-point bandwidth would result in a more comparable sample but contain only five data points on each side of the cutoff, whereas a 150-point bandwidth would result in a less comparable sample. Results from the alternative specifications can be found in the main tables for comparison purposes.

Similar to the RDD model, the identification assumption for the difference in regression discontinuity design is that students on either side of the cutoff of 530 are similar and that there is no manipulation around the cutoff. Since the 530 threshold is publicly available, students might exert just enough effort to score above 530 to avoid taking TM. However, the probability of such manipulation is low, as it would require students to have access to the point distribution and adjust their answers accordingly. Alternatively, students with access to the cutoff may be more likely to retake the assessment if they are just below the 530 threshold. Since 99 percent of the students took the PSAT/SAT for the first time during the study period, retaking is not a concern. Furthermore, the math section of the PSAT/SAT exam is not evaluated by the student's teachers, proctors, school counselors, making it plausible that whether a student scores just above or below the cutoff is essentially random. To empirically assess this identification assumption, we present the results of the McCrary density test for math PSAT/SAT score in Figure 1.

Figure 1. *McCrary Density Test*



This figure illustrates the density of the running variable (math PSAT/SAT scores) for students in TM schools, non-TM schools, and all schools in our sample. We observed continuity in density of math scores in the prior year around the cutoff in the three histograms. We also provided a formal estimate of the discontinuity in the density function of the running variable. The estimated log differences in discontinuity are statistically insignificant for all three samples, indicating that we do not find evidence to suggest manipulation at the cutoff.

In addition, the placement policies of TM and the two above-mentioned confounding policies are consistent over the periods of study. We find no evidence that there are any changes in the implementation of dual credit math and DevEd policies around the study period. To further explore the possibility of selection around the cutoff, we examine the continuity of the observable baseline characteristics by estimating equation 1 using observable student characteristics as the dependent variable. Table 3 presents the results of the coefficient of interest for each observable student characteristic using a quadratic model for three different bandwidths. Across the three bandwidth selections, we only found significant differences in two out of nineteen specifications. Within our preferred bandwidth choice of 100, we found significant differences for female, overall GPA in the prior year, and math GPA in the prior year at 5% level. Appendix figure 1 plots the means of the three variables around the cutoff for both TM and non-TM schools. The results show that the jump around the cutoffs is driven by functional fit, except for overall GPA and math GPA in the prior year for TM schools. To account for these differences, we run a version of the model excluding these covariates as controls and find the study results are consistent (Appendix Tables 2, 3, and 4).

Table 3: *Covariate Smoothness Test Around the Discontinuity Threshold*

	BW 100 (preferred)	**BW 50**	**BW 150**
Female	-0.081**	-0.024	-0.061*
	(0.038)	(0.068)	(0.031)
Age	0.042	0.036	0.027
	(0.030)	(0.052)	(0.026)
White	-0.036	0.016	-0.042**
	(0.023)	(0.041)	(0.018)
Asian	-0.013	-0.085***	-0.001
	(0.017)	(0.030)	(0.013)
Black	0.030	0.049	0.005
	(0.024)	(0.043)	(0.019)
Hispanic	0.011	0.007	0.043*
	(0.031)	(0.057)	(0.025)
Other races	0.010	0.013	-0.005
	(0.010)	(0.019)	(0.008)
Grade repeater, prior year	0.004	-0.008	-0.006
	(0.010)	(0.016)	(0.009)
Free/reduced lunch, prior year	0.030	0.111**	-0.009
	(0.031)	(0.056)	(0.024)
Special education, prior year	0.004	0.022	0.001
	(0.015)	(0.021)	(0.015)
ESL, prior year	-0.009	-0.028	-0.005
	(0.015)	(0.024)	(0.014)
Homeless, prior year	-0.009	0.017	-0.012
	(0.011)	(0.017)	(0.010)
504 status, prior year	-0.022	-0.058	-0.021
	(0.019)	(0.035)	(0.015)
GPA overall year, prior year	-0.125**	-0.215**	-0.113***
	(0.053)	(0.095)	(0.044)
GPA Math, prior year	-0.176**	-0.354***	-0.115*
	(0.075)	(0.134)	(0.061)
Credits attempted, prior year	0.023	0.066	0.021
	(0.033)	(0.057)	(0.029)
Credits earned, prior year	-0.011	-0.094	-0.028
	(0.055)	(0.094)	(0.048)
Math credits attempted, prior year	0.003	-0.010	0.005
	(0.014)	(0.024)	(0.012)
Math credits earned, prior year	-0.002	-0.047	-0.008
	(0.018)	(0.031)	(0.015)
Observations	**25,581**	**14,250**	**35,538**

Note: All models use a quadratic fit and control for school fixed effects and cohort fixed effects.

TM Take-Up Probability

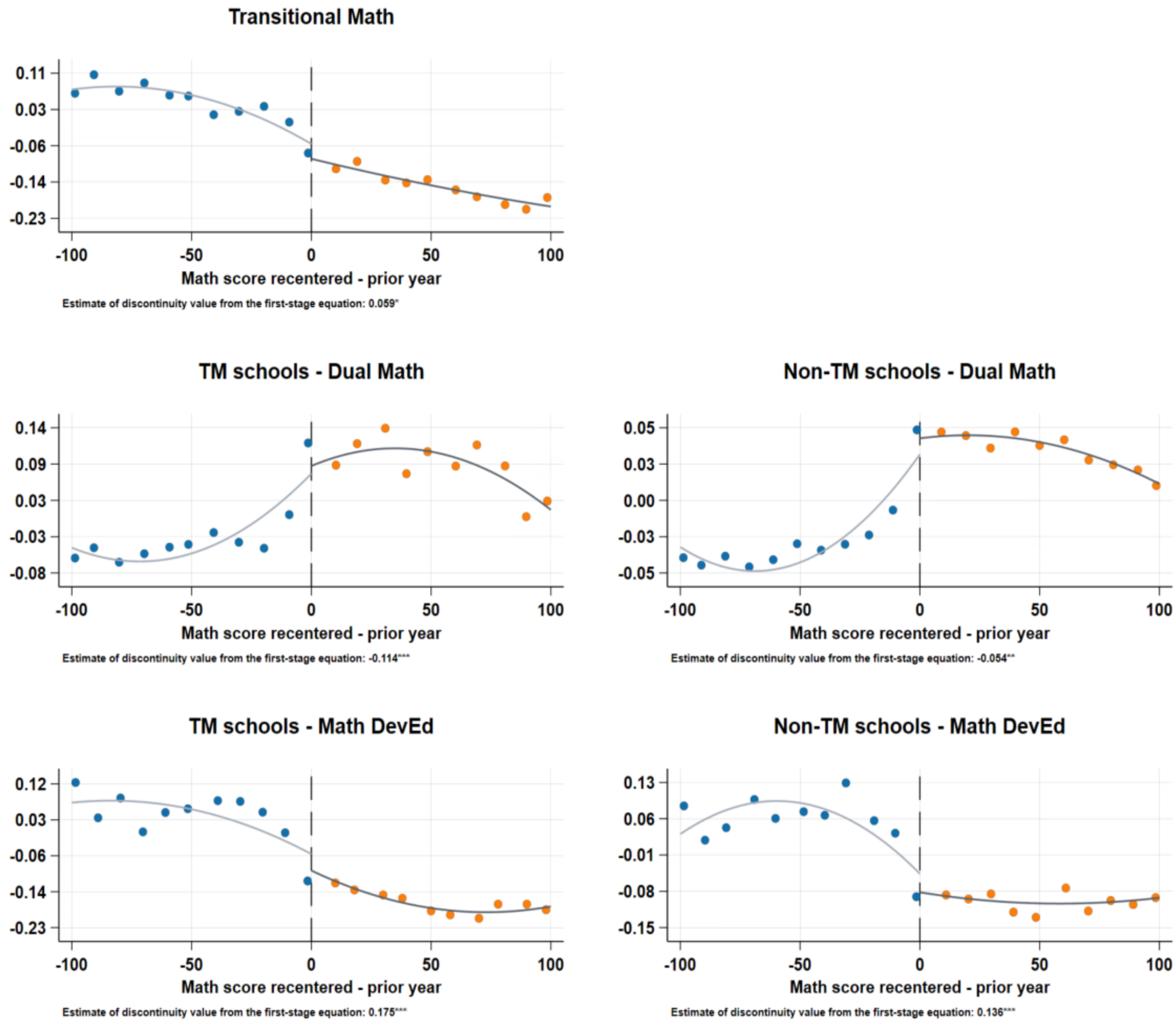
We first assess the feasibility of the Difference-in-Discontinuity approach by examining the likelihood of taking up TM among TM-school students who scored below 530. One would expect a significant decrease in the probability of taking TM as moving from the left side to the right side of the 530 cutoff. Since this cutoff also determines eligibility for dual credit math courses and DevEd placement at CCC, we would also expect a significant increase in the probability of enrolling in dual-math credit courses and a decrease in the probability of enrolling in DevEd class around the cutoff for both TM-school and non-TM school students. To test these hypotheses, we estimate the following equation separately for dual math enrollment, math DevEd enrollment for TM and non-TM schools. For TM school, we also examined TM take-up probability:

$$Y_{isct} = \gamma_0 + \gamma_1 B_{isc} + \gamma_2 f(S_{isc}) + \gamma_3 B_{isc} f(S_{isc}) + X_i + \mu_s + \theta_c + \epsilon_{isc} \quad (2)$$

where Y_{isct} represents dual math enrollment, math DevEd enrollment, or TM enrollment (for TM-school students) for a student *i* in cohort *c* who attends school *s* in time *t*. B_{isc} is an indicator equaling to 1 if student *i* scores below 530 in the math SAT the prior year. $f(S_{ic})$ is the functional form of the normalized math PSAT/SAT score centered at 0 in the prior year. X_i represents a vector of student i's demographic and academic characteristics. μ_s are school fixed effects and θ_c are cohort fixed effects. Including the fixed effects accounts for any unobserved mean differences across schools and across cohorts. ϵ_{isc} is the idiosyncratic error term and is clustered at school level. The coefficient of interest, γ_1, represents the change in the enrollment probability around the cutoff.

Figure 2 shows evidence of clear jumps around the cutoff for all three outcomes. Among TM-school students, those who scored right below the cutoff are 5.9 percentage points more likely to take TM, 5.4 percentage points less likely to enroll in dual credit math courses, and 17.5 percentage points more likely to enroll in math DevEd classes than those who score right above. Among non-TM-school students, we observed no change in the likelihood of taking TM (as expected), a 7.8 percentage points lower probability of enrolling in Dual Math and a 13.6 percentage points higher in the probability of enrolling in math DevEd class among those right below the cutoff compared to those right above the cutoff. These results confirm that the estimate from the traditional RD would conflate the effect of all three placement policies and thus the difference in regression discontinuity design is required to isolate the effect of the TM program.

Figure 2. *Take-up Probability of Transitional Math, Dual Math, and Math DevED by PSAT/SAT Score (Prior Year)*



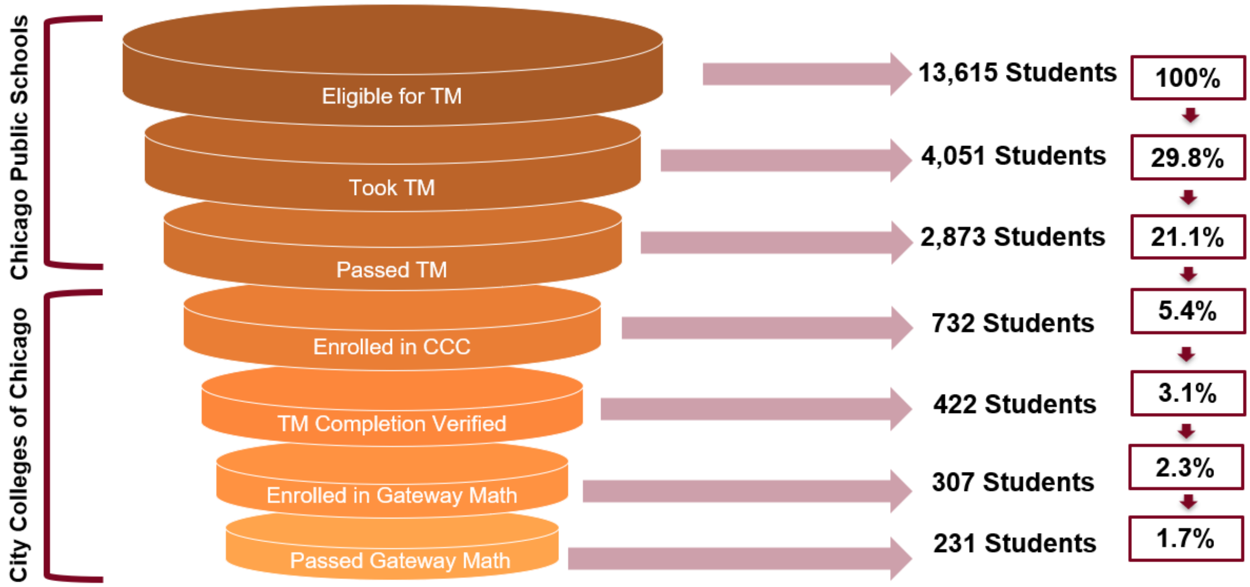
Note: The graphs show the first-stage estimates using a quadratic model. All models include student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.
**p<0.10, **p<0.05, ***p<0.01*

Results

Descriptive Picture of TM Pipeline

Before diving into the main results, we present an overview of the TM pipeline to provide a picture of how students are interacting with the TM program. Figure 3 provides an overview of student engagement with the program. Students are eligible to participate in the TM program if they have an SAT or PSAT score below 530 and attend a school that offers the course. However, not all students who are eligible enroll. During the study period, of the 13,615 eligible students, only 4,051 or 29.8 percent enrolled in a TM course.

Figure 3. *Transitional Math Pipeline*



Note: Students who took TM in these samples are those who took TM for two semesters in schools that follow regular schedule and those who took TM for one semester in schools that follow block schedule.

Of the students who took TM, 2,873 or 70.92 percent received a passing grade. Among CPS students who took TM, those who passed were more likely to be female (52.21 percent compared to 44.82 percent), less likely to have free or reduced lunch (85.69 percent compared to 87.77 percent), less likely to have special education status (12.26 percent compared to 16.48 percent), and slightly younger in age (17.60 compared to 17.63) (Table 4). On average, students who passed TM have higher high school GPA (2.54 compared to 1.95), higher math GPA (2.43 compared to 1.61), and higher numbers of overall high school credits earned (6.85 compared to 6.51) and higher math credits earned (0.98 compared to 0.91) than those who did not pass TM.

Table 4. *Summary Statistics for Students Who Passed and Did Not Pass TM*

	Took and passed TM	Took but did not pass TM	Difference
Female	52.21%	44.82%	7.39%***
White	5.36%	5.26%	0.10%
Asian	2.44%	2.12%	0.32%
Hispanic	57.95%	59.51%	-1.56%
Black	33.24%	32.00%	1.24%
Race others	1.11%	1.19%	-0.08%
Grade repeater	1.43%	2.21%	-0.78%
Have free or reduced lunch	85.69%	87.77%	-2.08%*
Special education status	12.26%	16.48%	-4.22%***
ESL status	11.28%	12.83%	-1.55%
Homeless/STLS	3.83%	3.23%	0.60%
504 status	5.05%	5.10%	-0.05%
Age	17.60	17.63	-0.03**
Overall HS GPA	2.54	1.95	0.59***
HS Math GPA	2.43	1.61	0.82***
HS Credits earned	6.85	6.51	0.34***
HS Math Credit earned	0.98	0.91	0.07***
Observations	**2,873**	**1,178**	

Note: **p<0.10, **p<0.05, ***p<0.01*
The difference column shows the differences in means between TM takers who did and did not pass TM.

Students who pass the TM course and go on to enroll in CCC can provide high school transcripts to CCC and enroll directly in a gateway math course. Out of 2,873 students who passed TM, 732 enrolled in CCC. However, only 422 students verified their TM completion with CCC, 307 of whom enrolled in gateway math courses. This means that of the 732 students who had passed TM and enrolled in CCC, only slightly more than half (57.7 percent) verified TM completion and slightly more than a third (41.9 percent) passed the gateway math courses, suggesting administrative friction may be inhibiting the program from operating as intended.

Table 5 shows students who successfully have their TM completion verified are more likely to be female (60.66 percent compared to 53.23 percent), less likely to be grade repeater (0.47 percent compared to 2.90 percent), and less likely to have free or reduced lunch status

(82.46 percent compared to 88.39 percent). In addition, they are also slightly older in age (17.59 compared to 17.52), have a lower number of high school math credits earned (0.98 compared to 1.01), and higher math GPA (2.52 compared to 2.35) than students who did not have their TM completion verified.

Table 5. *Summary Statistics for Students Who Had and Did Not Have TM Completion Verified.*

	Had TM completion verified	**Did not have TM completion verified**	**Difference**
Female	60.66%	53.23%	7.43%**
White	7.82%	5.81%	2.01%
Asian	2.37%	3.55%	-1.18%
Hispanic	69.67%	72.26%	-2.59%
Black	18.25%	18.06%	0.18%
Race others	1.90%	0.32%	1.57%
Grade repeater	0.47%	2.90%	-2.43%**
Have free or reduced lunch	82.46%	88.39%	-5.92%**
Special education status	13.27%	12.90%	0.37%
ESL status	12.56%	14.19%	-1.63%
Homeless/STLS	1.90%	1.61%	0.28%
504 status	4.74%	5.16%	-0.42%
Age	17.59	17.52	0.08**
Overall HS GPA	2.64	2.57	0.07
HS Math GPA	2.52	2.35	0.17**
HS Credits earned	6.89	6.92	-0.03*
HS Math Credit earned	0.98	1.01	-0.03
Observations	422	310	

*Note: *p<0.10, **p<0.05, ***p<0.01*
The difference column shows the differences in means between CCC students who did not have their TM completion verified and who had their TM completion verified. Both groups of CCC students had passed TM.

Interestingly, we find that among the 307 students who enrolled in gateway math courses, 231 students, or 75.2 percent, passed. Traditional pass rates for these courses at CCC are approximately 70 percent, suggesting that the students who successfully navigated the administrative barriers of having their TM completion verified were just as or more likely to pass than students placed into gateway math through other avenues.

Main Results

We first examine the effects of TM on high school credit accumulation, GPA, and on-time high school graduation using linear and quadratic models. Table 6 shows the difference-in-discontinuity estimates for each model with three choices of bandwidths (50, 100, and 150). As indicated in the empirical model section, our preferred specification uses the 100-point bandwidth with quadratic fit, but the estimates are relatively consistent across specifications. Overall, we find little evidence that an offer of TM changes students' high school credits earned, GPA, and the probability of graduating on time. Specifically, we find insignificant negative point estimates for credits earned, math credits earned, and positive point estimates for overall year GPA and math GPA across all six specifications. The signs of the estimates for overall cumulative GPA and on-time graduation vary across models. The estimates are also statistically insignificant except for the two models associated with on-time graduation (a reduction of 1.9 percentage points for bandwidth 50 of parametric order 1 and 2.6 percentage points for bandwidth 150 of parametric order 2). In Appendix Table 5 we also explored the effects of TM on high school math course-taking patterns. The results suggest that students appeared to shift from taking other types of math courses to TM, while the probability of taking any math courses remains unchanged.

Table 6. *Effects of TM on High School Credits, GPA, and On-time Graduation*

	Parametric Order 1			**Parametric Order 2**		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
Credits Earned	-0.032	-0.042	0.002	0.002	0.001	-0.044
	(0.055)	(0.076)	(0.052)	(0.087)	(0.169)	(0.066)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Math Credits Earned	-0.022	-0.028	-0.024	-0.009	-0.019	-0.026
	(0.028)	(0.033)	(0.029)	(0.032)	(0.061)	(0.029)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Overall Year GPA	0.044	0.082**	0.030	0.063	0.091	0.030
	(0.034)	(0.039)	(0.032)	(0.045)	(0.095)	(0.039)
Observations	25,173	14,073	34,801	25,173	14,073	34,801
Math Year GPA	0.053	0.169**	0.033	0.187**	0.177	0.082
	(0.073)	(0.079)	(0.065)	(0.093)	(0.158)	(0.082)
Observations	20,733	11,968	27,517	20,733	11,968	27,517
Overall Cumulative GPA	0.014	0.018	0.008	0.027	-0.007	0.009
	(0.017)	(0.024)	(0.017)	(0.025)	(0.042)	(0.018)
Observations	25,238	14,105	34,920	25,238	14,105	34,920
On-time graduation	-0.011	-0.019*	-0.003	-0.016	-0.005	-0.026**
	(0.009)	(0.012)	(0.009)	(0.013)	(0.023)	(0.012)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

We continue to examine the effects of TM on college enrollment and CCC math course enrollment. We find no statistically significant differences in the probability of enrolling in any college or enrolling in CCC specifically as a result of TM. These results are aligned with our expectations that there are many factors that students would consider when making their college enrollment decisions. When studying the effects of TM on enrollment in math courses at CCC, we also find little evidence suggesting that TM changes the probability of enrolling in any CCC math courses, including math development education courses and gateway math courses.

Table 7. *Effects of TM on College Enrollment and CCC Math Course Enrollment*

	Parametric Order 1			Parametric Order 2		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
Enrolled in any colleges	-0.014	0.010	0.021	0.019	0.017	-0.019
	(0.018)	(0.029)	(0.018)	(0.032)	(0.066)	(0.023)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in CCC	-0.006	0.020	0.020	0.017	0.033	-0.007
	(0.017)	(0.025)	(0.015)	(0.031)	(0.063)	(0.022)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in any CCC Math	0.003	-0.059	0.025	-0.112	-0.125	-0.031
	(0.043)	(0.066)	(0.036)	(0.075)	(0.131)	(0.054)
Observations	6,492	3,662	8,824	6,492	3,662	8,824
Enrolled in CCC Math Dev-Ed	0.002	0.003	0.013	0.030	0.036	0.006
	(0.030)	(0.041)	(0.029)	(0.042)	(0.089)	(0.039)
Observations	6,492	3,662	8,824	6,492	3,662	8,824
Enrolled in CCC Gateway Math	-0.000	-0.026	0.029	-0.078	-0.103	-0.032
	(0.043)	(0.056)	(0.035)	(0.068)	(0.126)	(0.053)
Observations	6,492	3,662	8,824	6,492	3,662	8,824

*Note: *p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

In addition to CCC math course enrollment, we also examined the effects of TM on overall CCC Math credits attempted and credits earned and in Math development education gateway courses, in particular. The results confirm our findings on CCC math course enrollment, namely TM does not result in a significant change in the numbers credits attempted or earned in CCC Math courses. Unsurprisingly, we also find no statistical differences in the number of all CCC credits attempted and credits earned across all models.

Table 8. *Effects of TM on CCC on College Credits*

	Parametric Order 1			Parametric Order 2		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
CCC Math Credits Attempted	-0.153	-0.108	0.059	-0.185	-0.436	-0.240
	(0.131)	(0.179)	(0.110)	(0.195)	(0.418)	(0.158)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Math Credits Earned	-0.098	0.034	-0.013	0.052	0.093	-0.051
	(0.127)	(0.163)	(0.103)	(0.186)	(0.337)	(0.156)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC DevEd Math Credits Attempted	-0.029	-0.001	0.054	0.017	-0.044	-0.058
	(0.062)	(0.070)	(0.069)	(0.079)	(0.149)	(0.070)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC DevEd Math Credits Earned	-0.022	0.001	0.019	0.046	0.123	-0.010
	(0.052)	(0.055)	(0.058)	(0.063)	(0.116)	(0.056)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Gateway Math Credits Attempted	-0.124	-0.107	0.005	-0.202	-0.391	-0.183
	(0.127)	(0.163)	(0.110)	(0.180)	(0.357)	(0.139)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Gateway Math Credits Earned	-0.076	0.033	-0.031	0.006	-0.030	-0.041
	(0.112)	(0.145)	(0.093)	(0.158)	(0.282)	(0.128)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
All CCC Credits Attempted	-0.391	-0.188	0.229	-0.536	0.003	-0.697
	(0.597)	(0.782)	(0.447)	(0.953)	(1.744)	(0.787)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
All CCC Credits Earned	-0.082	0.187	0.171	0.109	0.926	-0.003
	(0.463)	(0.714)	(0.380)	(0.760)	(1.268)	(0.598)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

The consistent null results found across outcomes can likely in part be attributed to low take-up rate and imperfect record transfer for students who complete TM. As shown in Figure 3 (Transitional Math Pipeline), only 29.8 percent of the eligible students took TM, and only 3.1 percent of the eligible students had their TM completion verified. With a relatively small sample of students who provided high school transcripts to CCC, we do not detect any significant changes in the probability of having TM completion verified after TM is implemented (Table 9).

Table 9. *Effects of TM on TM Completion Verification*

	Parametric Order 1			Parametric Order 2		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
TM Completion Verified	0.004	-0.003	0.016*	-0.007	-0.025	-0.006
	(0.007)	(0.012)	(0.009)	(0.015)	(0.015)	(0.009)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

Discussion

This paper contributes to the existing literature on the roles of transitional courses in advancing high school seniors' college readiness by evaluating the effectiveness of the Illinois Transitional Math program. Embedded in the Transitional Math program are three major components, namely automatic exemption, skill-building focus, and provision of additional math instruction. This feature provides us with a unique opportunity to assess the effects of a relatively comprehensive program on high school and college outcomes. To empirically estimate the effects of the Illinois Transitional Math program, we employ a difference-in-discontinuity approach that leverages a math SAT/PSAT threshold used to determine program eligibility while simultaneously addressing two other confounding policies.

We find limited evidence that offering TM leads to changes in students' high school overall credit or overall math credit accumulation, overall GPA or math GPA, or on-time graduation rates. Regarding college outcomes, our results do not suggest that TM has an effect on college enrollment or enrollment in CCC. Additionally, when looking further into the primary outcome of interest of the program, we find limited evidence suggesting that TM changes the likelihood of taking or passing gateway math. However, gateway math pass rate is higher for students who pass TM, enroll in CCC, and take gateway math compared to those who place into gateway through another pathway (75 percent vs. 70 percent). As such, we have reason to hypothesize that TM may help some additional students succeed in gateway coursework and at minimum is not leading to students being placed in gateway courses who are not likely to pass.

Two possible explanations for the consistent null results across outcomes are low take-up rates and imperfect record transfer. To increase take up, CPS and CCC could work to increase engagement with the program across the pipeline. This could include efforts to make sure students and their teachers understand the goals of the TM program and how they might benefit from participating. Engagement efforts that stress that passing TM could reduce the number of math courses students will have to take (and pay for) once they get to college might be particularly helpful in driving engagement. Likewise, TM instructors could emphasize to students who pass TM that they should be eligible for direct placement into gateway math courses, so they enroll in these classes once they matriculate at CCC.

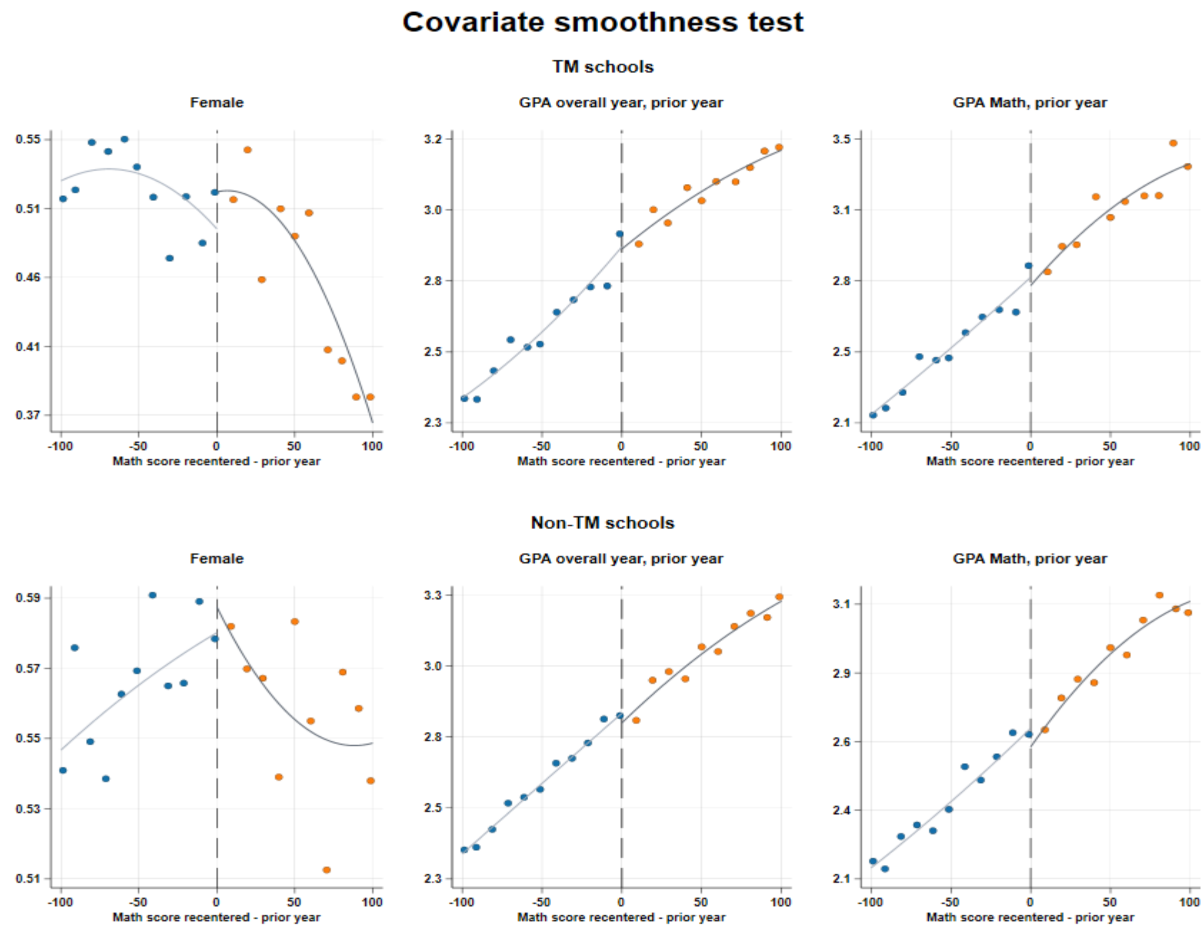
Likewise, efforts to reduce administrative friction in programs like TM that require coordination across districts could increase their efficacy. For example, based on the results of this research, CCC and CPS are collaborating to automatically have students' high school transcripts provided to CCC. Currently, CPS graduates must agree to have their transcript shared with CCC or separately submit their transcript to CCC when they apply to CCC. This process could be simplified if students who passed TM automatically have their TM completion verified by CCC, thereby increasing their chances of taking gateway math during their first year at CCC. In addition, guaranteed placement to gateway math is only available after 18 months post completion, increasing enrollment in gateway math courses will require more effective administrative and counseling efforts to inform students about the importance of immediate gateway math enrollment.

When considering the results from this study, it is important to remember that much of the implementation occurred during the COVID-19 pandemic when many of the TM courses were provided partially or entirely online, and cross-system collaboration was even more challenging than usual. The abrupt transition to online learning resulted in significant learning loss for many students, compounding existing inequities. While overall high school graduation rates remained relatively stable, there was a disproportionate impact on schools serving low-income, high-poverty, and high-minority populations.

Furthermore, college enrollment saw a marked decline during the pandemic, with total undergraduate enrollment decreasing by 6.8 percent in fall 2020 compared to 2019, a decline 4.5 times greater than the drop between the previous two years. Community colleges experienced the most significant drop in enrollment, with a 13.2 percent decline in immediate enrollment among 2020 high school graduates. This decline was attributed to economic uncertainties, the shift to online learning, and other pandemic-related challenges (Causey et al., 2021). Since then, enrollment rates have surpassed pre-pandemic trends, so it will be important to continue monitoring the program's effectiveness under these more favorable conditions to truly understand its promise.

Appendix

Appendix Figure 1. *Covariate Smoothness Test around the Discontinuity Threshold*



Note: The graph shows a quadratic fit for TM and non-TM schools.

Appendix Table 2. *Robustness Check - Effects of TM on High School Credits, GPA, and On-time Graduation Excluding Female, Overall GPA, and Math GPA as Covariates*

	Parametric Order 1			**Parametric Order 2**		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
Credits Earned	-0.055	-0.061	-0.015	-0.028	-0.023	-0.070
	(0.055)	(0.079)	(0.053)	(0.089)	(0.172)	(0.068)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Math Credits Earned	-0.027	-0.033	-0.027	-0.020	-0.032	-0.033
	(0.027)	(0.032)	(0.029)	(0.032)	(0.062)	(0.029)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Overall Year GPA	-0.006	0.035	-0.003	-0.009	0.042	-0.027
	(0.040)	(0.048)	(0.040)	(0.054)	(0.109)	(0.046)
Observations	25,173	14,073	34,801	25,173	14,073	34,801
Math Year GPA	0.006	0.112	0.002	0.096	0.057	0.021
	(0.078)	(0.086)	(0.072)	(0.102)	(0.184)	(0.088)
Observations	20,733	11,968	27,517	20,733	11,968	27,517
Overall Cumulative GPA	-0.032	-0.023	-0.022	-0.038	-0.049	-0.044*
	(0.022)	(0.034)	(0.023)	(0.034)	(0.062)	(0.024)
Observations	25,238	14,105	34,920	25,238	14,105	34,920
On-time graduation	-0.013	-0.021*	-0.005	-0.019	-0.006	-0.028**
	(0.009)	(0.012)	(0.009)	(0.014)	(0.023)	(0.012)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*

All models control for student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

Appendix Table 3. *Robustness Check - Effects of TM on College Enrollment and CCC Math Course Enrollment Excluding Female, Overall GPA, and Math GPA as Covariates*

	Parametric Order 1			**Parametric Order 2**		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
Enrolled in any colleges	-0.025	0.001	0.012	0.003	0.009	-0.033
	(0.019)	(0.030)	(0.019)	(0.033)	(0.066)	(0.024)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in CCC	-0.003	0.023	0.022	0.021	0.037	-0.005
	(0.018)	(0.025)	(0.015)	(0.030)	(0.062)	(0.022)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in any CCC Math	0.007	-0.051	0.027	-0.103	-0.118	-0.029
	(0.043)	(0.066)	(0.036)	(0.075)	(0.133)	(0.054)
Observations	6,492	3,662	8,824	6,492	3,662	8,824
Enrolled in CCC Math Dev-Ed	0.003	0.011	0.016	0.038	0.046	0.009
	(0.031)	(0.043)	(0.028)	(0.044)	(0.092)	(0.039)
Observations	6,492	3,662	8,824	6,492	3,662	8,824
Enrolled in CCC Gateway Math	0.000	-0.025	0.027	-0.078	-0.104	-0.034
	(0.043)	(0.055)	(0.035)	(0.068)	(0.127)	(0.052)
Observations	6,492	3,662	8,824	6,492	3,662	8,824

Note: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$
All models control for student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

Appendix Table 4. *Robustness Check - Effects of TM on CCC on College Credits Excluding Female, Overall GPA, and Math GPA as Covariates.*

	Parametric Order 1			Parametric Order 2		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
CCC Math Credits Attempted	-0.137	-0.092	0.068	-0.165	-0.417	-0.229
	(0.132)	(0.180)	(0.110)	(0.195)	(0.409)	(0.158)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Math Credits Earned	-0.100	0.034	-0.015	0.051	0.090	-0.056
	(0.127)	(0.163)	(0.103)	(0.186)	(0.338)	(0.156)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC DevEd Math Credits Attempted	-0.025	0.005	0.055	0.026	-0.032	-0.054
	(0.062)	(0.070)	(0.068)	(0.079)	(0.146)	(0.070)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC DevEd Math Credits Earned	-0.021	0.003	0.017	0.049	0.129	-0.011
	(0.052)	(0.054)	(0.058)	(0.062)	(0.115)	(0.056)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Gateway Math Credits Attempted	-0.112	-0.097	0.013	-0.191	-0.385	-0.174
	(0.127)	(0.165)	(0.110)	(0.181)	(0.352)	(0.139)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
CCC Gateway Math Credits Earned	-0.078	0.031	-0.033	0.002	-0.039	-0.045
	(0.112)	(0.145)	(0.093)	(0.158)	(0.284)	(0.128)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
All CCC Credits Attempted	-0.341	-0.129	0.253	-0.458	0.094	-0.662
	(0.595)	(0.782)	(0.445)	(0.946)	(1.709)	(0.785)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
All CCC Credits Earned	-0.102	0.185	0.145	0.102	0.928	-0.036
	(0.464)	(0.715)	(0.379)	(0.757)	(1.274)	(0.599)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, and school fixed effects, and cohort fixed effects. Student demographic characteristics include race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1,* and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

Appendix Table 5. *Effects of TM on High School Math Course Enrollment*

	Parametric Order 1			**Parametric Order 2**		
	BW 100 (preferred)	BW 50	BW 150	BW 100 (preferred)	BW 50	BW 150
Did not enroll in any Math	0.029	0.036	0.029	0.028	0.029	0.030
	(0.025)	(0.029)	(0.026)	(0.027)	(0.043)	(0.026)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in TM	0.096***	0.082***	0.125***	0.068**	0.090	0.070***
	(0.030)	(0.028)	(0.034)	(0.026)	(0.054)	(0.027)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in Math-Non TM	-0.127***	-0.122***	-0.155***	-0.094**	-0.098	-0.102***
	(0.031)	(0.033)	(0.036)	(0.036)	(0.067)	(0.032)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in Math IB/AP	-0.017	-0.058**	-0.020	-0.058*	-0.187***	-0.032
	(0.019)	(0.025)	(0.020)	(0.031)	(0.052)	(0.023)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in Dual Math	-0.063*	-0.064*	-0.066*	-0.064*	-0.040	-0.057*
	(0.034)	(0.033)	(0.036)	(0.032)	(0.036)	(0.032)
Observations	25,581	14,250	35,538	25,581	14,250	35,538
Enrolled in other regular Math	-0.005	-0.001	-0.005	0.001	-0.035	-0.003
	(0.021)	(0.019)	(0.024)	(0.021)	(0.046)	(0.019)
Observations	25,581	14,250	35,538	25,581	14,250	35,538

Note: **p<0.10, **p<0.05, ***p<0.01*
All models control for student demographic characteristics, academic characteristics, school fixed effects, and cohort fixed effects. Student demographic characteristics include gender, race, age, grade repeater status, free/reduced lunch status, special education status, English as a second language, homeless/STLS status, 504 status. Student academic characteristics include overall GPA in *t-1*, Math GPA in *t-1*, credits attempted in *t-1*, credits earned in *t-1*, Math credits attempted in *t-1*, and Math credits earned in *t-1*. Robust standard errors are clustered at school level and are in parentheses.

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