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The Effects of Corequisite Remediation: Evidence From a Statewide Reform in Tennessee

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Abstract

Corequisite remediation, which mainstreams students deemed academically underprepared into college-level courses with additional learning support, is rapidly being adopted by colleges across the nation. This paper provides the first causal evidence on a system-wide corequisite reform, using data from all 13 community colleges affiliated with the Tennessee Board of Regents. Using regression discontinuity and difference-in-regression-discontinuity designs, we estimated the causal effects of placement into corequisite remediation compared with placement into traditional prerequisite remediation and direct placement into college-level courses. For students on the margin of the college readiness threshold, those placed into corequisite remediation were 15 percentage points more likely to pass gateway math and 13 percentage points more likely to pass gateway English within one year of enrollment than similar students placed into prerequisite remediation. Compared with their counterparts placed directly into college-level courses, students placed into corequisite remediation had similar gateway course completion rates and were about 8 percentage points more likely to enroll in and pass a subsequent college-level math course after completing gateway math. The positive effects of corequisite remediation compared with prerequisite remediation in math were largely driven by efforts to guide students to take math courses aligned with the requirements for their program rather than placing most students into the algebra–calculus track by default, as has been the standard practice. We found no significant impacts of placement into corequisite remediation on enrollment persistence, transfer to a four-year college, or degree completion. This suggests that corequisite reforms, though effective in helping students pass college-level math and English, are not sufficient to improve college completion rates overall.

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1. Introduction

More than two thirds of incoming community college students enroll in at least one remedial course designed to strengthen their content knowledge in math, writing, or reading and bring them up to an adequate skill level for future college coursework (Chen, 2016). Conventionally, students deemed underprepared have had to complete a remedial course or sequence of courses before enrolling in college-level math or English. However, research has called into question the effectiveness of this prerequisite approach. A variety of rigorous studies have found that students assigned to prerequisite remediation never make up for time lost in these courses; their outcomes are not better and are sometimes worse than those of otherwise similar students placed directly into college-level courses (see, e.g., Calcagno & Long, 2008; Dadgar, 2012; Martorell & McFarlin, 2011; Xu, 2016). Among the causes for this are inaccurate placement into remedial education (Scott-Clayton, Crosta, & Belfield, 2014) and high attrition from prerequisite remedial course sequences (Bailey, Jeong, & Cho, 2010). Some studies (e.g., Boatman & Long, 2018) have found some positive outcomes for students who are further away from the cutoff for college readiness, but no studies have shown consistently positive results for the prerequisite approach to remediation, particularly for students at the margin of remedial placement (Jaggars & Stacey, 2014).

Because so many students fail to make it to college-level courses, remedial education has been the focus of major reforms to improve college success. Corequisite remediation—an alternative to the traditional prerequisite approach—is gaining popularity among colleges and state systems. In a corequisite model, students deemed not college-ready are mainstreamed into college-level courses upon enrollment, and colleges provide them with additional learning support through concurrent courses, labs, or tutoring sessions. In many colleges, corequisite remediation is implemented alongside math pathways reforms, which enable students who do not intend to pursue a program in science, technology, engineering, and mathematics (STEM) to take statistics, math for liberal arts, or other types of math courses with content more relevant to their program of study than what students learn in the conventional algebra–calculus track (Denley, 2016; Logue, Douglas, & Watanabe-Rose, 2019; Logue, Watanabe-Rose, & Douglas, 2016).

Advocates for corequisite remediation suggest that it could help students succeed in gateway courses (introductory college-level courses) and even improve longer term academic outcomes for several reasons. First, evidence from some studies suggests that many students assessed as in need of remediation could have completed gateway courses, had they been allowed to enroll (Scott-Clayton et al., 2014), and corequisite courses offer students access to gateway courses. Second, mainstreaming students into college-level courses, as opposed to requiring them to first dedicate one or more semesters to remediation, could make students feel more motivated and less stigmatized (Bailey, 2009). Third, corequisite remediation has the potential to improve retention from term to term, as it eliminates the many exit points created by remedial course sequences (Bailey et al., 2010). Fourth, aligning the content in corequisite learning support with college-level coursework makes the additional instruction more relevant to students and helps familiarize them with the content they encounter in the college-level course (Logue et al., 2016). Lastly, accumulating college credits early on could help students build academic momentum, setting them on a trajectory toward transfer to a four-year college and degree completion (Attewell, Heil, & Reisel, 2012; Wang, 2017). Indeed, early studies on the effectiveness of corequisite remediation show promising results in terms of gateway course outcomes and enrollment persistence (Boatman, 2012; Cho, Kopko, Jenkins, & Jaggars, 2012; Jenkins, Speroni, Belfield, Jaggars, & Edgecombe, 2010; Logue et al., 2016; Logue et al., 2019).

The current paper is the first to provide causal evidence on the effects of a statewide corequisite reform. We analyzed outcomes across the 13 community colleges under the Tennessee Board of Regents (TBR), which in 2015 became the first state system to implement corequisite remediation system-wide. Drawing on data from these colleges from 2010–11 to 2017–18, we provide estimates of the effects of corequisite remediation for students on the margin of the college readiness threshold compared with both prerequisite remediation and direct placement into college-level courses, using regression discontinuity (RD) and difference-in-regression-discontinuity (DiRD) designs.

This study deepens and adds nuance to current understandings of the impacts of remedial reforms on student outcomes in three ways. First, unlike previous research that mostly focused on the comparison between prerequisite and corequisite remediation, this paper also provides estimates of the causal effects of corequisite remediation compared with placement into college-level courses with no additional academic support. Consistent with previous studies using rigorous research methods, we found that students placed into corequisite remediation were 15 percentage points more likely to pass gateway math and 13 percentage points more likely to pass gateway English within one year of enrollment than otherwise similar students placed into prerequisite remedial courses. In addition, students placed into corequisite remediation were equally likely to enroll in and pass any subsequent college-level math courses and 8 percentage points more likely to enroll in the next college-level English course, compared with similar students placed into prerequisite remedial courses. Compared with their peers who were placed directly into college-level courses, students placed into corequisite learning support in math had comparable gateway course completion rates and were about 8 percentage points more likely to enroll in and pass a subsequent college-level math course, and students placed into corequisite learning support in English had similar outcomes in gateway course completion, subsequent enrollment and performance in the next college-level English course.

Furthermore, this study is the first to examine the effects of corequisite remediation by math pathway. The most rigorous evidence and only experimental study to date with published results on corequisite reforms measured the effects of replacing the traditional prerequisite math sequence in the algebra–calculus track with corequisite learning support in statistics (Logue et al., 2016; Logue et al., 2019).[1] It is not clear whether the improvements in gateway math completion and subsequent college-level credits accumulated observed in this study were largely driven by the mainstreaming approach, the math pathways approach, or a combination of both. In the current study, we were able to disentangle the effects of these two approaches and found that the positive effects of corequisite reform in Tennessee in math, relative to prerequisite remediation, were largely driven by efforts to guide students not interested in a STEM program to take statistics, math for liberal arts, or other types of math that align with their program requirements. Students placed into corequisite algebra had gateway completion rates

[1] There is also an ongoing experimental evaluation of corequisite remediation in nine Texas community colleges; see https://ies.ed.gov/funding/grantsearch/details.asp?ID=1754.

similar to those of students taking prerequisite remedial math on the algebra–calculus track. This suggests that one key to implementing corequisite math successfully is coordinating it with math pathways reforms, as well as reforms that strengthen pathways to program completion and new student advising, as the TBR community colleges have done at scale (Jenkins, Brown, Fink, Lahr, & Yanagiura, 2018).

Lastly, the current study provides evidence of strong causal effects of corequisite remediation on gateway course completion across a system of colleges with various institutional contexts, suggesting that corequisite remediation is a scalable approach to improving student success in gateway courses. However, we did not find any significant effects on enrollment persistence, transfer to a four-year college, or degree completion, suggesting that corequisite remediation is not a panacea for the impediments to college success. It has to work with a broader set of reforms to improve overall college completion rates.

2. Research Context

2.1 Previous Evidence on Corequisite Remediation

Corequisite remediation has gained increasing attention across colleges and state systems in recent years. TBR is the only system where all affiliated colleges have adopted corequisite remediation at scale, while another 14 states have adopted or committed to adopting policies supportive of the corequisite approach to remediation (Education Commission of the States, 2018). According to a national survey of remedial education practices, 16% of public two-year colleges offered some form of corequisite courses in math in 2016, and 35% offered corequisite courses in reading and writing (Rutschow & Mayer, 2018).

Broadly speaking, under a corequisite system, students deemed not college-ready are mainstreamed into college-level courses with additional support, but the way this approach is implemented varies across contexts. The Accelerated Learning Program (ALP) in English at the Community College of Baltimore County, one of the earliest models of corequisite remediation, specifies a fixed ratio of students at the remedial and college levels in gateway course sections (with 10 seats reserved for ALP students and 10 seats for students who placed into college-level English) and has the same instructor teach both the gateway and companion courses. Many colleges and states have also utilized technology to provide individualized or computer-adaptive modules tailored to students' academic needs when implementing corequisite remediation (see, e.g., Boatman, 2012; Daugherty, Gomez, Carew, Mendoza-Graf, & Miller, 2018). In addition, some colleges and states, such as TBR and three City University of New York (CUNY) colleges in a pilot study, added corequisite math in statistics or other types of math aligned with program requirements instead of requiring every student to take math courses in the algebra–calculus track (Jenkins et al., 2018; Logue et al., 2016).

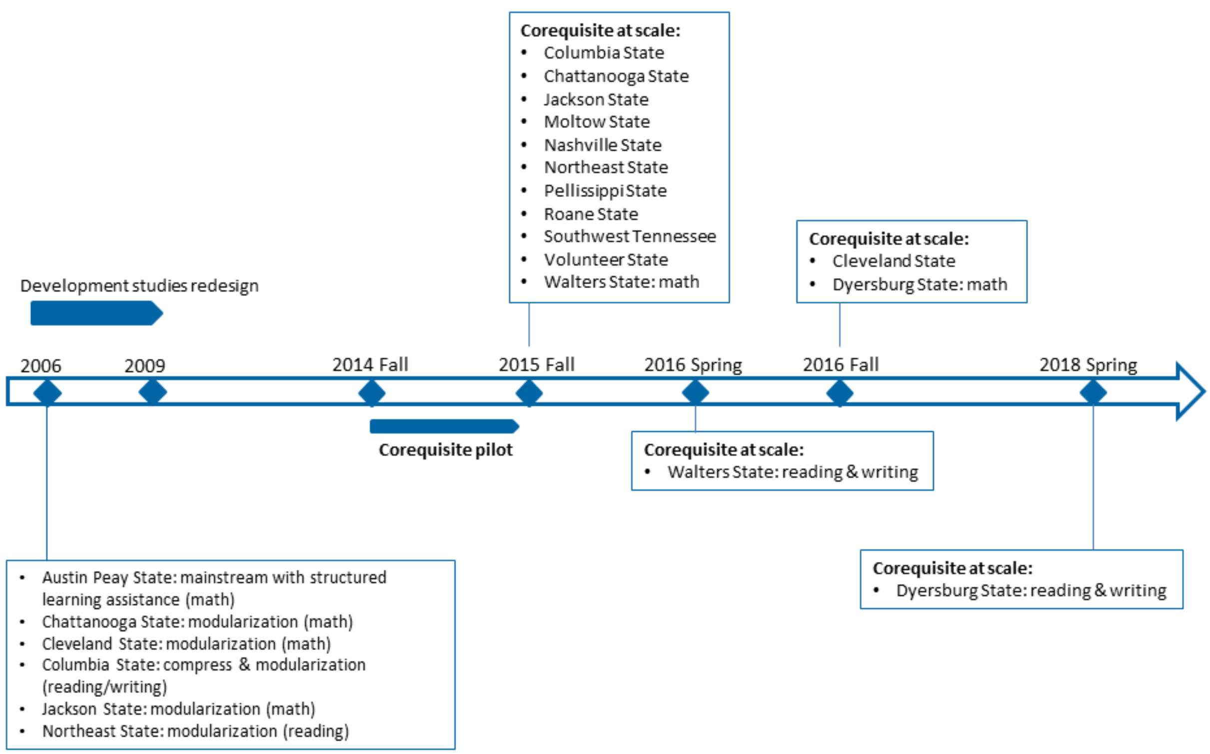
Early evidence on the effects of corequisite reforms reveals promising patterns. The ALP model is associated with sizable improvements in gateway English completion (Jenkins et al., 2010) and next-year enrollment persistence (Cho et al., 2012). In a program piloted in a four-year college in Tennessee,[2] Boatman (2012) found that mainstreaming students into college-level math courses linked with learning assistance workshops significantly improved students' early academic outcomes, including persistence from the first to the second semester, persistence from the first to the second year, and number of credits (both cumulative and college-level) attained in the first two years. The most recent and rigorous study on corequisite remediation reform was conducted in three CUNY community colleges, where around 900 students were randomly assigned to remedial elementary algebra, remedial elementary algebra with workshops, or college-level statistics with workshops (corequisite remediation). Students assigned to corequisite statistics were significantly more likely to pass college-level math, subsequently accumulated more credits (Logue et al., 2016), and demonstrated higher transfer and graduation rates (Logue et al., 2019) than students assigned to remedial elementary algebra.

[2] The college—Austin Peay State University—was affiliated with TBR at the time of the remediation redesign but has operated autonomously since 2017.

2.2 Tennessee College Access and Readiness Reforms

TBR piloted corequisite remediation in 2014 and scaled it up system-wide in fall 2015. As shown in Figure 1, this reform followed a period in which TBR colleges implemented a modularized approach to remediation with some improvements in student outcomes (Boatman, 2012). Student transcript data acquired from TBR show that 11 out of the 13 community colleges fully implemented corequisite remediation as of fall 2015, with virtually no students taking standalone remedial courses afterward. Figure 1 shows the full implementation timeline for TBR's reforms to remedial education across institutions and subjects.

Figure 1
Timeline of Reforms to Remediation at TBR Community Colleges



Note. Compiled by the authors based on TBR administrative transcript data and TBR corequisite reform documents retrieved from https://www.tbr.edu/academics/co-requisite-remediation.

Under the corequisite system, all degree-seeking students who do not meet TBR's college readiness criteria are placed into gateway courses and corequisite learning support. According to interviews with TBR administrators, the full process of learning support placement is as follows. Students testing below the ACT cutoff score for college-level placement (19 for math and reading, 18 for writing) and students without a placement test score are automatically placed into learning support. From there, students have the option to (a) enroll in learning support, (b) provide evidence that they have completed a bridge program to satisfy the learning support requirement, or (c) challenge the placement to have it waived. The last option typically requires taking the Accuplacer test (see Tennessee Board of Regents, 2019). Once the student is designated as in need of learning support, the institution will not allow him or her to graduate without fulfilling the learning support requirement. Most of the TBR colleges have their course registration systems configured so that these students cannot register for college-level courses without registering for corequisite learning support.

TBR does not require a standard format for learning support, though each institution had to submit a plan to TBR for approval. In most colleges, learning support is a semester-long course that is linked with the college-level, credit-bearing course. At colleges with modularized learning support, the support is tailored to students' individual pace. The college-level course is identical to that taken by students who meet the established score for initial college-level placement, and no elements of the corequisite learning support experience contribute to the grade earned in the college-level course.

Transcript data show that the credit hours and delivery methods for learning support vary across institutions. Learning support courses have three credit hours at most colleges, though some colleges offer courses with fewer credit hours for students with different ACT subscores or within specific majors: 23% of math learning support courses, 18% of writing learning support courses, and 4% of reading learning support courses are less than three credit hours. The credit hours for these courses are counted toward the 12 credit hours required for students' full-time enrollment status, and students can use Pell grants or other scholarships to pay for learning support credits. In terms of delivery method, on average, about one third of learning support is delivered online (32%) or in a hybrid format (3%). Four colleges offer all of their corequisite learning support face-to-face; three colleges offered all learning support through online or hybrid formats; and the other six offer a combination of face-to-face, hybrid, and online learning support.

TBR implemented corequisite remediation slightly differently for English and math. In English, students who do not meet the ACT cutoff score in writing and/or reading are required to take the gateway course (usually English Composition I) linked with learning support in writing and/or reading, following the procedure described above. In math, corequisite remediation was implemented in conjunction with math pathways. Entering students are now guided to choose a program area early on and take the math course(s) that will best prepare them for employment and further education in their chosen field (Jenkins et al., 2018). Degree-seeking students enrolled in a field with algebra or calculus requirements, such as STEM, are guided to take the traditional algebra course as their gateway math course. Degree-seeking students enrolled in a field without an algebra-intensive math requirement are guided to take a non-algebra-based course, such as statistics, quantitative reasoning, or math for liberal arts, that is relevant to their major and satisfies transfer requirements in their field. As a result, the proportion of students who took math courses on the algebra–calculus track declined from more than 50% in 2010 to less than 20% in 2016. Learning support is tailored to the college-level math course students are taking and are designed to address deficiencies in skills required for that course. All gateway math course and learning support pairings are listed in Appendix Table A1. The change from prerequisite to corequisite math in multiple pathways allows us to identify the effects of math pathways and the effects of mainstreaming students into college-level courses separately.

While the Tennessee community colleges were implementing corequisite remediation, the public education system in Tennessee was also enacting major policy and programmatic changes designed to improve college access and success that may have changed student composition and outcomes at TBR colleges. First, the Seamless Alignment and Integrated Learning Support (SAILS) program, which was launched in 2012 and scaled up to 243 high schools in 2015, made it possible for students to complete math remediation in high school and enroll directly in college-level math upon matriculation. Second, the Tennessee Promise Scholarship program was launched in fall 2015 to provide last-dollar scholarships, covering tuition and fees not covered by other financial aid, to Tennessee high school seniors who obtain their diploma or GED before their 19th birthday. Because the program requires students to attend college full-time and provides them with financial support, it may have improved early outcomes for new Tennessee community college students. In this paper, we disentangle the effects of corequisite reform from these other policy changes, as we explain in more detail in Section 4.

3. Data

We used deidentified state administrative data on first-time students who entered one of the 13 community colleges in Tennessee in the fall semester between 2010–11 and 2016–17, excluding dual enrollment students. We focused on students who had ACT scores on record (around 80% of the full sample) and tracked their outcomes through spring 2018.[3] This sample restriction was necessary because scores from other types of placement tests, in particular Accuplacer, can be used to challenge the placement designation to avoid remediation, and students who chose to present Accuplacer scores could be different from those who did not in unobservable ways. Since colleges generally use ACT scores for initial placement, focusing on students with ACT scores allows us to construct comparable samples of students above and below the cutoff score for remedial placement. The data include demographic information, transcripts, ACT scores, and credentials earned. We derived measurements of enrollment, credits attempted and earned, grade point average (GPA), and certificates and associate degrees completed from students' community college transcripts. These data were further linked to data from the National Student Clearinghouse, which we used to capture transfer to four-year institutions and credentials earned outside of the TBR system.

Table 1 contains descriptive statistics for all background variables and mean outcome levels for our full sample as well as our analytic sample, which includes only students who scored up to 2 points above or below the ACT math cutoff score.[4] As we

[3] Students who did not have ACT scores on record include those who reported other types of standardized test scores, such as SAT, COMPASS, ASSET, and Accuplacer scores, and those who did not have any standardized test scores on record. Members of the latter group were significantly older when they first enrolled.
[4] For analyses by subject, the analytic samples include students who scored up to 2 points above or below the ACT cutoff score for that subject. For analyses at the student level, we use ACT math scores to construct the analytic sample, as math score is the lowest ACT subscore for most students. We also conducted robustness checks using ACT reading or writing scores to construct the student-level analytic sample. The results are fairly consistent with those presented in the paper. These results are available upon request.

explain in more detail in Section 4, we made these sample restrictions to form groups of college-ready and remedial education students that are largely comparable based on predetermined characteristics. The analytic sample contains more than one third of the students in the full sample. Students in the analytic and full samples are largely comparable in terms of background variables, with a few exceptions: 73% of all fall entrants with ACT scores are White, but 80% of the analytic sample are White. Students in the analytic sample also had slightly higher ACT scores in reading, writing, and math.

In general, students in the analytic sample had better outcomes in gateway course completion, credit attainment, and other enrollment and credential completion outcomes compared with students in the full sample. Students in the analytic sample were 5 percentage points more likely to complete gateway math and 6 percentage points more likely to complete gateway English by the end of Year 1. They enrolled in and earned around three additional college-level credits by the end of Year 1, and this gap in credits persisted through Year 3. They were 4 percentage points more likely to reenroll in the fall of Year 2 and 3 percentage points more likely to enroll in the fall of Year 3. Their transfer and credential completion rates within three years of initial enrollment were also slightly better than the overall average. This is not surprising, given that the analytic sample excludes students with very low ACT scores. It is also an important caveat to keep mind when considering the generalizability of the results.

Table 1
Student Descriptive Statistics: Fall Entrants in 2010–2016 Cohorts

Variable	Full Sample	Analytic Sample
A. Background variables		
Female	56%	57%
Age at college entry	18.39	18.32
White	73%	80%
Black	19%	11%
Hispanic	4%	4%
Other race	4%	4%
Entered college within one year of high school graduation	75%	75%
High school GPA	2.93	3.03
Enrolled full-time during first term	72%	73%
Earliest ACT score—reading	19.38	20.16
Earliest ACT score—writing	18.46	19.38
Earliest ACT score—math	18.09	18.11
B. Outcome variables		
Gateway math		
Completed by end of Year 1	27%	32%
Completed by end of Year 2	42%	49%
Completed by end of Year 3[1]	47%	54%
Gateway English		
Completed by end of Year 1	54%	61%
Completed by end of Year 2	64%	71%
Completed by end of Year 3[1]	66%	73%
College-level credit attainment (excluding gateway)		
Attempted by end of Year 1	15.95	17.61
Attempted by end of Year 2	28.84	32.01
Attempted by end of Year 3[1]	37.25	41.21
Earned by end of Year 1	11.53	13.02
Earned by end of Year 2	22.10	24.87
Earned by end of Year 3[1]	27.84	31.20
Enrollment, transfer, and early credential completion		
Enrolled in Year 2	60%	64%
Enrolled in Year 3[1]	35%	38%
Transferred to a four-year college in Year 1	1%	1%
Transferred to a four-year college in Year 2	3%	4%
Transferred to a four-year college in Year 3[1]	9%	9%
Earned a certificate by end of Year 3[1]	7%	8%
Earned an associate degree by end of Year 3[1]	15%	18%
Earned any credential by end of Year 3[1]	19%	21%
N	99,776	35,707

Note. Source: Authors' calculations based on TBR administrative data for 2010–2016 first-time fall entrants with ACT scores. We used the analytic sample to conduct the main analyses using a DiRD model.

[1] All calculations for Year 3 outcomes are based on the 2010–2015 cohorts. The observation numbers are 83,477 for the full sample and 29,787 for the analytic sample.

4. Empirical Strategy

To estimate the impacts of corequisite remediation, we used two approaches: an RD analysis for students just above and below the college readiness threshold and a DiRD analysis to compare the two RD estimates. Both approaches provide estimates of the causal impacts of corequisite remediation, although as discussed later, each method requires a different interpretation. We focus on the reduced-form effects of remedial placement instead of remedial course enrollment because the remedial designation itself may have a direct effect on college enrollment decisions (Martorell, McFarlin, & Xue, 2015; Scott-Clayton & Rodriguez, 2015).

4.1 Regression Discontinuity

The RD method compares students who were assigned to remediation because they placed just below the college readiness threshold with otherwise similar students who scored just above the threshold and thus received no additional learning support. Therefore, it provides the effects of remediation under prerequisite and corequisite systems compared with no remediation at all. The only assumption required is that observable and unobservable student characteristics are comparable for students above and below the college-level cutoff within a certain range of the cutoff—the optimal bandwidth. Within the optimal bandwidth, we assume that the relationship between ACT score and the outcome of interest is linear but allow the relationship to differ above and below the cutoff (Imbens & Lemieux, 2008). Based on our optimal bandwidth analysis, we focused on a bandwidth of 2 points below and above the cutoff score. For consistency and transparency, we used the same bandwidth for all outcomes and across all subjects. We tested the sensitivity of our findings to bandwidth selection by reestimating the results using twice this bandwidth (± 4).

The basic model, which we ran on the sample restricted to students who entered one of the TBR community colleges after the corequisite reform was implemented and scored within the optimal bandwidth, takes the following form:

$$Y_i = \beta_0 + \beta_1 Below_i + \beta_2 (ACT\ Distance_i * Below_i) + \beta_2 (ACT\ Distance_i * Above_i) + HS\ District * HS\ Grad\ Year\ FE + CollegeFE + Cohort\ FE + \beta_n X_i + \varepsilon_i \quad (1)$$

Here, Y_i represents the outcome for student i, and β_1 is the estimate of the effect of falling below the college readiness cutoff. We allow for differential correlations between ACT score and outcomes above and below the cutoff by controlling the interaction terms of the distance from the ACT score to the cutoff and the indicators for below/above cutoff.

As discussed in Section 2, Tennessee started piloting the SAILS program in 2012 in an effort to shift the locus of math remediation from college back to high school, and the program was scaled up to reach a majority of Tennessee high schools in the 2014–15 academic year. We accounted for the differential timing of SAILS implementation by controlling for the fixed effects of the interactions of the student's high school district (using zip code as a proxy) and the indicators for the year of high school graduation. This essentially allowed us to compare outcomes only for students who were from the same high school district and graduated from high school in the same year. We also controlled for college fixed effects, which is important because the community colleges piloted and scaled up corequisite reforms on different timelines. $Cohort\ FE$ is a vector of cohort fixed effects, a necessary inclusion because of potential changes in the student population over time due to the introduction of the Tennessee Promise Scholarship program. X_i represents a vector of individual-level covariates, including a set of dummy variables for race/ethnicity (with White as the reference group), gender (with male as the reference group), age at initial enrollment, whether the student entered college within one year of high school graduation, high school GPA, and major at entry. We clustered standard errors by college–cohort. We tested the sensitivity of our results to models with and without covariates. For comparison purposes, we also estimated Equation 1 for the sample of students who entered one of the TBR community colleges before the corequisite reform, to capture the impact of prerequisite remediation over no additional support.

4.2 Difference-in-Regression-Discontinuity

The DiRD approach provides the difference between the RD estimates for corequisite remediation and the RD estimates for prerequisite remediation. The DiRD estimates can be interpreted as the impact of corequisite remediation relative to prerequisite remediation, isolated from any potential effect of other policies affecting students at the college readiness threshold.

The model, which we ran on students from the 2010 to 2016 cohorts within the optimal bandwidth, takes the following form:

$$Y_i = \gamma_0 + \gamma_1(Below_i * CoReq_i) + \gamma_2\, Below_i + \gamma_3 CoReq_i + \gamma_4(ACT\ Distance_i * Below_i * CoReq_i) + \gamma_5(ACT\ Distance_i * Above_i * CoReq_i) + \gamma_6(ACT\ Distance_i * Below_i * PreReq_i) + \gamma_7(ACT\ Distance_i * Above_i * PreReq_i) + HS\ District * HS\ Grad\ Year\ FE + CollegeFE + Cohort\ FE + \beta_n X_i + \varepsilon_i \quad (2)$$

The γ_1 in this regression provides the estimate of the difference in the two RD estimates. We allow for differential correlations between ACT score and the outcome for students above and below the college readiness threshold, as well as before and after corequisite remediation. The other controls in the regression are the same as those described in Equation 1.

5. Main Results

5.1 Plausibility Tests

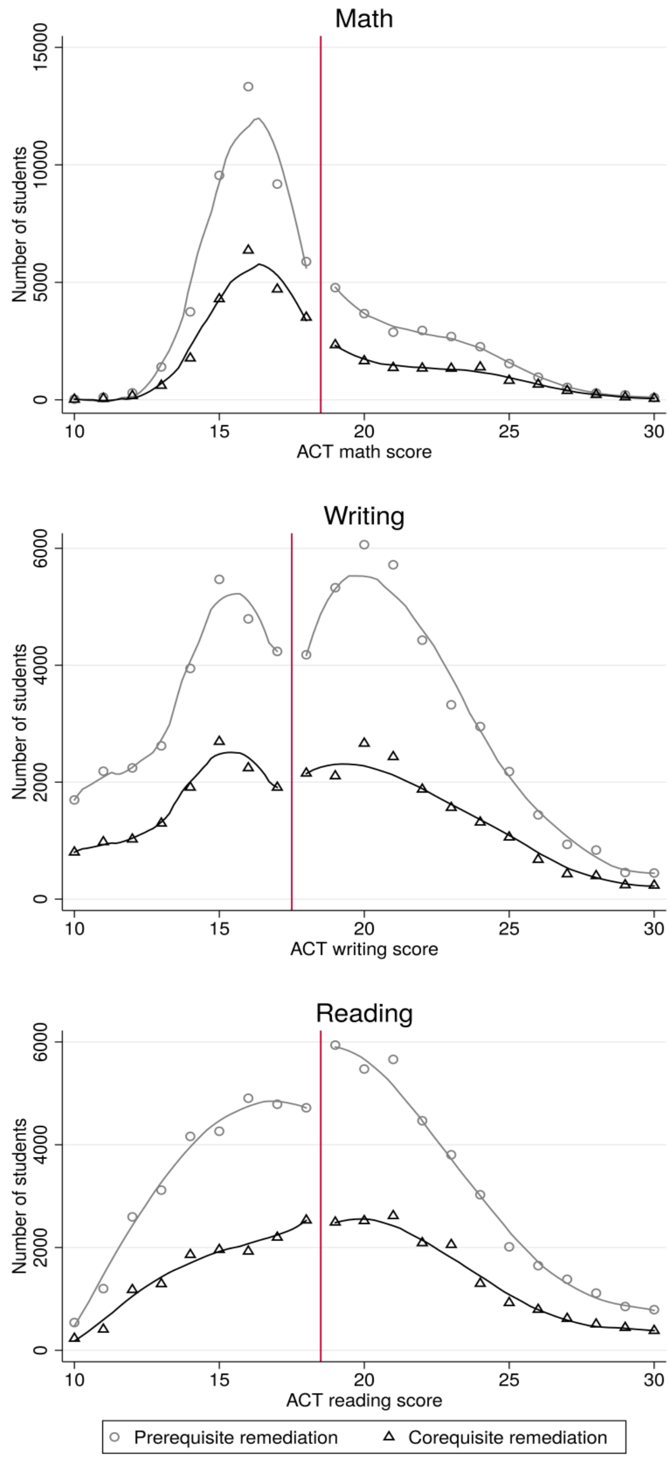
For the RD and DiRD estimates to be valid, one key assumption needs to be satisfied: that observable and unobservable student characteristics are comparable right above and below the college readiness cutoff score, and thus any differences in the outcomes of interest should be driven by placement into remediation rather than individual characteristics. To test this assumption, we followed the convention of checking the smoothness in the density through the college readiness threshold using the McCrary (2008) test and estimating the equation using pretreatment covariates and predicted outcomes based on observables as outcomes.

We first examined whether there were any jumps in the density of ACT scores around the college readiness threshold to test whether students “manipulate” their placement scores to avoid placement into remediation (for example, by retaking the ACT or challenging their placement decisions using Accuplacer). As shown in Figure 2, which plots the number of students with each ACT score by subject and remediation regime, there is visual evidence of a discontinuity in the density of reading scores around the cutoff under the prerequisite system. To confirm that there is indeed a discontinuity, we conducted a McCrary (2008) test, which rejected the null hypothesis that the density is smooth. In other words, we found evidence that some students, at least in prerequisite reading, avoided enrolling in remedial classes. This may lead to differences in student characteristics above and below the cutoff scores and bias the results.

We then evaluated whether predetermined student characteristics were comparable for students just above and below the college readiness cutoff. In Table 2, we formally tested for significant differences in these observable covariates under both RD and DiRD estimation strategies across subjects. Each coefficient in the table illustrates the relationship between the covariate and the indicator for remedial placement based on a version of Equation 1 (for RD specifications for the prerequisite and corequisite subsamples) and Equation 2 (for the DiRD specification) with covariates on the left-hand side. We detected some discontinuities—notably, different racial compositions around the math and writing cutoff scores; different age levels at college entry (predominantly for reading scores); and variations in high school GPA, timing of college entrance, and first-term enrollment intensity for certain specifications.

However, since we ran more than 80 regressions with some outcome variables highly correlated with each other (for example, the racial composition covariates), it is hard to determine how much these differences in individual characteristics around the cutoff affect the ultimate student outcomes. We conducted further tests following a method employed by Carrell, Hoekstra, and Kuka (2018) that takes account of not only the magnitude of any differences in covariates but also how much these differences in aggregate relate to the outcomes under study. To do this, we first ran a set of regressions in which we predicted each one-year gateway course completion outcome using the full set of covariates examined in Table 2. Then, we ran each of our main estimating equations, excluding covariates, with the predicted outcome variable on the left-hand side. The results are plotted in Figure 3. The predicted outcomes are smooth across the college readiness threshold, suggesting there are no significant selections on observable characteristics above and below the cutoff scores.

Figure 2
ACT Score Density by Subject and Remediation System



Note. Samples include fall entrants in the 2010–2016 cohorts for whom we have ACT scores. Points represent the number of students (sum count) with a given ACT score under the prerequisite and corequisite remediation systems. Lines are local smoothed polynomial lines with Degree 2. The cutoff score is 19 for math and reading and 18 for writing.

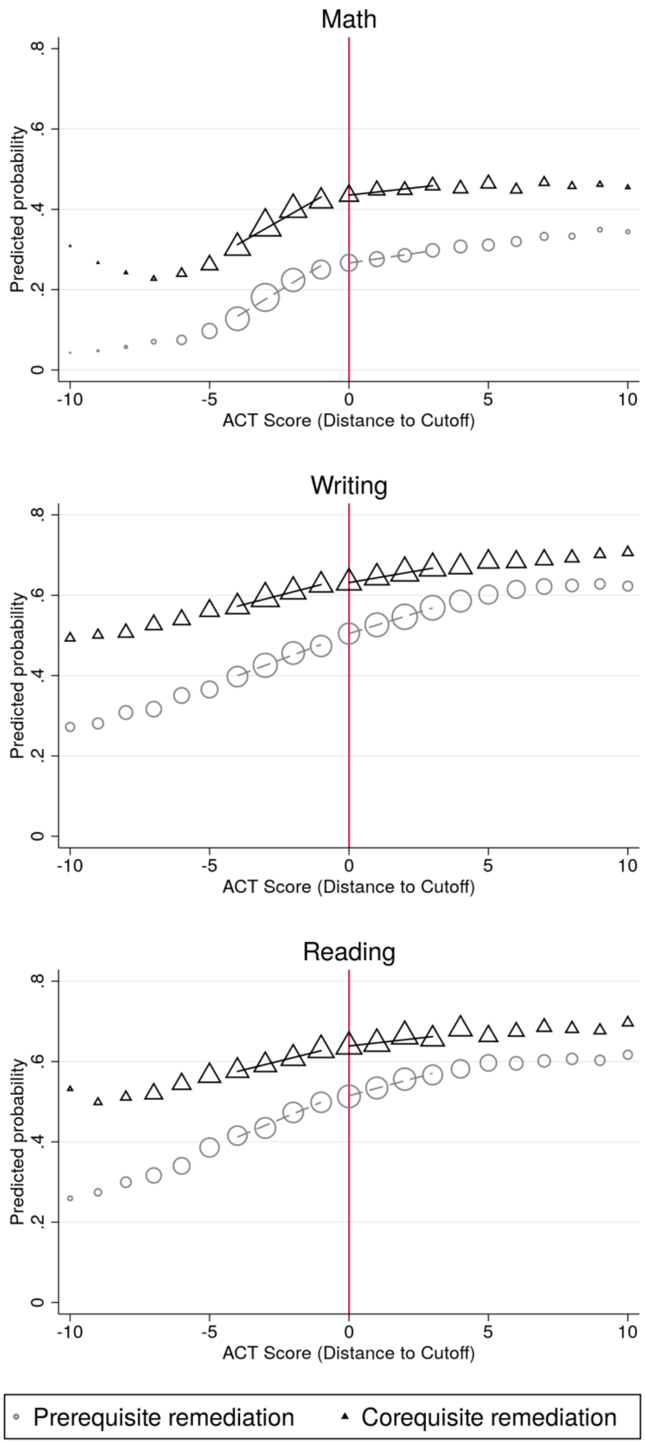
Table 2
Covariates Balance Test

Covariate	Math RD: Prerequisite (1)	Math RD: Corequisite (2)	Math DiRD (3)	Writing RD: Prerequisite (4)	Writing RD: Corequisite (5)	Writing DiRD (6)	Reading RD: Prerequisite (7)	Reading RD: Corequisite (8)	Reading DiRD (9)
Female	-0.001	0.009	0.011	0.006	-0.017	-0.022	0.006	-0.001	-0.007
	(0.014)	(0.020)	(0.023)	(0.013)	(0.020)	(0.024)	(0.013)	(0.027)	(0.034)
Age at college entry	-0.033	-0.044	-0.042	0.070	0.173**	0.098	0.091*	-0.170***	-0.278***
	(0.036)	(0.057)	(0.066)	(0.055)	(0.063)	(0.106)	(0.049)	(0.043)	(0.047)
Race									
White	0.020*	-0.024	-0.046**	-0.014	0.039*	0.051	-0.011	0.005	0.015
	(0.009)	(0.016)	(0.020)	(0.020)	(0.021)	(0.030)	(0.017)	(0.019)	(0.016)
Black	-0.008	0.020	0.0280	0.031*	-0.010	-0.040	-0.004	-0.010	-0.006
	(0.007)	(0.013)	(0.017)	(0.015)	(0.019)	(0.025)	(0.010)	(0.021)	(0.021)
Hispanic	-0.013**	0.013	0.026**	-0.009	-0.005	0.004	0.006	-0.001	-0.007
	(0.006)	(0.009)	(0.011)	(0.006)	(0.020)	(0.023)	(0.005)	(0.009)	(0.008)
Other race	0.001	-0.008	-0.008	-0.009	-0.024**	-0.014	0.009	0.006	-0.002
	(0.007)	(0.009)	(0.014)	(0.009)	(0.008)	(0.011)	(0.008)	(0.011)	(0.011)
Entered college 1 year after high school	0.003	0.013	0.014	-0.021	0.012	0.034	0.032**	0.005	-0.026
	(0.015)	(0.020)	(0.023)	(0.013)	(0.017)	(0.020)	(0.014)	(0.024)	(0.017)
High school GPA	0.037***	0.007	-0.030	-0.029	-0.004	0.023	0.011	0.025	0.018
	(0.011)	(0.020)	(0.021)	(0.017)	(0.036)	(0.045)	(0.022)	(0.026)	(0.029)
Enrolled full-time in first term	0.010	-0.006	-0.019	-0.004	0.035**	0.038	0.014	-0.012	-0.026
	(0.014)	(0.024)	(0.026)	(0.016)	(0.015)	(0.022)	(0.014)	(0.023)	(0.026)
N	23,509	12,192	35,676	18,515	8,404	26,919	20,921	9,738	30,659

Note. Estimates use the student covariate in each row as a dependent variable, controlling for cohort fixed effects and HS * HS-cohort fixed effects. We do not include other student covariates in the model to provide more conservative results. Each regression uses the analytic sample of first-time fall entrants with ACT math and reading scores from 17 to 20 and ACT writing scores from 16 to 19. Standard errors are clustered at the college–cohort level. Robust standard errors are shown in parentheses.

**p* < .1. ***p* < .05. ****p* < .01.

Figure 3
Predicted One-Year Gateway Course Completion Outcomes Based on Covariates



Note. Samples include fall entrants in the 2010–2016 cohorts for whom we have ACT scores. Predicted probability of gateway course completion is computed using the full set of covariates listed in Table 1, Panel A. Each point is the mean value of the predicted probability for students with a given ACT score. Lines are local linear fitted lines of the mean points within 4 points of the college-level cutoff scores.

5.2 Impacts of Corequisite Reform

Gateway course completion. In this section, we present the main RD and DiRD results for gateway course completion over time. For each specification, we present estimates with and without the interaction of high school and high school cohort fixed effects (HS * HS-cohort FE). The estimates without HS * HS-cohort FE (as in Columns 1, 3, and 5 of Table 3) can be interpreted as the impacts of placing into remediation in the context of the SAILS program. The estimates with HS * HS-cohort FE (as in Columns 2, 4, and 6) are our preferred results, as they show the effects of placing into remediation independent of other policy changes. The first two columns of Table 3 present the effects of prerequisite remediation over no remediation; similarly, Columns 3 and 4 show the effects of corequisite learning support over no remediation. The last two columns present the DiRD results that demonstrate the effects of corequisite remediation relative to prerequisite remediation. All of the tables that follow use a similar structure.

Figures 4 and 5 illustrate the effects of remediation on gateway course completion under different remediation regimes up to three years after initial enrollment. Overall, the patterns in these figures suggest that being placed into prerequisite remediation significantly lowers students' likelihood of gateway course completion, while there are no visually detectable differences in gateway course completion for students under corequisite remediation.

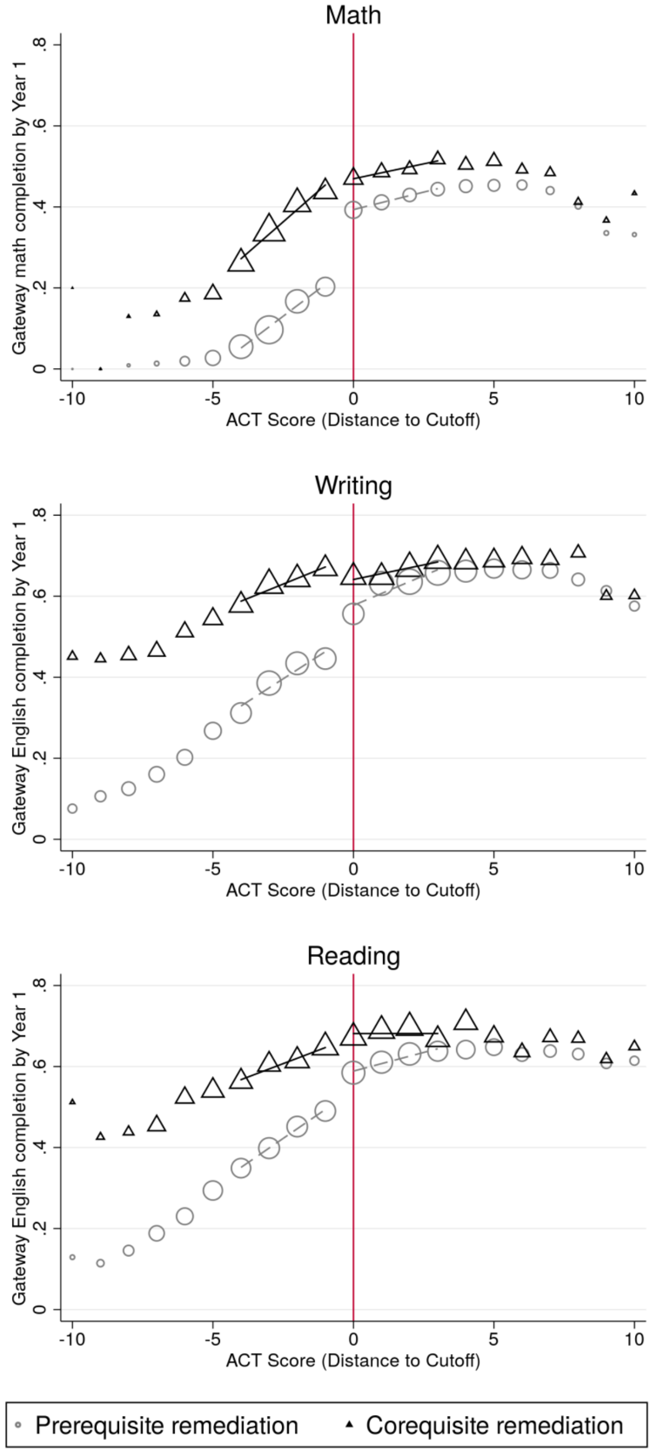
The results in Table 3 confirm these patterns. First, the RD estimates suggest that prerequisite course placement had large negative impacts on gateway course completion in both English and math relative to no remediation, as is largely consistent with findings from previous literature. Corequisite course placement, on the other hand, had no significant impacts on gateway course completion compared with no remediation for students at the margin of college readiness. After taking the possible effects of SAILS into consideration, students placing into corequisite remediation were equally likely to complete gateway math and English by the end of their first year compared with similar students placed into college-level courses without additional support.

Second, corequisite remediation was significantly more effective than the prerequisite approach in improving gateway course completion. The DiRD estimates indicate that students placed into corequisite learning support were 15 percentage points more likely to pass gateway math courses and 13 percentage points more likely to pass gateway English courses in their first year compared with students placed into prerequisite remedial education courses. These two patterns combined suggest that the positive trends in gateway course completion for students who were placed into corequisite remediation rather than prerequisite remediation are primarily driven by the mitigation of the negative impacts of the latter.

Third, the positive effects of corequisite placement relative to prerequisite placement diminish somewhat over time, but the magnitudes remain substantial. For example, by the end of Year 3, the positive effects of corequisite course placement relative to prerequisite course placement on gateway course completion decrease to about 9 percentage points—a 40% drop for math and a 27% drop for English from the end of Year 1. Thus, it appears that the positive effects of corequisite remediation are driven by students enrolling in gateway courses early on.

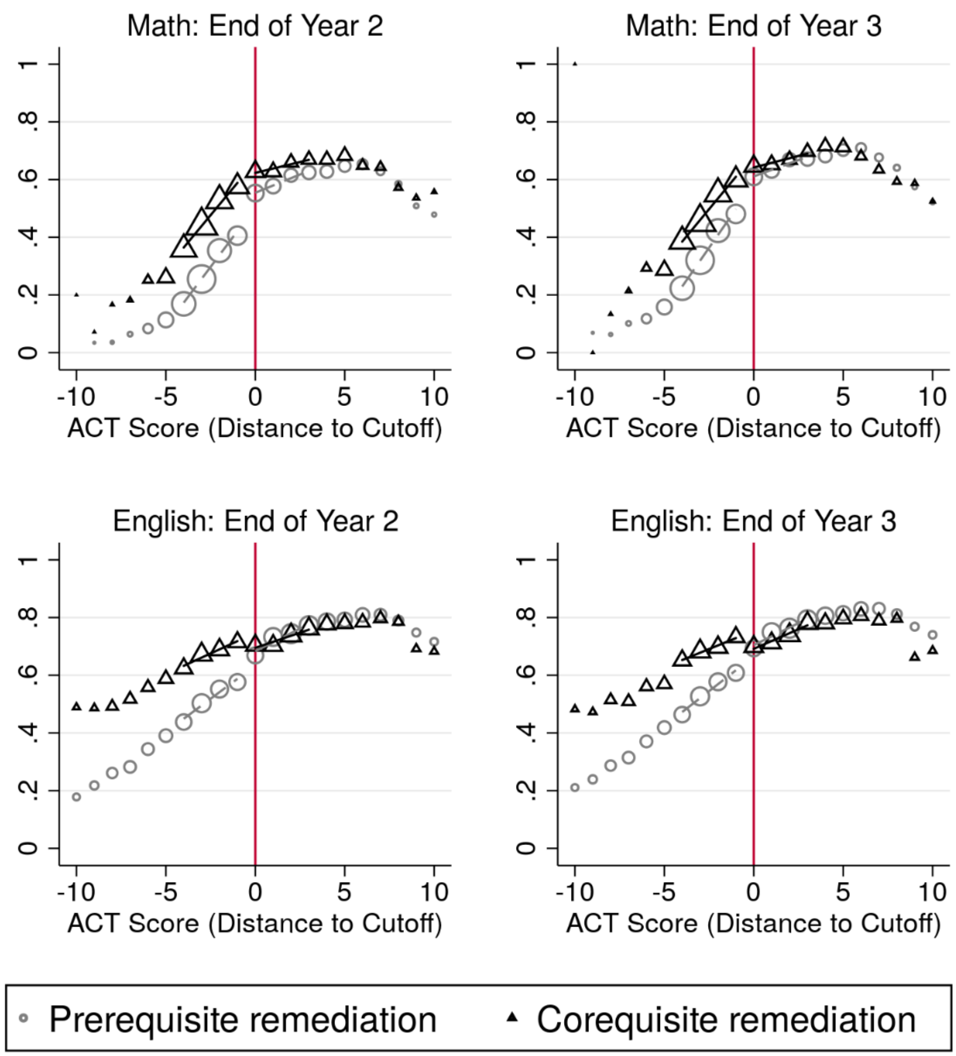
Lastly, the results with and without HS * HS-cohort FE are very similar in terms of both significance and effect size. This is not surprising, given that Kane et al. (2018) found that, after the corequisite policy was introduced, SAILS no longer had an impact on the percentage of students taking or passing college-level math during their first year, or on the total number of credits students completed by the end of their second year.

Figure 4
One-Year Gateway Course Completion



Note. Samples include fall entrants in the 2010–2016 cohorts for whom we have ACT scores. Each point is a mean value of the outcome for students with a given relative ACT score (in relation to the cutoff). Lines are local linear fitted lines of the mean points within 4 points of the college-level cutoff scores.

Figure 5
Gateway Course Completion After Two Years and Three Years



Note. Samples include fall entrants for whom we have ACT scores in math and writing. Year 2 outcomes are based on students in the 2010–2016 cohorts, and Year 3 outcomes are based on students in the 2010–2015 cohorts. Each point is a mean value of the outcome for students with a given relative ACT score (in relation to the cutoff).

Table 3
Gateway Course Completion Outcomes: Math and English

	RD: Prerequisite		RD: Corequisite		DiRD	
Outcome	(1)	(2)	(3)	(4)	(5)	(6)
			A. Gateway course outcomes: Math			
Completed by end of Year 1	-0.159*** (0.015)	-0.162*** (0.015)	-0.010 (0.024)	-0.023 (0.026)	0.154*** (0.029)	0.148*** (0.026)
Completed by end of Year 2	-0.106*** (0.012)	-0.103*** (0.012)	-0.009 (0.028)	-0.013 (0.032)	0.101*** (0.026)	0.095*** (0.025)
Completed by end of Year 3[1]	-0.084*** (0.010)	-0.086*** (0.013)	-0.006 (0.033)	-0.004 (0.042)	0.085** (0.030)	0.092** (0.031)
N	23,484	23,484	12,192	12,192	35,676	35,676
			B. Gateway course outcomes: English			
Completed by end of Year 1	-0.089*** (0.020)	-0.104*** (0.022)	0.035 (0.022)	0.034 (0.027)	0.125*** (0.033)	0.133*** (0.032)
Completed by end of Year 2	-0.058*** (0.017)	-0.065*** (0.019)	0.037* (0.019)	0.032 (0.020)	0.099*** (0.030)	0.103*** (0.031)
Completed by end of Year 3[1]	-0.044*** (0.013)	-0.048** (0.016)	0.058** (0.022)	0.047 (0.029)	0.104*** (0.025)	0.095** (0.031)
N	18,515	18,515	8,404	8,404	26,919	26,919
College–cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
HS * HS-cohort FE	No	Yes	No	Yes	No	Yes

Note. Each regression uses the analytic sample of first-time fall entrants with ACT math scores from 17 to 20 and ACT writing scores from 16 to 19. Standard errors are clustered at the college–cohort level. Robust standard errors are shown in parentheses.

**p* < .1. ***p* < .05. ****p* < .01.

[1] Estimates for Year 3 outcomes exclude the 2016 cohort. Sample sizes are 6,275 for corequisite math, 4,317 for corequisite English, 29,759 for DiRD math, and 22,717 for DiRD English.

Subsequent course enrollment and performance. Here, we examine the impacts of corequisite placement on students' enrollment in and completion of any subsequent college-level math and English courses, along with their course performance conditional on enrollment.[5] As shown in Table 4, the effects of corequisite remediation on subsequent course enrollment and performance are different for math and English. The RD estimates suggest that students placed into corequisite math were around 8 percentage points more likely to enroll in and pass a subsequent college-level math course compared with similar students placed directly into college-level math. These students performed similarly in the subsequent math course, as there was no significant difference in their course grades once they enrolled. The DiRD estimates on subsequent enrollment and performance in college-level math are insignificant, suggesting that students placed into corequisite remediation and prerequisite remediation in math had similar likelihoods of ever enrolling in and passing an additional math course after completing a gateway course.

For English, the pattern is reversed. Perhaps because English Composition II, the course we examined for subsequent enrollment and performance in English, is required for graduation for all degree-seeking students,[6] we found no significant impact of corequisite placement on enrollment in this course compared with no remediation. However, compared with students placed into prerequisite remediation, students in corequisite remediation were about 8 percentage points more likely to enroll in a subsequent English course. Their course performance once enrolled was not significantly different.

While critics of corequisite remediation have raised concerns that students who are not deemed college-ready upon entry may struggle in college-level courses, these results suggest that, at least for students right below the college readiness threshold, this is not the case. Compared with students placed directly into college-level math and English, those placed into corequisite remediation not only have comparable outcomes in gateway courses but also perform at least as well in subsequent courses.

[5] These outcomes are tracked up to two years after initial enrollment, since we could observe the latest cohort of students (the 2016 cohort) two years after their first term. We also examined the results tracked up to one year and up to three years (excluding the 2016 cohort). The patterns are generally similar.
[6] For more details on the TBR policy, see https://policies.tbr.edu/policies/general-education-requirements-and-degree-requirements

Table 4
RD and DiRD Estimates of Subsequent Course Outcomes: Math and English

	RD: Prerequisite		RD: Corequisite		DiRD	
Outcome	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Math			
Enroll in subsequent math course	0.030 (0.026)	0.026 (0.033)	0.075*** (0.022)	0.084*** (0.025)	0.043 (0.034)	0.044 (0.033)
Pass any subsequent math course	0.045* (0.021)	0.045 (0.028)	0.081*** (0.025)	0.087** (0.029)	0.034 (0.030)	0.036 (0.032)
Grades in subsequent math course[1]	0.179 (0.124)	0.248 (0.151)	0.218 (0.159)	0.287 (0.212)	0.026 (0.196)	0.148 (0.248)
N	23,484	23,484	12,192	12,192	35,676	35,676
			Panel B. English			
Enroll in subsequent English course	-0.072*** (0.016)	-0.065** (0.022)	0.011 (0.024)	0.006 (0.024)	0.087** (0.029)	0.077** (0.034)
Pass any subsequent English course	-0.052*** (0.017)	-0.043* (0.023)	-0.009 (0.026)	-0.013 (0.025)	0.048 (0.032)	0.036 (0.036)
Grades in subsequent English course[1]	0.050 (0.065)	0.109 (0.063)	-0.118 (0.105)	-0.127 (0.140)	-0.166 (0.113)	-0.220 (0.163)
N	18,515	18,515	8,404	8,404	26,919	26,919
HS * HS-cohort FE	No	Yes	No	Yes	No	Yes

Note. Each regression uses the analytic sample of first-time fall entrants with ACT math scores from 17 to 20 and ACT writing scores from 16 to 19. Standard errors are clustered at college–cohort level. Robust standard errors are shown in parentheses.

*p < .1. **p < .05. ***p < .01.

[1] Estimates of grades in subsequent courses are restricted to students who enrolled in subsequent math or English courses. Sample sizes for the DiRD estimates are 9,116 for math and 12,575 for English. We include course fixed effects for grades in subsequent math courses to control for differences in difficulty between math courses. The subsequent English course is College Composition II in all colleges.

Effects of math pathways. As discussed in Section 2.2, TBR community colleges introduced math pathways around the same time they implemented corequisite remediation. The effects in math discussed above thus may be partially or fully explained by the impacts of math pathways reform. To disentangle the effects of the corequisite and math pathways reforms, we looked at the effects of corequisite remediation by math pathway.

In Table 5, the RD results show heterogeneous impacts of corequisite math placement relative to no remediation for programs with different math requirements.[7] Results in Column 4 of Table 5 are from our preferred model. The results suggest that corequisite remediation had no significant impact on college gateway course completion for most programs. The exception is the programs for which students took Math for Liberal Arts as the gateway course: Students placed into corequisite learning support were 7 percentage points less likely to complete gateway math than were similar college-ready students in these programs. As for subsequent college-level math enrollment and performance, students in corequisite algebra and statistics courses were about 8 to 10 percentage points more likely to continue to enroll in a second college-level math course compared with similar students who were placed directly into college-level courses in algebra–calculus and statistics pathways.

The DiRD estimates compare the changes over time and thus help us disentangle the mainstreaming effects of corequisite remediation from the effects of the math pathways reform. The rationale is as follows: The DiRD estimates for the algebra–calculus pathway should represent the mainstreaming effects of corequisite remediation alone, since there was no change in the type of math course required for programs with this pathway, while the DiRD estimates for the statistics, math for liberal arts, and other math pathways should represent the combination of mainstreaming effects and pathways reform effects.

The effect of placement into corequisite remediation for students in the algebra–calculus pathway on gateway course completion is positive but nonsignificant compared with the effect of placement into prerequisite remediation. However, in other math

[7] We categorized programs into math pathways by the type of math courses program students most commonly take, designated by 6-digit CIP code. For example, if Introduction to Statistics is the gateway math course with the largest number of program students enrolled after the math pathways reform, we categorized the program as belonging to the statistics math pathway.

pathways, the mainstreaming effects combined with the alignment effects from math pathways are substantial: Compared with students in prerequisite remediation, which was largely focused on algebra, students in corequisite statistics were 16 percentage points more likely to complete gateway math by the end of Year 1, students in math for liberal arts were 20 percentage points more likely to do so (not significant at the 10% level due to large standard errors), and students in other math were 23 percentage points more likely to do so. These findings suggest that the pathways effects are the dominating factor driving the overall positive effects of corequisite placement on math gateway course completion. Even though there are no significant effects on subsequent math course enrollment and performance in general, the strong positive effects on gateway course completion alone are noteworthy, especially considering that gateway math is often the only math course required for graduation for students in these programs.

Table 5
Estimates of Math Outcomes by Math Pathway

	RD: Prerequisite		RD: Corequisite		DiRD	
Math Pathway	(1)	(2)	(3)	(4)	(5)	(6)
			A. Completed gateway math by Year 1			
Algebra–calculus	-0.172***	-0.162***	-0.090	-0.101	0.074	0.063
	(0.022)	(0.031)	(0.076)	(0.106)	(0.079)	(0.112)
Statistics	-0.149***	-0.155***	-0.003	-0.009	0.154***	0.160***
	(0.019)	(0.018)	(0.036)	(0.034)	(0.035)	(0.033)
Math for liberal arts	-0.187**	-0.239	-0.002	-0.072***	0.155*	0.195
	(0.070)	(0.107)	(0.025)	(0.011)	(0.079)	(0.096)
Other	-0.193***	-0.186**	0.049**	0.034	0.250***	0.226***
	(0.044)	(0.060)	(0.022)	(0.021)	(0.039)	(0.039)
			B. Enrolled in subsequent college-level math			
Algebra–calculus	0.107	0.158*	0.104***	0.098*	-0.017	-0.061
	(0.075)	(0.084)	(0.017)	(0.049)	(0.079)	(0.063)
Statistics	0.029	0.021	0.065**	0.076**	0.034	0.042
	(0.025)	(0.030)	(0.028)	(0.029)	(0.042)	(0.043)
Math for liberal arts	-0.061	0.123	0.040	0.089	0.102**	-0.035
	(0.049)	(0.102)	(0.054)	(0.109)	(0.039)	(0.126)
Other	-0.027	-0.018	0.095*	0.070	0.121**	0.107**
	(0.024)	(0.020)	(0.043)	(0.047)	(0.049)	(0.036)
			C. Enrolled in and passed subsequent college-level math			
Algebra–calculus	0.145*	0.190*	0.135***	0.131**	-0.020	-0.024
	(0.074)	(0.106)	(0.035)	(0.059)	(0.060)	(0.101)
Statistics	0.036**	0.034	0.073**	0.086**	0.036	0.045
	(0.016)	(0.019)	(0.029)	(0.032)	(0.035)	(0.035)
Math for liberal arts	0.015	0.100	0.020	0.094	0.007	-0.015
	(0.079)	(0.105)	(0.028)	(0.087)	(0.083)	(0.132)
Other	0.004	0.005	0.071*	0.012	0.070	0.018
	(0.031)	(0.030)	(0.039)	(0.034)	(0.059)	(0.034)
HS * HS-cohort FE	No	Yes	No	Yes	No	Yes

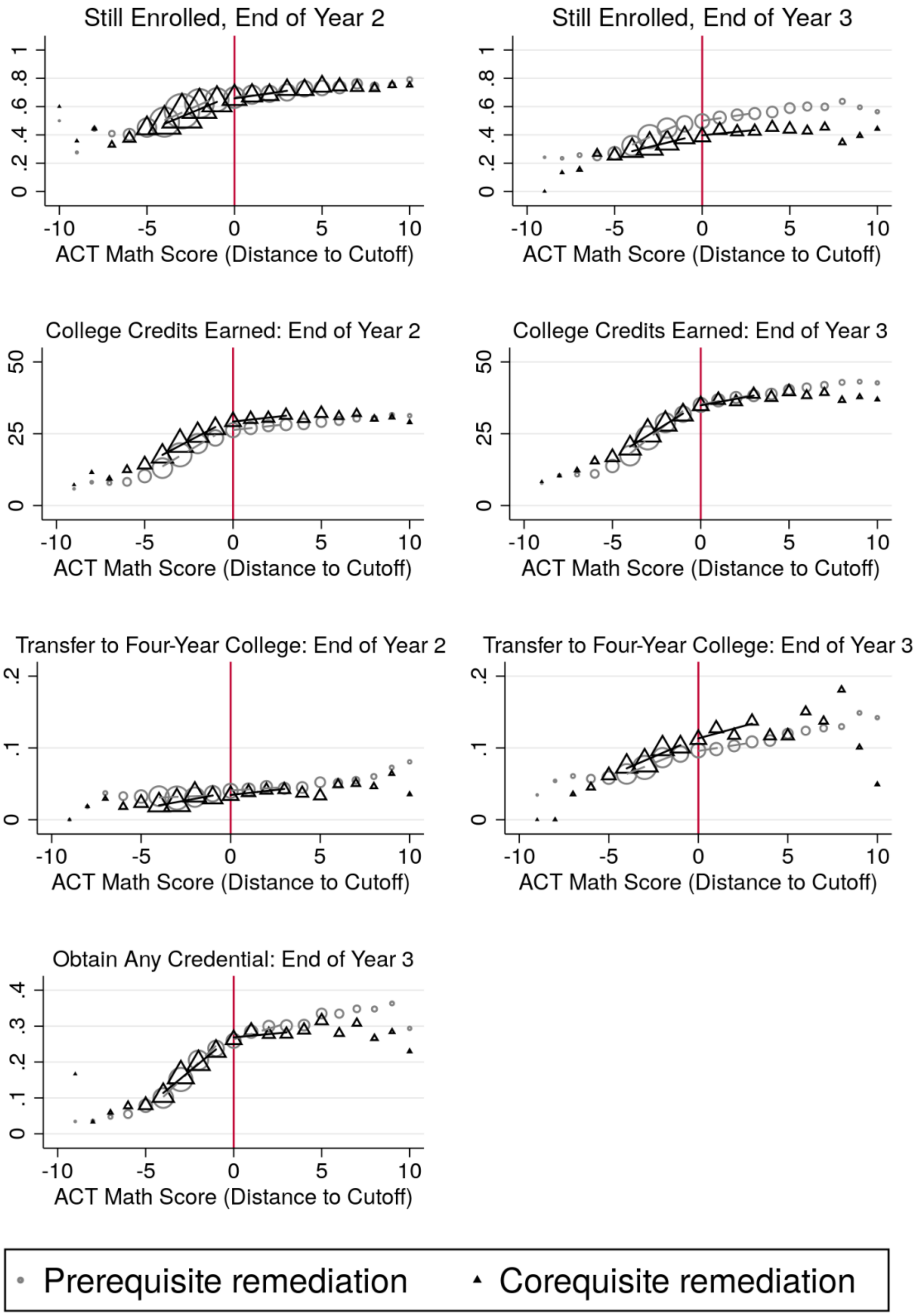
Note. Each regression uses sample of first-time fall entrants with ACT math scores from 17 to 20. Sample sizes for the DiRD model are as follows: Algebra/Calculus (4,614), Statistics (25,118), Math for Liberal Arts (1,601), other (4,110). Other includes Finite Mathematics, Trigonometric Applications, Survey of Mathematics, and Math for Elementary Education. Standard errors are clustered at the college–cohort level. Robust standard errors in parentheses.

*$p < .1$. **$p < .05$. ***$p < .01$.

Credit attainment, persistence, transfer, and credential completion. To understand the longer term impacts of corequisite placement, we conducted further analyses on outcomes associated with college-level credits attempted and earned (excluding gateway courses), enrollment persistence, transfer to a four-year college, and credential completion. In Figure 6, there are no visible jumps around the college readiness cutoffs under the prerequisite or corequisite systems for these longer term outcomes, suggesting that placement into remediation does not affect these outcomes under either remediation regime. The formal results are shown in Table 6. The RD estimates suggest that students placed into corequisite learning support attempted about 0.7 fewer college-level credits by the end of Year 1 compared with otherwise similar students who were placed into college-level courses. This is not surprising, considering that students in corequisite remediation have to allocate time and financial aid resources to learning support. By the end of Year 2 and Year 3, there were no significant differences in college-level credits attempted and earned between the two groups. The DiRD estimates show that students placed into corequisite remediation enrolled in 0.7 more college-level credits by the end of Year 1 compared with students placed into prerequisite remediation. This difference is no longer significant by the end of Year 2 and Year 3.

Other results in Table 6 reveal that corequisite remediation had no impacts on enrollment, persistence, transfer to four-year colleges, or credential completion, either compared with no remediation or with prerequisite remediation. These findings are consistent with the previous discussion that the main effects of corequisite remediation are largely driven by their mitigation of the negative, delaying effects of prerequisite remediation. They also imply that improvements in transfer and completion are not guaranteed after gateway course completion. Students need additional support at every step along the way to college completion.

Figure 6
Persistence, Credit Accumulation, Transfer, and Degree Completion
After Two Years and Three Years



Note. Samples include fall entrants for whom we have ACT scores. Year 2 outcomes are based on students in the 2010–2016 cohorts, and Year 3 outcomes are based on students in the 2010–2015 cohorts. Each point is the mean value of the outcome for students with a given relative ACT score (in relation to the cutoff).

Table 6
Estimates of Credit Attainment, Persistence, Transfer, and Credential Attainment

	RD: Prerequisite		RD: Corequisite		DiRD	
Outcome	(1)	(2)	(3)	(4)	(5)	(6)
			A. Year 1 outcomes			
College-level credits attempted	-1.569***	-1.516***	-0.627**	-0.715***	1.003**	0.733*
	(0.233)	(0.293)	(0.250)	(0.225)	(0.333)	(0.379)
College-level credits earned	-0.843***	-0.718**	-0.302	-0.346	0.600	0.329
	(0.265)	(0.288)	(0.416)	(0.401)	(0.414)	(0.489)
N	23,484	23,484	12,192	12,192	35,676	35,676
			B. Year 2 outcomes			
College-level credits attempted	-1.757***	-1.730***	-0.383	-0.533	1.507**	1.078
	(0.313)	(0.410)	(0.562)	(0.567)	(0.604)	(0.808)
College-level credits earned	-1.335***	-1.100**	-0.384	-0.495	1.053	0.592
	(0.426)	(0.434)	(0.680)	(0.748)	(0.658)	(0.890)
Still enrolled	-0.002	-0.004	-0.002	-0.009	0.002	-0.004
	(0.018)	(0.021)	(0.023)	(0.027)	(0.022)	(0.022)
Transferred to 4-year college	0.001	0.003	-0.009	-0.011	-0.010	-0.014
	(0.006)	(0.009)	(0.008)	(0.009)	(0.007)	(0.010)
N	23,484	23,484	12,192	12,192	35,676	35,676
			C. Year 3 outcomes[1]			
College-level credits attempted	-1.704**	-1.714**	0.189	0.602	2.179*	2.128
	(0.584)	(0.783)	(1.135)	(1.359)	(1.158)	(1.406)
College-level credits earned	-1.138*	-0.904	-0.179	0.235	1.091	1.116
	(0.574)	(0.691)	(1.237)	(1.528)	(1.017)	(1.306)
Still enrolled	-0.003	-0.002	0.029	0.051	0.032	0.047
	(0.015)	(0.015)	(0.037)	(0.043)	(0.030)	(0.038)
Transferred to 4-year college	-0.001	0.003	-0.011	-0.018	-0.010	-0.012
	(0.011)	(0.014)	(0.019)	(0.022)	(0.023)	(0.027)
Received any degree	0.004	0.009	0.005	0.010	-0.003	-0.004
	(0.014)	(0.016)	(0.021)	(0.028)	(0.024)	(0.031)
N	23,484	23,484	6,275	6,275	29,759	29,759
HS * HS-cohort FE	No	Yes	No	Yes	No	Yes

Note. Each regression uses the analytic sample of first-time fall entrants with ACT math scores from 17 to 20. Standard errors are clustered at the college–cohort level. Robust standard errors in parentheses.

[1] Estimates for Year 3 outcomes exclude the 2016 cohort.

**p* < .1. ***p* < .05. ****p* < .01.

5.3 Robustness Checks

We conducted several robustness checks to confirm that our main results are robust to various model specifications and sample restrictions. First, we conducted a series of robustness checks to ensure that our main results are not driven by a small subset of particular schools, given the variations in the delivery formats of corequisite courses and the timing of their implementation across colleges. Specifically, we reran analyses based on a sample excluding the three colleges that offered all of their corequisite courses via online or hybrid formats, as well as on a sample excluding the three colleges that had not fully implemented corequisite remediation by fall 2015. These results are available upon request and, despite small variations, are essentially the same as our main results.

Additionally, we tested the robustness of our main results on gateway course completion using different model specifications and bandwidths, as shown in Appendix Table A2. First, we conducted the analyses using alternative specifications without student covariates, as shown in Columns 1, 4 and 7 for the RD prerequisite sample, RD corequisite sample, and DiRD estimates, respectively. The results are very consistent with those from our preferred specification. Second, we conducted analyses with more flexible local quadratic specifications, as shown in Columns 2, 5, and 8. Again, the change made little difference to our results. Lastly, we tested our results' sensitivity to bandwidth selection by reestimating them using double the optimal bandwidth (± 4 points). Only for the RD estimates on corequisite English courses (Column 6) did doubling the bandwidth size slightly increase the magnitude of the results and generate more statistically significant findings, but many more background characteristics failed our covariate balance tests, suggesting that the characteristics of college-ready students and students placed into corequisite writing diverge at ACT scores further away from the college-level cutoff.

6. Discussion

This study advances the current understandings of reforms to remedial education by providing the first causal evidence on a system-wide corequisite remediation reform in math and English in Tennessee. It provides estimates of the effects of placement into corequisite remediation on students' academic outcomes, including gateway course completion and subsequent course enrollment and performance up to three years after initial enrollment, compared with both prerequisite remediation and direct placement into college-level courses. In addition, this is the first study to identify the effects of mainstreaming students into college-level courses and the effects of math pathways reforms separately.

We found strong and robust positive effects of placement into corequisite remediation on student outcomes in gateway courses, compared with placement into prerequisite remediation. Students placed into corequisite learning support were significantly more likely to complete gateway math and English by the end of their first year, by 15 percentage points and 13 percentage points respectively, compared with students placed into prerequisite remediation. Even though the effects diminished somewhat over time, they remained significantly positive and sizable until the end of the third year after students' initial enrollment. These results are consistent with findings from earlier studies comparing corequisite remediation with the traditional approach in a single site or a small number of institutions (e.g., Boatman, 2012; Cho et al., 2012; Jenkins et al., 2010; Logue et al., 2016; Logue et al., 2019). Since our study examined the effects across an entire college system, it suggests that corequisite remediation is a scalable approach to improving student success in gateway courses.

Additionally, compared with direct placement into college-level courses, corequisite remediation does not compromise, and even improves in some subjects under some models, students' enrollment and performance in subsequent courses. For English, students placed into corequisite learning support were equally likely to enroll in and pass the next college-level English course compared with students directly placed into college-level courses. For math, students placed into corequisite learning support were 8 percentage points more likely to enroll in and pass an additional college-level math course compared with students placed into college-level directly. In absence of direct learning assessments, students' performance in subsequent courses can serve as a proxy for instructional quality in their gateway courses and corequisite learning support experiences. Our findings should thus lessen any concerns that instructors lowered their standards when all students had the option to enroll in college-level courses.

Since TBR implemented math pathways in conjunction with corequisite remediation, we were able to identify the effects of these two approaches separately. The positive impacts of placing into corequisite math were largely driven by the colleges' math pathways reforms. It is worth noting that Tennessee community colleges were simultaneously redesigning their approach to new student onboarding to help students choose a program of study early on, allowing students to determine which type of math courses would be most suitable for them (Jenkins et al., 2018). Since community colleges historically have not had such processes, many colleges will need to implement stronger supports for early program exploration and selection in order to scale corequisite math effectively. Math pathways reforms, along with the efforts to clearly map programs and specify the appropriate type of math courses for each program, are important to ensuring the successful implementation of corequisite reforms.

However, we did not find any significant effects of corequisite remediation on enrollment persistence, transfer to four-year colleges, or degree completion up to three years after initial enrollment. This suggests that improvements in gateway course outcomes are important but insufficient barometers of academic momentum and college success. The types of higher education interventions that have produced improvements in overall college completion, such as the highly effective Accelerated Study in Associate Programs (ASAP) at CUNY, usually address multiple barriers to student success (Strumbos, Linderman, & Hicks, 2018). To get more students to college completion, colleges need to support them with enhanced advising, academic and career services, financial aid, and more structured pathways to degrees.

Future research should examine two aspects of corequisite remediation reforms. Due to the limitation of RD and DiRD designs, we focused on students at the margin of the college readiness threshold. It is unclear how corequisite remediation affects students who score further below cutoff and presumably have greater academic needs. Some evidence suggests that students with lower levels of academic preparation benefit from an intensive focus on building basic academic skills, either in prerequisite remedial sequences (Boatman & Long, 2018) or in programs delaying college matriculation, such as CUNY Start (Scrivener et al., 2018). It is thus important for future research to examine how corequisite reforms affect the students who are the most academically vulnerable.

Additional research is also needed to understand the equity implications of math pathways reforms. In particular, research should examine whether students from disadvantaged backgrounds are more likely to be advised away from math courses on the algebra–calculus track. These courses are required for STEM degrees, which are associated with large wage premiums, so student tracking of this kind could have large unintended consequences for students' employability and labor market returns. Further, since the positive outcomes we found for corequisite remediation compared with prerequisite were mostly driven by pathways other than algebra–calculus, it will be important to explore ways to improve student outcomes on the algebra–calculus track, such as reforms to curriculum or instructional practices.

There are several limitations to the study. First, we could only track one cohort of students up to three years after initial enrollment, since corequisite remediation was scaled up in most TBR colleges in fall 2015. It might be still too early to detect any significant impacts of the reform on college completion. Second, we do not have detailed information on the types of learning support available and its implementation quality, and therefore we were not able to quantify whether and how different implementation features, such as the delivery method of corequisite courses, affect student success.

References

Attewell, P., Heil, S., & Reisel, L. (2012). What is academic momentum? And does it matter? *Educational Evaluation and Policy Analysis*, *34*(1), 27–44.

Bailey, T. (2009). Challenge and opportunity: Rethinking the role and function of developmental education in community college. *New Directions for Community Colleges*, *2009*(145), 11–30.

Bailey, T., Jeong, D. W., & Cho, S. W. (2010). Referral, enrollment, and completion in developmental education sequences in community colleges. *Economics of Education Review*, *29*(2), 255–270.

Boatman, A. (2012). *Evaluating institutional efforts to streamline postsecondary remediation: The causal effects of the Tennessee developmental course redesign initiative on early student academic success* (NCPR Working Paper). New York, NY: National Center for Postsecondary Research.

Boatman, A., & Long, B. T. (2018). Does remediation work for all students? How the effects of postsecondary remedial and developmental courses vary by level of academic preparation. *Educational Evaluation and Policy Analysis*, *40*(1), 29–58.

Calcagno, J. C., & Long, B. T. (2008). *The impact of postsecondary remediation using a regression discontinuity approach: Addressing endogenous sorting and noncompliance* (NBER Working Paper No. 14194). Cambridge, MA: National Bureau of Economic Research.

Carrell, S. E., Hoekstra, M., & Kuka, E. (2018). The long-run effects of disruptive peers. *American Economic Review*, *108*(11), 3377–3415.

Chen, X. (2016). *Remedial coursetaking at US public 2-and 4-year institutions: Scope, experiences, and outcomes* (NCES Statistical Analysis Report 2016-405). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics.

Cho, S. W., Kopko, E., Jenkins, D., & Jaggars, S. S. (2012). *New evidence of success for community college remedial English students: Tracking the outcomes of students in the Accelerated Learning Program (ALP)* (CCRC Working Paper No. 53). New York, NY: Columbia University, Teachers College, Community College Research Center.

Dadgar, M. (2012). *Essays on the economics of community college students' academic and labor market success* (Doctoral dissertation). Teachers College, Columbia University, New York, NY.

Daugherty, L., Gomez, C. J., Carew, D., Mendoza-Graf, A., & Miller, T. (2018). *Designing and implementing corequisite models of developmental education: Findings from Texas community colleges*. Santa Monica, CA: RAND Corporation.

Denley, T. (2016). *Co-requisite remediation pilot study–Fall 2014 and spring 2015 and full implementation fall 2015*. Nashville, TN: Tennessee Board of Regents, Office of the Vice Chancellor for Academic Affairs.

Education Commission of the States. (2018). Developmental education policies. Are instructional methods addressed? If so, which methods are used or allowed? Retrieved from http://ecs.force.com/mbdata/MBQuestDEP2?Rep=DEP1805N

Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, *142*(2), 615–635. https://doi.org/10.1016/j.jeconom.2007.05.001

Jaggars, S. S., & Stacey, G. W. (2014). *What we know about developmental education outcomes*. New York, NY: Columbia University, Teachers College, Community College Research Center.

Jenkins, D., Brown, A. E., Fink, J., Lahr, H., & Yanagiura, T. (2018). *Building guided pathways to community college student success: Promising practices and early evidence from Tennessee*. New York, NY: Columbia University, Teachers College, Community College Research Center.

Jenkins, D., Speroni, C., Belfield, C., Jaggars, S. S., & Edgecombe, N. (2010). *A model for accelerating academic success of community college remedial English students: Is the Accelerated Learning Program (ALP) effective and affordable?* (CCRC Working Paper No. 21). New York, NY: Columbia University, Teachers College, Community College Research Center.

Kane, T., Boatman, A., Kozakowski, W., Bennett, C., Hitch, R., & Weisenfeld, D. (2018). *Remedial math goes to high school: An evaluation of the Tennessee SAILS program*. Cambridge, MA: Harvard University, Center for Education Policy Research.

Logue, A. W., Douglas, D., & Watanabe-Rose, M. (2019). Corequisite mathematics remediation: Results over time and in different contexts. *Educational Evaluation and Policy Analysis*, *41*(3), 294–315.

Logue, A. W., Watanabe-Rose, M., & Douglas, D. (2016). Should students assessed as needing remedial mathematics take college-level quantitative courses instead? A randomized controlled trial. *Educational Evaluation and Policy Analysis*, *38*(3), 578–598.

Martorell, P., & McFarlin, Jr., I. (2011). Help or hindrance? The effects of college remediation on academic and labor market outcomes. *The Review of Economics and Statistics*, *93*(2), 436–454.

Martorell, P., McFarlin, I., Jr., & Xue, Y. (2015). Does failing a placement exam discourage underprepared students from going to college? *Education Finance and Policy*, *10*(1), 46–80.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714. https://doi.org/10.1016/j.jeconom.2007.05.005

Rutschow, E. Z., & Mayer, A. K. (2018). *Early findings from a national survey of developmental education practices*. New York, NY: Center for the Analysis of Postsecondary Readiness.

Scott-Clayton, J., Crosta, P. M., & Belfield, C. R. (2014). Improving the targeting of treatment: Evidence from college remediation. *Educational Evaluation and Policy Analysis*, *36*(3), 371–393.

Scott-Clayton, J., & Rodriguez, O. (2015). Development, discouragement, or diversion? New evidence on the effects of college remediation policy. *Education Finance and Policy*, *10*(1), 4–45.

Scrivener, S., Gupta, H., Weiss, M. J., Cohen, B., Cormier, M. S., & Brathwaite, J. (2018). *Becoming college-ready: Early findings from a CUNY Start evaluation.* New York, NY: MDRC.

Strumbos, D., Linderman, D., & Hicks, C. C. (2018). Postsecondary pathways out of poverty: City University of New York Accelerated Study in Associate Programs and the case for national policy. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *4*(3), 100–117.

Tennessee Board of Regents. (2019). Exhibit 2: Approved cut scores for placement into college level courses. Retrieved from https://policies.tbr.edu/policies/learning-support-formerly-100

Wang X. (2017). Toward a holistic theoretical model of momentum for community college student success. In M. B. Paulsen (Ed.), *Higher education: Handbook of theory and research*. Cham, Switzerland: Springer.

Xu, D. (2016). Assistance or obstacle? The impact of different levels of English developmental education on underprepared students in community colleges. *Educational Researcher*, *45*(9), 496–507.

Appendix

Table A1
Math Gateway and Corequisite Course Pairings

College	Gateway Course	Corequisite Course	Math Pathway
Chattanooga State	MATH 1030 Introduction to College Math	MATH 0030 Learning Support for Math 1030	Algebra/Calculus
	MATH 1530 Introductory Statistics	MATH 0530 Learning Support for Math 1530	Statistics
Cleveland State	MATH 1000 Algebra Essentials	MATH 0130 Corequisite Algebra Support	Algebra/Calculus
	MATH 1530 Introductory Statistics	MATH 0530 Corequisite Statistics Support	Statistics
Columbia State	MATH 1010 Math for General Studies	MATH 0010 Learning Support for Math 1010	Math for Liberal Arts
	MATH 1530 Elementary Statistics	MATH 0530 Learning Support for Math 1530	Statistics
	MATH 1130 College Algebra	MATH 0130 Learning Support for MATH 1130[1]	Algebra/Calculus
Dyersburg State	MATH 1005 Foundations of College Mathematics	MATH 0105 Support for Math 1005	Algebra/Calculus
	MATH 1530 Elementary Probability and Statistics	MATH 0530 Support for Math 1530	Statistics
Jackson State	MATH 1010 Math for Liberal Arts	MATH 0010 Lab for Math 1010	Math for Liberal Arts
	MATH 1030 Essentials of Mathematics	MATH 0030 Lab for Math 1030	Algebra/Calculus
	MATH 1530 Statistics and Probability	MATH 0530 Lab for Math 1530	Statistics
Motlow State	MATH 1003 Intermediate Algebra	MATH 0810 Learning Support Mathematics for Intermediate Algebra	Algebra/Calculus
	MATH 1010 Math for General Studies	MATH 0101 Learning Support Mathematics for Mathematics for General Studies	Math for Liberal Arts
	MATH 1530 Introductory Statistics	MATH 0530 Learning Support for Probability and Statistics	Statistics
	MATH 1630 Finite Mathematics	MATH 0630 Learning Support for Finite Mathematics	Other
Nashville State	MATH 1000 Foundations of Algebra	MATH 0815 Algebra Support	Algebra/Calculus
	MATH 1010 Math for General Studies	MATH 0825 Liberal Arts Math Support	Math for Liberal Arts
	MATH 1530 Introductory Statistics	MATH 0835 Statistics Support	Statistics
	MATH 1630 Finite Mathematics	MATH 0845 Finite Math Support	Other

Table A1 (cont.)
Math Gateway and Corequisite Course Pairings

College	Gateway Course	Corequisite Course	Type
Northeast State	MATH 1010 Math for General Studies	MATH 0010 Principles of Applied Math	Math for Liberal Arts
	MATH 1050 Trigonometric Applications	MATH 0050 Principles of Trig Apps	Other
	MATH 1100 Intermediate Algebra	MATH 0030 College Mathematics Principles	Algebra/Calculus
	MATH 1530 Introductory Statistics	MATH 0530 Statistics Principles	Statistics
Pellissippi State	MATH 1010 Survey of Mathematics	MATH 0010 Survey Math Principles W/Lab	Other
	MATH 1030 Introduction to College Mathematics	MATH 0030 College Math Principles W/Lab	Algebra/Calculus
	MATH 1530 Introductory Statistics	MATH 0530 Statistics Principles W/Lab	Statistics
Roane State	MATH 1000 Algebra Essentials	MATH 0900 Math Learning Support A	Algebra/Calculus
	MATH 1530 Probability and Statistics	MATH 0530 Statistical Principles	Statistics
Southwest Tennessee	MATH 1000 Essentials of Algebra	MATH 0100 Support Course for Math 1000	Algebra/Calculus
	MATH 1410 Math for Elementary Education	MATH 0410 Support Course for Math 1410	Other
	MATH 1530 Probability and Statistics	MATH 0530 Support Course for Math 1530	Statistics
	MATH 1630 Finite Mathematics	MATH 0630 Support Course for Finite Math	Other
Volunteer State	MATH 1005 Algebra Essentials	MATH 0105 Skills for Algebra Essentials	Algebra/Calculus
	MATH 1010 Math for Liberal Arts	MATH 0101 Skills for Liberal Arts Math	Math for Liberal Arts
	MATH 1530 Introductory Statistics	MATH 0153 Skills for Probability and Stats	Statistics
Walters State	MATH 1030 Intermediate Algebra	MATH 0030[2] Mathematics Learning Support	Algebra/Calculus
	MATH 1530 Introductory Statistics	MATH 0030 Mathematics Learning Support	Statistics
	MATH 1630 Finite Mathematics	MATH 0030 Mathematics Learning Support	Other

[1] Columbia State Community College started to offer MATH 0130: Learning Support for MATH 1130 in 2016.

[2] In Walters State Community College, students required to take Math 1030, Math 1530, and Math 1630 must be jointly enrolled in Math 0030 if placed below college-level. The topics covered in Math 0030 include real number sense, algebraic operations, analysis of linear equations and inequalities, systems of equations, and systems of inequalities.

Table A2
Robustness Check on Estimates of Gateway Course Completion

	RD: Prerequisite			RD: Corequisite			DiRD		
Outcome	No Covariates (1)	Quadratic Form (2)	x2 Bandwidth (3)	No Covariates (4)	Quadratic Form (5)	x2 Bandwidth (6)	No Covariates (7)	Quadratic Form (8)	x2 Bandwidth (9)
				Panel A. Math					
Completed by end of Year 1	-0.153***	-0.162***	-0.159***	-0.015	-0.023	0.006	0.145***	0.150***	0.182***
	(0.016)	(0.015)	(0.017)	(0.028)	(0.026)	(0.023)	(0.025)	(0.026)	(0.025)
Completed by end of Year 2	-0.091***	-0.103***	-0.089***	-0.003	-0.013	0.005	0.089***	0.094***	0.101***
	(0.013)	(0.011)	(0.010)	(0.034)	(0.032)	(0.027)	(0.024)	(0.026)	(0.024)
Completed by end of Year 3	-0.073***	-0.086***	-0.069***	0.006	-0.004	0.011	0.080*	0.091**	0.084***
	(0.016)	(0.013)	(0.010)	(0.055)	(0.042)	(0.025)	(0.038)	(0.032)	(0.025)
N	23,484	23,484	52,142	12,192	12,192	25,542	35,676	35,676	77,684
Sample	17 ≤ x ≤ 20	17 ≤ x ≤ 20	15 ≤ x ≤ 22	17 ≤ x ≤ 20	17 ≤ x ≤ 20	15 ≤ x ≤ 22	17 ≤ x ≤ 20	17 ≤ x ≤ 20	15 ≤ x ≤ 22
				Panel B. English					
Completed by end of Year 1	-0.116***	-0.104***	-0.073***	0.038	0.034	0.039***	0.143***	0.133***	0.126***
	(0.019)	(0.022)	(0.009)	(0.030)	(0.027)	(0.012)	(0.027)	(0.032)	(0.022)
Completed by end of Year 2	-0.076***	-0.065***	-0.042***	0.033	0.032	0.041***	0.110***	0.103***	0.097***
	(0.016)	(0.019)	(0.009)	(0.019)	(0.019)	(0.010)	(0.024)	(0.031)	(0.021)
Completed by end of Year 3	-0.058***	-0.048**	-0.031***	0.061*	0.047	0.061**	0.120***	0.095**	0.096***
	(0.014)	(0.016)	(0.007)	(0.031)	(0.029)	(0.027)	(0.033)	(0.031)	(0.023)
N	18,515	18,515	39,682	8,404	8,404	18,097	26,919	26,919	26,919
Sample	16 ≤ x ≤ 19	16 ≤ x ≤ 19	14 ≤ x ≤ 21	16 ≤ x ≤ 19	16 ≤ x ≤ 19	14 ≤ x ≤ 21	16 ≤ x ≤ 19	16 ≤ x ≤ 19	14 ≤ x ≤ 21
Student covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
College and cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Linear	Quadratic	Linear	Linear	Quadratic	Linear	Linear	Quadratic	Linear

Note. Results in Columns 1, 4, and 7 are based on an alternative specification without controls for student covariates. Results in Columns 2, 5, and 8 are based on an alternative specification controlling for local quadratic terms. Results in Columns 3, 6, and 9 are based on the preferred specification using a bandwidth that is double the optimal size. Standard errors are clustered at college–cohort level. Robust standard errors are shown in parentheses.

*$p < .1$. **$p < .05$. ***$p < .01$.