Educational Evaluation and Policy Analysis
September 2019, Vol. 41, No. 3, pp. 294–315
DOI: 10.3102/0162373719848777
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Corequisite Mathematics Remediation: Results Over Time and in Different Contexts

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Traditional mathematics remediation is based on the theory that traditional mathematics remedial courses increase students' subsequent academic performance. However, most students assigned to these courses do not pass them and thus cannot graduate. An alternative approach, corequisite remediation, assigns students instead to college-level quantitative courses with additional academic support, often aligned to a student's major. Here, we report the longer-term results of a randomized controlled trial comparing corequisite remediation (with statistics) and traditional algebra remediation (297 students per group). The corequisite group not only demonstrated significantly higher quantitative course pass rates but also success in many other disciplines, as well as significantly higher graduation rates. We also report the results of two quasi-experimental analyses (propensity score matching) demonstrating higher pass rates for corequisite mathematics remediation with 347 additional students in different settings. Policies requiring corequisite mathematics remediation can result in greater student success than is obtained with traditional remediation.

Keywords: *educational policy, community colleges, educational reform, higher education, mathematics education, experimental research, quasi-experimental analysis, regression analyses, corequisite remediation, randomized controlled trial*

College policies usually require students assessed as needing remediation (developmental education) to complete remedial courses prior to taking college-level courses in the remedial courses' disciplines, based on the theory that students need to pass the remedial courses to have the knowledge and skills needed to pass the college-level courses. However, completion of mathematics remediation may be the single largest academic barrier to increasing overall college graduation rates (Attewell, Lavin, Domina, & Levey, 2006). Mathematics is the most frequently assessed remedial need (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). Approximately, 59% of students who begin their postsecondary education at an associate's degree (2-year, community) public college, and 33% of students who begin their postsecondary education at a bachelor's degree (4-year) public college, take one or more remedial (developmental) courses in mathematics (Chen & Simone, 2016). Many other students are assessed as needing such courses but never take them (Bailey, Jeong, & Cho, 2010), and only 50% of community college students who take at least one remedial mathematics course finish their mathematics remediation requirements (Chen & Simone, 2016). It is thus not surprising that students assessed as needing remediation are less likely to graduate than are other students. For example, the 3-year associate-degree graduation rates for these two types of students who, in 2013, entered The City University of New York (CUNY; a 19-college university system currently totaling about 240,000 undergraduate students) are 19% and 33%, respectively.

Increasing the low completion rates in remedial mathematics could not only help overall graduation rates, but it could also help close racial/ethnic/economic performance gaps. Students assessed as needing remediation are more likely to be members of underrepresented groups and to be from families with limited financial resources (Attewell et al., 2006; Chen & Simone, 2016). At CUNY, in fall 2016, the percentages of Asian, Black, Hispanic, and White first-time freshmen in associate programs who were assessed as needing remediation in mathematics were 45%, 81%, 78%, and 67%, respectively. Low mathematics remediation completion rates may contribute to the lower college attainment rates of students who are Black, Hispanic, and/or from families with limited financial resources.

Due to the low success rates of traditional remedial mathematics, multiple states and institutions of higher education have recently made optional, or abolished, all or virtually all traditional prerequisite remediation. The Florida College System, the California Community College and State University systems, the Texas public colleges and universities, and the Tennessee community colleges are notable examples (Belfield, Jenkins, & Lahr, 2016; Hu et al., 2016; Jackson, 2017; Mejia, 2018; Smith, 2017). The remedial landscape is changing so rapidly, and it is so difficult to assess the prevalence of reforms among individual course sections, that there are no published national surveys accurately depicting the current relative frequency of traditional remediation and reforms. A survey published in 2018 by the Education Commission of the States shows that 20 states have "authorized the use of innovative developmental education instructional methods and interventions" (Whinnery & Pompelia, 2018). However, this report does not state the degree to which these innovations have actually been implemented. Parts or all of 38 states have joined Complete College America's (n.d.) Alliance to "increase the number of students successfully completing college," but remedial reform is only one component of the advocated strategies, and being part of the alliance does not indicate a certain level of use of any particular strategy. A third example is the Center for the Analysis of Postsecondary Readiness's survey of United States developmental education practices (Rutschow & Mayer, 2018). The most recent data reported are from 2016, and a college had only to offer more than two sections of a particular reform to qualify as having that reform. Indisputable, however, is that the remedial landscape is in flux, and information about the effects of reforms could be useful in helping the field to coalesce around specific innovations.

Various means of increasing low remedial course completion rates have been proposed. In one, students address remedial needs the summer before college. Although there is supporting research (Douglas & Attewell, 2014), a randomized controlled trial (RCT) found modest positive effects 1 year later—effects that did not persist (Barnett et al., 2012). Also, not all students have the time needed to attend remedial courses the summer before college.

Another approach is the CUNY Start program: Students assessed as having deep remedial needs defer initial matriculation for a semester while engaging in full-time remediation. Although CUNY Start's initial results are promising, it is only for students with severe assessed remedial needs, and not every student can devote an entire semester to remediation. An RCT of CUNY Start is in progress (Allen & Horenstein, 2013; Scrivener et al., 2018; Scrivener & Logue, 2016).

As yet another approach, some educators have recommended *streamlining* remedial material so students focus on topics needed for their other coursework and/or remedial work is condensed and/or remedial material is combined with college-level work. Recent research has shown success with such approaches (Schudde & Keisler, 2019). As a related example, The Carnegie Foundation for the Advancement of Teaching's Statway program combines remedial mathematics with introductory, college-level statistics. A rigorous analysis supports Statway as increasing student success (Yamada & Bryk, 2016). However, Statway can require that students take a full academic year to obtain credits for one college-level course, and can require that students master far more than just the algebra topics they need for introductory statistics. Furthermore, whether being assigned to such a lengthy course affects students enrolling in it is unknown.

Still another approach involves requiring students to learn just the quantitative information that is appropriate given the students' majors and other interests. This type of reform is known as *alignment* and involves some students taking courses such as statistics and quantitative reasoning, instead of only courses on the algebra-calculus track. The Charles A. Dana Center is a strong advocate of alignment, and preliminary data indicate that the Dana Center's Mathematics Pathways Program enhances student learning and motivation (Ganga & Mazzariello, 2018; Rutschow, 2018).

Often combining both the streamlining and alignment approaches, some colleges and states are instituting policies in which students assessed as needing remediation take college-level courses with extra academic support covering just the remedial mathematics needed for the college-level course (known as *corequisite remediation* or supplemental instruction; see, for example, Daugherty, Gomez, Carew, Mendoza-Graf, & Miller, 2018; Hern & Snell, 2014; Jenkins, Lahr, & Fink, 2017; Vandal, 2017). Corequisite remediation has been effectively used with college-level courses in chemistry, mathematics, reading, sociology, and writing (e.g., Parker, Traver, & Cornick, 2018; for an extensive list of publications of such examples see Logue, 2018). Adoption of corequisite remediation for mathematics has been slower than for reading/writing (Rutschow & Mayer, 2018).

There have been comparisons of two groups of students, both assessed as needing remediation, in which one enrolls first in traditional, prerequisite, remediation, and the other directly in college-level courses, often with support (i.e., corequisite remediation). Some of this research has used quasi-experimental methods (propensity score matching [PSM] and regression discontinuity). Results have been mixed (for a summary, see Logue, Watanabe-Rose, & Douglas, 2016). However, recent studies have found that traditional remediation has either no effect on a student's academic progress or sometimes a negative effect (Bailey & Jaggars, 2016; Boatman & Long, 2018; Page & Scott-Clayton, 2016; Valentine et al., 2017; Witteveen & Attewell, 2017).

There are several reasons why corequisite remediation can have relatively high success rates (in addition to the fact that the college-level course taught with corequisite remediation is sometimes aligned with a student's major and/or career interests). First, some students assessed as needing remediation can pass college-level courses simply because placement mechanisms can be inaccurate, identifying some students as needing remediation even though they have college-level skills (Scott-Clayton, Crosta, & Belfield, 2014). Second, assigning a student to a college-level, as compared with a remedial, course can be more motivating. A student assigned to a remedial course may have a delayed graduation, may have to retake an aversive high school course, and/or may feel stigmatized (see, for example, Bailey, 2009; Bowen & McPherson, 2016; Complete College America, 2011; Goldrick-Rab, 2007; Logue, 1995; Scott-Clayton & Rodriguez, 2012). Third, in a typical example of corequisite remediation (college-level statistics with additional support), researchers have proposed that students can pass the college-level course (statistics) more easily than remedial algebra because statistics is less abstract and uses everyday examples (Burdman, 2013; Yamada, 2014). Fourth, by combining remediation with a college-level course, corequisite remediation eliminates a possible exit point from the sequence of quantitative courses that a student needs to pass to graduate, providing fewer opportunities for the student's environment to interfere with completion (Hern & Snell, 2014).

Supporting these points are the results from the only RCT published to date comparing the effects of traditional and corequisite remediation (Logue et al., 2016). Logue et al. (2016) compared elementary algebra with college-level introductory statistics accompanied by additional support (thus combining, as is often the case with corequisite remediation, the remedial math reforms of streamlining and alignment). In the work by Logue et al. (2016), independent of students' race/ethnicity, there was a significantly higher pass rate with corequisite than traditional remediation, there was evidence that the students randomly assigned to corequisite remediation were more motivated, and those students earned more credits in the year following the intervention than did the students randomly assigned to traditional remediation.

These results all support the conclusion that student success is greater with corequisite than traditional remediation. However, there are at least three ways in which Logue et al.'s (2016) support of this conclusion is limited. First, educators often define college success as receipt of a college degree, and the positive effects of many freshman interventions appear to dissipate over time, with little or no improvement in graduation rates (Bailey, Jaggars, & Jenkins, 2015). Logue et al. (2016), the most rigorous test of corequisite remediation published to date, only followed students' progress for a year after the intervention. Second, providing students with corequisite remedial mathematics support tailored to specific college-level courses, instead of providing them with stand-alone prerequisite remedial courses, means not exposing students to some course material. It is therefore possible that corequisite remediation can harm a student's subsequent college success. Third, there has been little published rigorous analysis of the effects of corequisite remediation in different types of settings. Logue et al.'s (2016) experiment was conducted at three different CUNY community colleges, but all with similar statistics courses. For these three reasons, following the academic performance of students exposed to corequisite remediation until graduation, plus determining the success of corequisite remediation in a variety of settings, would provide a fuller assessment of the effects of corequisite remediation.

The present research therefore had two purposes. First was to examine the academic performance of Logue et al.'s (2016) students over the 3-years since they were assigned to traditional remediation or college-level introductory statistics with corequisite support. During that period, independent of students' race/ethnicity, the students assigned to statistics were significantly more likely to have graduated (by approximately 8 percentage points; close to 50% more of those students had graduated), and at least as likely to have passed their general education requirements. In addition, in that 3 years, Logue et al.'s (2016) students, who intended majors that did not require college algebra, were more likely to have passed advanced mathematics courses if they had been assigned to corequisite remediation. The second purpose of the present research was to determine whether the results obtained by Logue et al. (2016) would generalize to other courses at several colleges using a quasi-experimental analysis (PSM; Guo & Fraser, 2009). Some researchers have stated that PSM can provide estimates of the causal effects of an intervention when it is not possible to use an experimental design (West, 2009; Winship & Morgan, 1999) and have obtained results with PSM that are similar to those obtained with RCTs (Bifulco, 2012; Fortson, Verbitsky-Savitz, Kopa, & Gleason, 2012). More conservatively, were similar results to Logue et al. (2016) to be obtained in additional settings using PSM, this would provide external validity for Logue et al.'s (2016) results. Indeed, our PSM results show that students at several CUNY community colleges passed college-level statistics and quantitative reasoning courses, all taught with corequisite remediation, at higher rates than matched students who took traditional remedial elementary algebra. Together, these findings show corequisite mathematics remediation can result in academic success in a variety of settings and over time. Policies requiring that students be placed into corequisite mathematics remediation can increase student success, helping to decrease performance gaps.

Three-Year Effects of Corequisite Remediation

Summary of Experiment Design, Method, and Initial Results

The purpose of this research was to evaluate the longer-term (3-year) academic performance of the students in Logue et al.'s (2016) original RCT that examined the effects of corequisite remedial mathematics (for details concerning the design and method, see Logue et al., 2016). To summarize, at three of CUNY's seven community colleges, Logue et al. (2016) randomly assigned students to one of three fall 2013 course types: (a) traditional, remedial, noncredit, elementary algebra (Group EA), (b) the same course plus workshops (Group EA-WS), or (c) college-level, credit-bearing statistics with workshops (Group Stat-WS). Given there was significantly more attrition in the EA-WS group, possibly biasing the results, we focus here on the comparison between the EA (traditional remediation) and Stat-WS (corequisite remediation) groups. All of the experiment's students had been assessed as needing remedial elementary algebra (but not arithmetic), did not intend a major requiring college algebra, agreed in summer 2013 to participate, and were then immediately randomly assigned and informed of their assignment. A total of 297 consenting students were assigned to each of the EA and Stat-WS groups. A total of 244 EA and 246 Stat-WS students enrolled in their assigned research sections and were designated as experiment participants.

There were 12 instructors, 4 at each of the three colleges. To balance instructor effects across treatments, each instructor taught one section of each course type (Weiss, 2010), yielding 12 sections each of EA and Stat-WS. The instructors gave their workshop leaders assignments and exercises for the students to work on during the workshops and as homework. The workshop leaders were CUNY advanced undergraduates or recent graduates.

Elementary algebra sections covered topics such as linear equations, polynomials, and quadratic equations. Statistics sections covered topics such as probability, normal distributions, and hypothesis testing. Workshops were required, met for 2 hours each week, and primarily consisted of individual and group work on topics students had found difficult. If students in a statistics section needed to review algebra concepts to understand a particular statistics topic (e.g., using variables in equations), the workshop leader would cover those concepts.

Each college used the same syllabus for all of its sections. EA students took the required CUNY-wide elementary algebra final examination and received a final grade based on the CUNY-wide elementary algebra final grade rubric. Instructors graded their Stat-WS students at their discretion using the common syllabus for their college. All outcomes other than a passing grade, including any type of withdrawal or incomplete, were categorized as not passing.

All students who passed were exempt from any further remedial mathematics courses and were eligible to enroll in introductory, college-level, credit-bearing, quantitative courses. Passing Stat-WS students were also eligible to enroll in courses with introductory statistics as the prerequisite. A passing grade in statistics satisfied the quantitative category of the CUNY general education curriculum. All EA and Stat-WS students who did not pass then had to pass traditional remedial elementary algebra before taking any college-level quantitative courses.

Logue et al. (2016) used intent-to-treat (ITT) analysis with Equation 1 to compare the mean outcomes of groups as randomized, without regard to attrition and other forms of deviation from protocol, thus providing an unbiased estimate of the treatment effect:

$$\ln\left(\frac{p}{1-p}\right)_i = \delta + \beta_1 \times \text{STATS}_i + \varepsilon_i, \tag{1}$$

in which $\ln(p/1-p)_i$ is the log odds of a positive outcome for student i, δ is the equation constant, STATS represents whether the student was randomized into Group Stat-WS, β_1 is a coefficient, and ε_i is an error term. To explore further the relationships between passing the assigned course and other variables, Logue et al. (2016) also fit a model that included a vector of covariates (algebra placement test score, gender, high school grade point average [GPA], number of days to consent, and controls for missing values). This vector of covariates is represented by X in Equation 2:

$$\ln\left(\frac{p}{1-p}\right)_i = \delta + \beta_1 \times \text{STATS}_i + b\text{X}_i + \varepsilon_i, \tag{2}$$

with terms defined as in Equation 1 with the addition of another coefficient, *b*. This analysis showed that the students in Group Stat-WS were significantly more likely to pass than those in Group EA by a margin of 16 percentage points with no covariates included, and by 14 percentage points if covariates are included.

The Stat-WS students were also significantly more likely to form self-initiated study groups, to attend their workshops, and to report increased positive attitudes toward mathematics over the semester. Logue et al. (2016) also showed that the Stat-WS students' enhanced academic success lasted beyond the intervention's semester: One

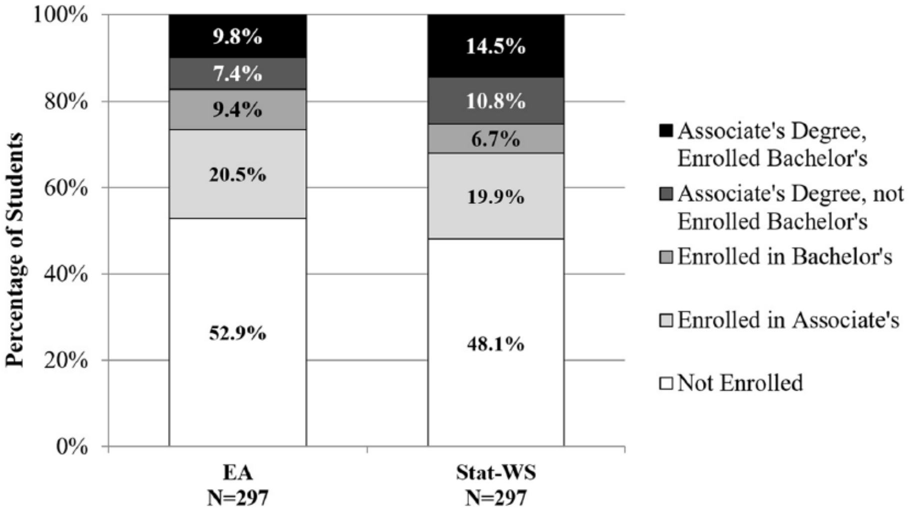


FIGURE 1. *Enrollment status of the EA and Stat-WS students in fall 2016.*
Note. EA = elementary algebra; WS = workshops.

year after the end of the intervention, the Stat-WS students had mean total accumulated credits of 21.7 versus 17.7 for EA students. ITT analyses of the effect of Stat-WS group assignment on credits passed at 1 year, both with and without covariates, and with and without statistics credits included, were all statistically significant ($p < .001$). There were no statistically significant interactions between student demographic variables and treatment status. Notably, Stat-WS students with any algebra placement test score were more likely to pass their assigned courses than were EA students with comparable scores.

Three-Year Results

We used CUNY databases and the National Student Clearinghouse to obtain EA and Stat-WS students' CUNY course enrollments and grades, as well as CUNY and non-CUNY college enrollments and degrees received for the 3-year period lasting from fall 2013 (when the original intervention was conducted) until fall 2016.

Overall Progress, Graduation, and Transfer. Figure 1 shows each EA and Stat-WS student's status as of fall 2016. Only associate degrees had been received, with all but two from CUNY. A total of 17.2% of the EA students had graduated, in comparison with 25.3% of the Stat-WS students, an 8.1 percentage point difference with 47.1% more students having graduated from the Stat-WS group. A total of 58 EA students and 63 Stat-WS students were enrolled in bachelor's degree programs in fall 2016 (a statistically nonsignificant difference), with the majority of these students enrolled at CUNY, and the remainder at institutions of comparable selectivity. To see how these figures may have differed 1 year earlier (2 years after the intervention), as of fall 2015, the percentages graduated were 4.4% and 8.7% for the EA and Stat-WS groups, respectively. The 4.3 percentage point difference and the absolute numbers of students who had graduated are not as large as 3 years after the intervention, but 2 years after the intervention almost twice as many Stat-WS students had graduated than EA students.

We used Equations 1 and 2 to compare the longer-term effects of randomly assigning students, originally assessed as needing remedial elementary algebra, instead to college-level introductory statistics with additional support. We used two dependent variables: (a) graduation and (b) graduation and/or transfer to a bachelor's degree program. Table 1 shows the logistic regression results. Both with and without covariates, Group Stat-WS has a statistically significant 8.1 percentage point higher probability of graduating than Group EA, and close to a 5 percentage point higher probability of graduating or transferring to a bachelor's degree program.

TABLE 1

Estimates of Treatment Effects on Graduation and on Graduation/Transfer to a Bachelor's Degree Program

	Outcome				
	Graduation		Graduation/transfer		
Group	No covariates (%)	With covariates (%)	No covariates (%)	With covariates (%)	*n*
Group means					
EA	17.2	16.0	27.3	30.1	297
Stat-WS	25.3	24.0	32.0	25.3	297
Treatment effects					
EA vs. Stat-WS	8.1*	8.1*	4.7	4.8	594

Note. EA = elementary algebra; WS = workshops.
*$p < .05$.

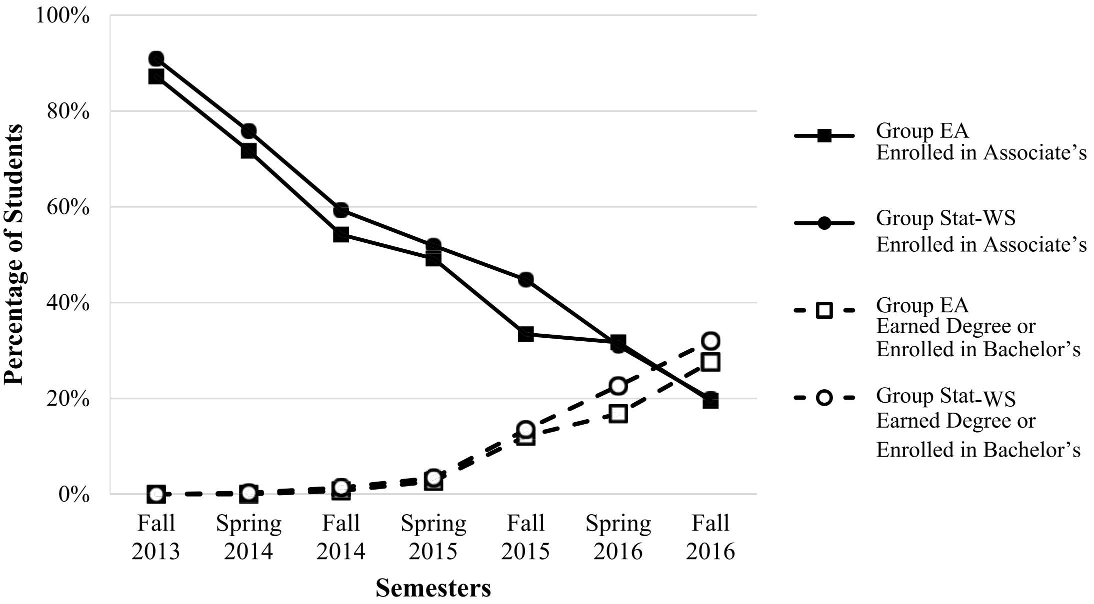


FIGURE 2. *Enrollment status of EA and Stat-WS students as a function of semester.*
Note. EA = elementary algebra; WS = workshops.

To assess further the theory that the course material in remedial mathematics courses is essential to students' later college success, we also examined the graduation rates solely of students who passed the course to which they were randomly assigned in fall 2013. Although fewer students pass remedial elementary algebra, if they do pass it, perhaps such students have a higher probability of success in college than students who do not take such a course. Our results showed that, for EA students who passed elementary algebra in fall 2013, 28% graduated within 3 years, but for Stat-WS students who passed statistics in fall 2013, 39% graduated within 3 years. Thus, a demonstrated knowledge of the remedial course material was not particularly beneficial to students' subsequent college success. Even Stat-WS students who passed statistics with a D had a 41% graduation rate.

Figure 2 shows the percentages of EA and Stat-WS students who were enrolled in an associate's degree program, or had received a degree or were enrolled in a bachelor's degree program

(Weiss, Ratledge, Sommo, & Gupta, 2019), for each of the seven semesters since the experiment's start. Over this 3-year period, the percentages of students enrolled in associate's degree programs consistently fell, whereas the percentages enrolled in bachelor's degree programs or who had graduated consistently rose, so that for both EA and Stat-WS groups, by the seventh semester, higher percentages of students were enrolled in bachelor's degree programs or had graduated than were enrolled in associate's degree programs. During each of the first five semesters, a higher percentage of Stat-WS students was enrolled in an associate's degree program. Beginning in the fifth semester, a higher percentage of Stat-WS students had graduated or transferred to a bachelor's degree college.

Relationships With Student Characteristics. Given students from underrepresented groups are more likely to be assigned to remediation than are other students (Attewell et al., 2006; Chen & Simone, 2016), and given there have been reports of gender as well as race/ethnicity differences in college graduation rates (e.g., Bowen, Chingos, & McPherson, 2009), we particularly examined the relationships between graduation and transfer to a bachelor's degree program with race/ethnicity and gender. In the original sample, 74% of the EA students and 72% of the Stat-WS students were Black, Hispanic, or American Indian; among graduates, those values were 82% and 75%. In the original sample, 51% of the EA students and 55% of the Stat-WS students were female; among graduates, those values were 67% and 65%, respectively. Regression analyses examining the relationships between race/ethnicity and either graduation or graduation/transfer to a bachelor's degree program found no significant differences (marginal effects of Black/Hispanic compared with Asian/White students are equal to +2.7 and −5.9 percentage points, with $p = .59$ and .32, respectively). However, female students were significantly more likely to graduate or to graduate/transfer within the 3-year period (by 10.0 and 9.3 percentage points, with $p = .008$ and .025, respectively), despite the fact that females and males did not differ significantly in their likelihood of passing the intervention's assigned course.

Rate of General Education Quantitative Requirement Completion. EA students had to pass two courses (elementary algebra and a college-level quantitative course) before they could satisfy their general education quantitative requirement, but Stat-WS students had to pass only one (statistics), plus the EA students' elementary algebra pass rate was lower than the Stat-WS students' statistics pass rate. Therefore, it would not be surprising were the EA students to take more time, with more course enrollments, to satisfy their general education quantitative requirement. To assess this, we calculated how many semesters it took the median student in each of the two groups to satisfy CUNY's general education "Mathematical and Quantitative Reasoning" requirement. Students can satisfy the general education quantitative requirement by passing many different courses, including introductory statistics (the course to which all Stat-WS students were assigned in the experiment's first semester), college algebra, and quantitative reasoning. The EA students (and the Stat-WS students who did not pass statistics in the experiment's first semester) could not take any of these courses until they had first passed elementary algebra. Considering all randomly assigned students, the median Stat-WS student satisfied the general education quantitative requirement during the semester following the intervention (spring 2014). However, the median EA student had not yet finished the general education quantitative requirement by the end of the first 3 years since the beginning of the experiment. Considering only students who actually enrolled in the fall 2013 quantitative course to which they were assigned for the experiment, the median Stat-WS student finished the CUNY general education quantitative requirement the same fall, and the median EA student finished it in spring 2016 (the sixth semester since the start of the experiment).

Another way to estimate the efficiency with which EA and Stat-WS students completed their general education quantitative course requirement is to calculate, for the 2 years since the start of the experiment (a typical time interval for assessing completion of a college's mathematics course requirement; Saxe & Braddy, 2015; Yamada, 2014), the total number of enrollments

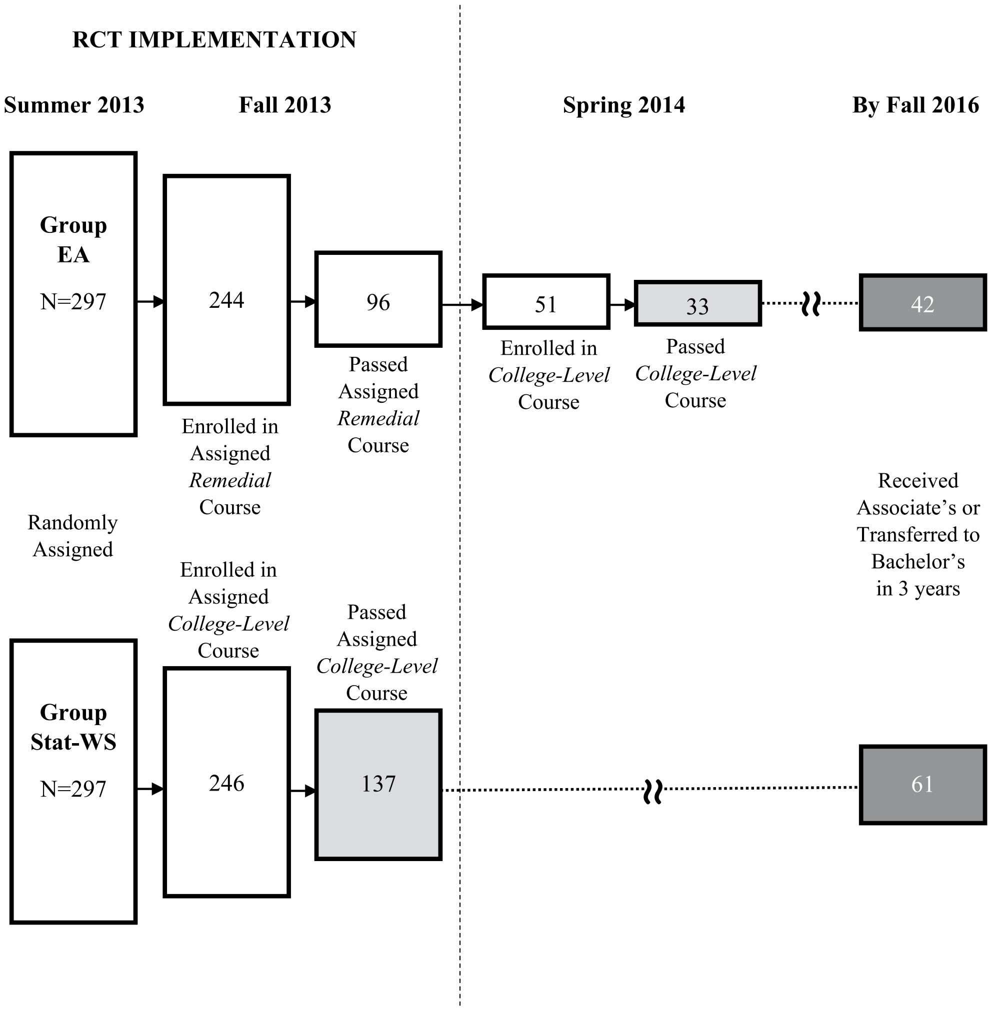


FIGURE 3. *Progress of EA and Stat-WS students in satisfying the CUNY general education quantitative requirement.*
Note. EA = elementary algebra; WS = workshops; CUNY = The City University of New York; RCT = randomized controlled trial.

in remedial and nonremedial quantitative courses by students in each group prior to these students completing their general education quantitative requirement, divided by the number of students in the same group who completed their general education quantitative requirement. For EA students this value was 5.2, but for Stat-WS students it was 2.6. It took twice as many course enrollments, and twice as much educational expense, for an EA, as opposed to a Stat-WS, student to satisfy the general education quantitative requirement.

Figure 3 shows the number of EA and Stat-WS students who completed each step toward satisfaction of their CUNY general education quantitative requirement in the soonest possible semester, ending with graduating within 3 years since the start of the experiment. To be included, EA students needed to enroll in remedial elementary algebra in fall 2013, pass it, enroll in a college-level quantitative course in spring 2014, pass it, and then complete their other graduation requirements by fall 2016. Stat-WS students needed to enroll in college-level introductory statistics in fall 2013, pass it, and then complete their other graduation requirements by fall 2016. This figure demonstrates that the sequence ending with graduation for the EA students had more possible exit points than did the sequence for the

TABLE 2

Percentage of Students Completing Each of CUNY's Eight General Education Course Categories Within the 3 Years Since the Start of the Experiment

	Percentage completed	
General education category	Group EA	Group Stat-WS
Mathematical and quantitative reasoning**	42.8	62.0
English composition	66.7	73.7
Life and physical science	35.0	41.1
Scientific world	42.8	42.4
Individual and society	52.5	59.9
U.S. experience in its diversity	33.7	41.8
World cultures and global issues	38.7	44.1
Creative expression	56.2	57.6

Note. CUNY = The City University of New York; EA = elementary algebra; WS = workshops.
$^{**}p < .01$.

TABLE 3

Number of All College-Level Mathematics Courses Passed by the EA and Stat-WS Students in the 3 Years Beginning With the Experiment

Course	EA	Stat-WS
Health-related mathematics	16	13
Quantitative reasoning	4	2
Liberal arts mathematics	35	12
Statistics (intro. and advanced)	80	174
College algebra[a]	42	32
Precalculus	14	19
Calculus I	6	14
Calculus II	3	3
Calculus III	3	1
Linear algebra	0	2
Differential equations	1	0
Total**	204	272

Note. EA = elementary algebra; WS = workshops.
[a]Includes intermediate algebra at College A, which has no college algebra course.
$^{**}p < .01$.

Stat-WS students, and that students were lost at every possible exit point, with a higher total number of EA students lost.

Additional Courses Passed. We also determined how many students in each group passed CUNY's eight general education requirements during the 3 years between the fall 2013 intervention and the end of the follow-up period in fall 2016. Table 2 shows that a larger percentage of Stat-WS than EA students satisfied each of the eight categories, except for the Scientific World category, for which the percentages were approximately the same for both groups. Although only the quantitative category difference is statistically significant, clearly the students assigned to statistics instead of elementary algebra were at least as able to complete their general education courses, including those in natural and social sciences. Completing their general education mathematics requirement on average earlier than EA students may have increased the opportunities for Stat-WS students to take courses satisfying their other general education requirements.

We also examined the specific CUNY college-level mathematics courses the EA and Stat-WS students passed during the follow-up period (Table 3). The Stat-WS students passed 33.3% more such courses than did the EA students, $\chi^2(1) = 9.7$, $p < .01$. As expected, given the intervention's course assignments and CUNY's general education requirements, the EA students passed college algebra a greater number of times than did the Stat-WS students, and the Stat-WS students passed statistics a greater number of times than did the EA students. Note that, unless other mathematics courses were required for a student's major, the students passing statistics or college algebra were not required to pass any additional mathematics courses to graduate. Many of the EA students took (and passed) statistics even though the experiment did not assign them to it (however, they may have needed it for their majors). The majority of the Stat-WS students who passed college algebra (18 out of 32) had passed statistics in the first semester of the experiment, satisfying their general education quantitative requirement, but chose to continue taking mathematics courses. A total of 14 Stat-WS students passed their assigned statistics course in fall 2013 and later passed intermediate or college algebra without ever having taken the elementary algebra course they had been originally assessed as needing. Furthermore, although fewer Stat-WS students passed college algebra than did EA students, more Stat-WS students passed the next two courses in the algebra-calculus sequence (Precalculus and Calculus I). Few students in either group took and passed the most advanced mathematics courses. There is no evidence in Table 3 that assigning a student to statistics instead of elementary algebra results in a lower probability of successfully completing advanced mathematics courses.[1]

Quasi-Experimental Analyses of Corequisite Remediation in Multiple Settings

The purpose of these analyses was to compare, using PSM, the course pass rates of students enrolled in corequisite remediation (college-level quantitative reasoning or statistics, accompanied by supplemental instruction) to the course pass rates of matched students enrolled in traditional remediation (elementary algebra), using data from four CUNY community colleges (Colleges A, B, C, and D). All four are urban colleges, with two enrolling less than 10,000 students, and two enrolling more than 15,000 students. Colleges A, C, and D also participated in Logue et al.'s (2016) RCT.[2] For the current analyses, we used all available data for students in CUNY corequisite mathematics remediation courses for fall 2013 through fall 2015 (excluding corequisite remediation students who participated in Logue et al., 2016), plus matched CUNY students enrolled in traditional mathematics remediation in 2013.

Table 4 summarizes the courses used in these analyses, their basic characteristics, the numbers of students in each, and their pass rates. Two colleges (Colleges A and C) contributed both corequisite and matched comparison students to the analyses, one (College B) contributed only corequisite students, and one (College D) contributed only matched comparison students. College B enrolls all of its students in corequisite statistics courses. Therefore, we used College D students taking traditional remedial elementary algebra to select a matched comparison group for College B students. Our rationale was that both Colleges B and D are urban community colleges that follow a similar, unusual, academic calendar (a combination of 12- and 6-week terms). The comparison involving these two colleges was between students who received corequisite remediation at one college and matched students who received traditional remediation at a different college. For the analysis involving Colleges A and C, because the College C matching pool was relatively small, and because the Colleges A and C's course structures, student profiles, and (traditional) academic calendars were all similar, we combined Colleges A and C corequisite and control students each into a single pool prior to matching. This yielded the closest matches in the propensity scores of the corequisite and comparison groups, reducing between-group bias, and improving the quality of the effect estimates (Rosenbaum & Rubin, 1985).

Table 4 also includes the following pass rates for the traditional remedial courses: 30.9, 39.7, and 42.5, a range encompassing the value of 39.3 obtained by Logue et al. (2016). However, Table 4's corequisite course pass rates range from 70.0 to 80.5, all higher than Logue et al.'s (2016) value of 55.7, although not unusual in other studies of corequisite remedial mathematics (e.g., Denley, 2016; Henson, Huntsman, Hern, & Snell, 2017). The greater passing rate in the corequisite PSM courses versus the corequisite courses in Logue et al. (2016) may reflect selectivity bias in the students who took the PSM corequisite courses, but there are alternative explanations. For example, unlike in Logue et al.'s RCT, the same instructors did not teach the PSM corequisite and traditional remedial sections, so there could have been better instructors or more lenient graders teaching the corequisite sections. Furthermore, in Logue et al.'s (2016) RCT, neither the instructors nor the workshop leaders nor their supervisors had any prior experience teaching corequisite courses. Had they had more experience, Logue et al.'s (2016) corequisite pass rates might have been higher.

Table 5 shows the descriptive statistics for those students with no missing data, separately for each college and corequisite and comparison group, prior to the PSM procedure. The number of students with missing data can be determined by comparing the *N*s in Tables 4 and 5. For the College A/College C comparison, the percentages of students with missing data are 14.6% and 7.7% for the corequisite and traditional remediation samples, respectively. The College

TABLE 4

Courses Used for the Quasi-Experimental Analyses

College	Course	Credits/weekly hours	Number of students[a]	Pass rate (%)
Courses with corequisite remediation				
A	Statistics	4/6	130	70.8
B[b]	Statistics	3/7.5	80	70.0
C	Quant. reasoning	3/4.5	60	76.7
C	Statistics	3/4.5	77	80.5
Traditional remedial courses				
A	Elementary algebra	0/4	3,801	30.9
C	Elementary algebra	0/4.5	1,044	39.7
D	Elementary algebra	0/6	73	42.5

Note. Colleges A, C, and D also participated in Logue, Watanabe-Rose, and Douglas's (2016) RCT. RCT = randomized controlled trial.
[a]All students with a grade, including those with and without key covariate information.
[b]1.5 credits and 5 hours during each of two 12-week semesters, a total of 3 credits and about 7.5 hours if the entire course were taught in one traditional (16-week) semester.

TABLE 5

Prematching Descriptive Statistics for Students With No Missing Data

	Group			
	Colleges A/C	Colleges A/C	College B	College D
Student	Comparison	Corequisite	Comparison	Corequisite
Characteristic	(N = 4,471)	(N = 228)	(N = 80)	(N = 73)
Gender				
Female	54.5%	68.4%	47.5%	42.5%
Male	45.5%	31.6%	52.5%	57.5%
Race/ethnicity				
Black	34.1%	39.9%	18.8%	32.9%
Hispanic	50.6%	52.2%	52.5%	56.2%
White/Asian	15.4%	7.9%	28.8%	11.0%
Pell recipient	75.4%	80.3%	72.5%	74.0%
Age in fall 2013 (years): M (SD)	23.0 (6.1)	26.2 (8.1)	19.2 (2.8)	22.0 (7.4)
Compass placement test scores				
Arithmetic: M (SD)	38.0 (18.7)	31.6 (14.1)	50.8 (15.4)	51.9 (14.9)
Algebra: M (SD)	22.3 (6.2)	19.8 (5.5)	26.1 (7.5)	25.4 (5.9)

B/College D comparison had no students with missing data.

We used the *teffects psmatch* program in the Stata 15 software package to perform the PSM analyses, first employing a logit model to calculate a propensity score for each student in the treatment and comparison groups. The propensity score indicated how close a given student's characteristics were to the typical student in the corequisite group, a proxy measure for the likelihood of receiving the treatment. Given the goal for the next stage of the process was to make good propensity score matches, we used all available student characteristics to generate the most robust propensity score estimates for each student, including these covariates: arithmetic and

TABLE 6

Predicted Enrollment in Corequisite Mathematics and Standardized Differences

	Prematch	Standardized differences	
Independent variable	Coefficient (*SE*)	Prematch	Postmatch
Colleges A and C			
Fall 2013 age (years)	.048 (.008)***	.448	.062
Female (ref: male)	.366 (.151)*	.287	−.024
Race (ref: Hispanic)			
Black/African American	.056 (.147)	.126	−.012
White/Asian	–.567 (.261)*	−.234	−.053
Pell recipient	.171 (.176)	.116	−.088
Arithmetic score	–.010 (.005)	−.386	−.043
Algebra score	–.039 (.016)*	−.419	.076
Colleges B and D			
Fall 2013 age (years)	−.414 (.146)**	–.443	.015
Female (ref: male)	.167 (.410)	.004	.005
Race (ref: Hispanic)			
Black/African American	−.589 (.441)	–.256	.065
White/Asian	.879 (.711)	.079	.087
Pell recipient	−.272 (.477)	–.114	−.109
Arithmetic score	−.007 (.014)	.029	.082
Algebra score	−.015 (.031)	.046	−.102

*$p < .05$. **$p < .01$. ***$p < .001$.

algebra scores on the ACT Compass (placement) examination, Pell receipt status, gender, race/ethnicity, and age. Table 6 demonstrates that, prior to the PSM procedure, there were some significant differences between the corequisite and traditional remediation groups on several variables. Age, gender, race/ethnicity, and algebra placement test scores predict enrollment in a corequisite mathematics course for the College A/College C comparison, and age predicts enrollment in a corequisite mathematics course for the College B/College D comparison. Table 6 also shows the standardized differences between the two groups on each covariate, both pre- and postmatch, differences that are in most cases lower following the matching procedure, thus showing the usefulness of the PSM procedure.

Corequisite students were then matched to traditional remediation students with similar propensity scores on local intact groups using nearest neighbor matching (5:1 for the Colleges A and C comparison, and 3:1 for the Colleges B and D comparison, which had a smaller matching pool). Matching was conducted with replacement, a caliper set at 0.1, and the Abadie and Imbens (2011) bias correction. Any students in either group who could not be matched were removed from the analysis (5 students in the Colleges A and C analysis, and 29 students in the Colleges B and D analysis). These procedures yielded corequisite and traditional remediation groups containing students matched on the propensity for treatment.

The last step employed an outcome model, based on Equation 1, which predicted the likelihood of passing the assigned course, using the matched corequisite and comparison groups to estimate treatment effects. Table 7 shows the results: Average Treatment on the Treated (ATT; the estimated treatment effect on those students who participated), Average Treatment Effect (ATE; the estimated treatment effect if the entire population were treated; Austin, 2011), the raw unmatched comparison (the proportion of students in each group who passed the course), and results of logistic regressions conducted without

TABLE 7

Estimated Effects on Passing the Course of Corequisite Versus Traditional Remediation

	Analysis results		
Analysis type	Treated	Control	Difference (*SE*)
Colleges A and C			
Unmatched	77.1	33.0	44.1 (0.03)***
Non-PSM logistic regression	—	—	44.9 (3.1)***
PSM Average Treatment on the Treated	77.1	24.6	52.5 (0.03)***
PSM Average Treatment Effect	—	—	38.2 (0.04)***
Colleges B and D			
Unmatched	68.8	43.3	25.4 (0.09)**
Non-PSM logistic regression	—	—	21.7 (7.9)*
PSM Average Treatment on the Treated	68.8	46.4	22.4 (0.1)†
PSM Average Treatment Effect	—	—	28.8 (0.1)**

Note. For non-PSM logistic regression models, $N = 4{,}699$ and $N = 153$ for Colleges A/C and B/D analyses, respectively. For PSM logistic regression models, $N = 4{,}694$ and $N = 124$ for Colleges A/C and B/D analyses, respectively. PSM = propensity score matching.
$^{\dagger}p = .07$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

PSM (a correlational analysis that does not take into account the likelihood of receiving treatment, but does control for other possible covariates), all using passing the course as the dependent variable. All analyses—including using PSM or traditional logistic regression with either the Colleges A/C or the Colleges B/D groups—showed a significant ($p < .05$) passing advantage to the corequisite group, ranging from 22 to 53 percentage points, with the exception of the ATT analysis of Colleges B/D ($p = .07$). Whether the ATT or ATE estimate is preferred depends on the goal of the research—to use the results to guide practice in which whole populations are treated or only some portion. Regardless, in the present case, both ATT and ATE analyses give similar results.

As a check on the PSM results, particularly given the relatively low *N*s in the Colleges B and D comparison, we conducted Mantel–Haenszel sensitivity tests (Attewell & Jang, 2013; Becker & Caliendo, 2007) (see Note 2). The results show our PSM analyses are relatively robust to possible unmeasured variables. Any such variables would need to change the odds of treatment by a factor of at least 7.5 for the Colleges A and C comparison, and at least 1.6 for the Colleges B and D comparison, for the effect of the observed intervention not to be statistically significant.

General Discussion and Policy Implications

Taken together, the results do not support the theory that requiring college students to take traditional remedial mathematics prior to college-level quantitative courses provides them with either a short-term or a long-term academic benefit. Instead, the results show corequisite mathematics is effective at increasing students' success over time and in different contexts.

More specifically, the 3-year follow-up of Logue et al.'s (2016) students, all of whom had been assessed as needing remedial elementary algebra, demonstrated that the academic performance of the Stat-WS students was as good or better than the EA students. This was the case not only during the intervention and in the first year following, but throughout the 3 years since the beginning of the experiment. At least as many Stat-WS passed their general education requirements, and significantly more passed college-level mathematics courses. Furthermore, significantly more Stat-WS students graduated. Even Stat-WS students who passed statistics with a D graduated at a much higher rate than EA students. Passing statistics—with any passing grade—may be beneficial to student success because, for students who do not need additional mathematics courses for their majors, passing statistics completes a student's quantitative course graduation requirement, whereas all students who pass elementary algebra still need to pass at least one additional mathematics course to graduate.

There was, however, evidence that Logue et al.'s (2016) intervention's effects dissipated over time. There was a 14 percentage point difference between EA and Stat-WS students in their fall 2013 course pass rates, but only an 8 percentage point difference in their graduation rates. In addition, close to 100% more Stat-WS students had graduated than EA students 2 years after the intervention, but that value was 50% 3 years after the intervention. Nevertheless, the effects of the intervention were significant through 3-year graduation, a perhaps not surprising result given traditional mathematics remediation has been described as the single largest academic barrier to increasing overall college graduation rates (Attewell et al., 2006).

The current research did not assess the different groups' ability to perform in the workplace following college. However, two recent studies indicate that, for the great majority of jobs, algebra is not needed, but having taken statistics may help increase women's postgraduation salary (Belfield & Liu, 2015; Douglas & Attewell, 2017).

Ultimately, the Stat-WS students were able to move more quickly through the undergraduate curriculum than the EA (traditional remedial mathematics) students, saving student, financial aid, college, and taxpayer funds. The typical Stat-WS student was able to enter the workforce with a college degree sooner, likely earning more money and paying more taxes.

In addition, using PSM, the current research demonstrates that students at three colleges were more likely to pass college-level mathematics (statistics or quantitative reasoning) courses with additional support than were matched students in remedial mathematics (elementary algebra) courses. Despite lacking Logue et al.'s (2016) RCT's controls, the PSM results were consistent with those of the RCT and were demonstrated across colleges and course types.

Being assigned to corequisite remediation in Logue et al.'s (2016) experiment increased both the assigned course pass rates and graduation rates (the most proximal and the most distal outcome measures of the RCT), and in both cases independent of a student's race/ethnicity. Given students from underrepresented groups are more likely to be assigned to remediation than are other students, then assigning students to statistics with corequisite support instead of traditional remediation would decrease racial/ethnic graduation rate gaps. Traditional remediation, including its high course avoidance and failure rates, particularly for mathematics remediation and for students from underrepresented groups, has been labeled a civil rights issue (Edley, 2017). The results here show one way to address this civil rights issue.

It is possible to estimate the national impact on college student success were corequisite mathematics remediation widely instituted. Approximately 59% of new public community college students and 33% of new public bachelor's degree institution students take courses in remedial mathematics (Chen & Simone, 2016). Extrapolating these percentages to the some 2 million students who begin full-time postsecondary education each year (National Student Clearinghouse Research Center, 2017), with approximately 36% of all undergraduates being community college students (Ginder, Kelly-Reid, & Mann, 2017), indicates that many hundreds of thousands of students are taking remedial mathematics courses each year. Even just considering the community college students, were their three-year graduation rate to increase by 8 percentage points, as occurred in the current research with corequisite remediation, then tens of thousands of students would receive their degrees earlier each year.

The current research does have some limitations. Although the results involved a total of four different CUNY colleges and two different college-level quantitative courses (quantitative reasoning and statistics), that is a small proportion of the entire academic landscape, and only 60 students taking quantitative reasoning were included. Further, with the exception of some of the PSM College B students, the students had all indicated they did not need college algebra for their majors and had been assessed as needing remedial elementary algebra but not arithmetic. Thus, we do not know if the results would generalize to other types of colleges; to intended science, technology, engineering and mathematics (STEM) majors; to students with assessed deep remedial mathematics needs; and to using college algebra as the college-level course (thus separately testing the streamlining aspect of corequisite remediation without also involving alignment). Nevertheless, the variety of corequisite mathematics remediation situations that have been studied to date, and the consistency of the results, suggest that the current results have wide applicability.

We also do not know whether it might be better for students who need college algebra for their intended majors, but who have been assessed as needing elementary algebra (which they are likely to avoid taking or fail), to start their quantitative course taking in college instead by taking statistics with corequisite support (which they are likely to pass), so that their first college quantitative course experience is a positive one. Such students might be more likely to graduate as STEM majors if they have a positive experience with statistics first.

The present research also does not address why corequisite remediation students performed better than the traditional remediation students. Possible reasons already mentioned include decreased motivation of college students assigned to precollege-level courses, the increased expense to students of such courses, stigma associated with taking precollege-level courses, and being assigned to course material lacking clear, direct applications to students' lives and careers. Future research concerning these and other possibilities may help us increase further the greater success enjoyed by corequisite remediation students. However, what we do know is that the hypothesized advantage of taking traditional remedial courses—enhanced learning of material needed for future quantitative courses—does not exist.

Requiring students to take remedial mathematics prior to taking college-level quantitative courses, as compared with corequisite remediation, can result in lower academic performance and a decreased probability of advancing in mathematics. At the same time, traditional remediation incurs greater instructional and financial aid costs. These findings provide support for the work of policy makers who have been requiring individual institutions and systems of higher education to deliver primarily, or entirely, corequisite instead of traditional (prerequisite) remediation.

Appendix A

Additional Information on Logue et al.'s (2016) Participants' Majors and High School Records

Table A1 lists, for students in Logue, Watanabe-Rose, and Douglas's (2016) experiment who had graduated within 3 years of the intervention, the graduates whose majors required at least college algebra: two elementary algebra (EA) students and five statistics-workshop (Stat-WS) students. Of the five Stat-WS students, three did not enroll in their fall 2013 assigned statistics course. Instead, two took elementary algebra at CUNY. The third did not matriculate that fall, and later graduated from a non-CUNY college. The remaining two Stat-WS students passed their assigned statistics classes in fall 2013 and then took and passed more advanced mathematics classes, up to and including calculus. There is no evidence in Table A1 that assigning a student to statistics instead of elementary algebra resulted in a lower probability of a student completing a mathematics-intensive major.

TABLE A1

Listing of All EA and Stat-WS Students in Logue et al. (2016) Graduating With a Degree at Any Accredited Institution of Higher Education Within 3 Years of the Intervention With Majors That Required College Algebra and/or More Advanced Mathematics Courses

EA		Stat-WS	
College	Major	College	Major
A	Associate in engineering	D	Associate in computer sci.
A	A.S. in science	A	Associate in business admin.
		C	A.S. in liberal arts
		C	A.S. in liberal arts
		Public community College in SW USA	Associate in business

Note. EA = elementary algebra; WS = workshops.

A related question is whether some of these students actually should have been assessed as needing elementary algebra. Research has shown that placement tests make errors, and that high school grades can be more useful in predicting college course performance (Scott-Clayton, Crosta, & Belfield, 2014). In fall 2013, when the intervention was conducted, CUNY students needed a minimum score on the SATs, New York State Regents (high school) tests, or the CUNY placement test (then the Compass) to be exempt from remediation. Logue et al.'s (2016) student who took and passed the most mathematics courses in the 3 years since the intervention (including Calculus III and differential equations) had no SAT scores, missing placement test scores, and low Regents test scores, and so was assessed as needing elementary algebra, though he had a high school grade point average (GPA) of 80 to 81. CUNY analyses have shown that new students with high school GPAs of 80 or above have at least a .7 probability of passing a college-level mathematics course, and for low 70s GPAs it is still at least .5. Of the seven students who graduated with mathematics-intensive majors, their high school GPAs were, in order of magnitude' 73, 75, 75, 79, 80 to 81, 85, and 87. Thus, whether these were EA or Stat-WS students, it is not surprising that they were able to pass college-level mathematics courses.

Appendix B

Additional Information on the Theoretical Framework for the Propensity Score Matching Analyses

Propensity score matching (PSM) does not have the controls of a RCT. In the current research, students whose data were used for the PSM analyses were not randomly assigned to treatment (corequisite remediation) and control (traditional remediation) groups; a variety of other selection mechanisms were used across the involved colleges. Thus, it cannot be assumed that the students in the corequisite and traditional remediation groups are similar. Instead of the random assignment used by RCT's, PSM uses statistical techniques to account for differences in measurable participant characteristics that could influence group differences in both the likelihood of receiving the treatment and in the outcome. PSM has sometimes been found to have similar results to RCTs (Bifulco, 2012; Fortson, Verbitsky-Savitz, Kopa, & Gleason, 2012). However, PSM does not directly measure causal effects.

The validity of a PSM analysis is based on five key assumptions (Winship & Morgan, 1999): (1) Time Order (the intervention [taking a corequisite or traditional remedial course] occurs before the outcome [passing the course]), (2) NonZero Probability (every participant has some probability of taking a corequisite or traditional remedial course), (3) Stable Unit Treatment Value (whether a participant passes the course does not depend on whether another participant was assigned to the corequisite or traditional remedial course), (4) Conditional Independence (all variables that might influence whether a participant is assigned to a traditional or remedial course are measurable and are taken into account in the analysis), and (5) Common Support (there is sufficient overlap between the corequisite and traditional remediation groups on the likelihood of those two groups of students taking the corequisite course). Assumptions 1, 2, and 3 are all satisfied in the context of the current PSM analyses. Assumption 4 might or might not be true. Our PSM analyses used the following variables: arithmetic and algebra scores on the ACT Compass (placement) examination, Pell receipt status, gender, race/ethnicity, and age. Although this is not a long list of variables, it includes many that are investigated frequently in terms of their relationships with college student success, and includes the only two variables required by the What Works Clearinghouse (n.d.) for establishing baseline equivalence: a measure of academic achievement and a measure of student socioeconomic status. Furthermore, as described in the main text, the sensitivity analyses that we conducted (using Stata's *mhbounds* command) indicate that our PSM analyses are relatively robust to possible unmeasured variables. Table B1 shows the results of these analyses.

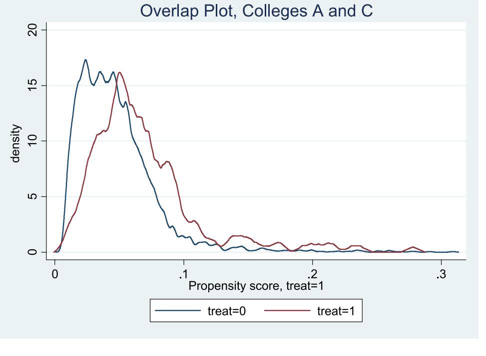
TABLE B1

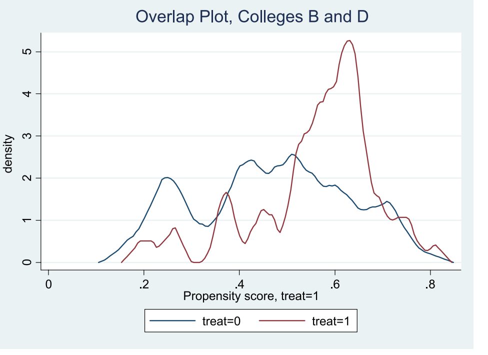
Sensitivity Analysis for Effects on Passing the Course of Corequisite in Comparison to Traditional Remediation

College A/College C (38.2%)[a]		College B/College D (28.8%)[a]	
Gamma	*p* value	Gamma	*p* value
1.0	<.00001	1.0	<.01
1.5	<.00001	1.1	<.01
2.0	<.00001	1.2	<.05
2.5	<.00001	1.3	<.05
3.0	<.00001	1.4	<.05
3.5	<.00001	1.5	<.05
4.0	<.00001	1.6	.067
4.5	<.00001	1.7	.087
5.0	<.00001	1.8	.111
5.5	<.0001	1.9	.138
6.0	<.01	2.0	.166
6.5	<.01		
7.0	<.05		
7.5	.064		
8.0	.124		

[a]Estimated treatment effect.

Regarding Assumption 5, following are overlap plots for each of the two PSM analyses, demonstrating that there is sufficient overlap in the propensity scores of students receiving traditional remediation ("treat = 0") and students receiving corequisite remediation ("treat = 1"):





Thus, all five assumptions for conducting PSM analyses appear to be met in the current research.

Authors' Note

Portions of the results reported here were presented at the November 2017 42nd Annual Conference of the Association for the Study of Higher Education and the 39th Annual Fall Research Conference of the Association for Public Policy Analysis and Management, and at the June 2018 Conference on Acceleration in Developmental Education.

Acknowledgments

We thank D. Allen, P. Attewell, C. Chellman, D. Crook, K. Gentsch, M. George, H. Gupta, M. Guy, C. Jordan, C. Littman, L. B. Pazich, M. Sapienza, S. Shrank, M. Sole, S. Truelsch, M. Weiss, and Z. Tang for assistance with data collection, analysis, and interpretation; the Presidents, Provosts, Vice Presidents, Deans, Mathematics Department Chairs, and staff of all of the involved CUNY colleges for facilitating the research; CUNY Central Office members G. Dine, K. Kapp, K. Mone, and R. Maruca for management assistance; and two anonymous reviewers for their excellent, constructive comments on a previous version of this manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was supported by a grant from the Spencer Foundation and by CUNY.

Notes

1. For information on how many students in each group graduated with math-intensive majors and the high school records of these students, please see Appendix A.

2. For more information on the theoretical framework of the PSM analysis, please see Appendix B.

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Manuscript received June 1, 2018
First revision received November 1, 2018
Second revision received February 15, 2019
Accepted March 30, 2019