Constructing Corequisites: How Community Colleges Structure Corequisite Math Coursework and the Implications for Student Success*

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Roughly 60% of two-year college entrants do not meet college-readiness standards for college math (Bailey et al., 2010). These students are typically required to complete prerequisite developmental education (dev-ed) courses—which do not count toward a degree—before enrolling in introductory college courses. Because students placed into dev-ed are more likely to come from racially minoritized and lower socioeconomic status backgrounds, dev-ed, in its current form, appears to exacerbate inequities in academic outcomes (Bailey et al., 2010, Marshall & Leahy, 2020). In response to dismal rates of dev-ed completion and calls for reform, states and college systems are adopting corequisite coursework: a model where students concurrently enroll in college-level and developmental coursework.

The corequisite model enables students to earn college-level credits immediately while providing hands-on support through a paired dev-ed (or "corequisite") course. Moving students through their dev-ed requirements and gateway math course can improve their momentum toward graduation (Adelman, 2006; Calcagno et al., 2007; Jenkins & Bailey, 2017; Wang et al., 2017). Inspired by promising evidence from early corequisite-adopters across the country (e.g., Denley, 2015, 2016; Logue et al., 2016, 2019; Ran & Lin, 2019), there has been a recent flurry of dev-ed policy reform toward corequisite coursework, where 24 states now include corequisite supports as a means to accelerate student access to college-level coursework (Education Commission of the States, 2021). As a result, states and colleges across the country are rapidly replacing the traditional dev-ed sequence with corequisite coursework.

As corequisite reforms proliferate, colleges must determine how to pair courses and which faculty should teach them. Despite evidence that corequisite models improve efficiency for completing introductory—or "gateway"—college-level courses (Logue et al., 2016, 2019; Meiselman & Schudde, 2020; Miller et al., 2021; Ran & Lin, 2019), some faculty and staff resist adopting them (Brower et al., 2017; Daugherty et al., 2018), with adoption lagging considerably in math compared with English (Cuellar Mejia et al., 2020; Morales-Vale, 2019). As personnel work to scale reforms, evidence of best practices can overcome faculty concerns and inform decision-making.

This study can inform corequisite model development by illuminating how corequisite math course features predict student outcomes. We leverage state administrative data to examine how public two-year colleges in Texas implemented a statewide mandate for corequisite coursework. Our results offer insights into how colleges structure corequisite courses in response to reforms and how corequisite coursework characteristics predict student outcomes.

Literature Review

Many students placed in dev-ed never complete their dev-ed coursework (Bailey et al., 2010; Clotfelter et al., 2015). Long multi-course dev-ed sequences may impede student progress and cost students time and money (Deil-Amen & Rosenbaum, 2002; Melguizo et al., 2016). Restructuring dev-ed pathways so that students quickly accrue college-level credits could expedite student progress, where corequisites immediately offer students access to college credit. Below, we describe evidence for the impacts of corequisite coursework, followed by an overview of research on corequisire course characteristics.

Background on Corequisites

Descriptive findings from Tennessee—the first state to mandate corequisite reforms—suggest that corequisite models improve completion rates of gateway college math (Denley, 2015, 2016). To date, one experimental study (Logue et al., 2016, 2019) and two quasiexperimental studies (Ran & Lin, 2019; Meiselman & Schudde, 2020) illustrate positive short-term outcomes of corequisite math coursework and one experimental study and one quasi experimental study illustrate positive short-term outcomes of corequisite English coursework (Cho et al., 2012; Miller et al., 2021). In a randomized controlled trial at City University of New York (CUNY), students were placed in either prerequisite algebra—the traditional dev-ed math course (the control group)—or a college-level statistics course with a developmental support course (the treatment group) (Logue et al., 2016). Those in the corequisite statistics coursework were more likely to pass college-level math and—3 years later—had completed more math courses, finished required coursework more quickly, and graduated at higher rates than those in prerequisite algebra. Studies in Tennessee and Texas found similar short-term positive impacts on passing college-level math, though they showed no increase in degree attainment after 3 years (Ran & Lin, 2019; Meiselman & Schudde, 2020).

Combined, the evidence of these three studies in different contexts supports the notion that corequisite math is more effective than prerequisite dev-ed math at increasing gateway math completion. At the same time, colleges implementing corequisites face logistical and financial concerns and need information about how to structure corequisites for student success.

The Role of Varied Course Designs

In response to policies aimed at increasing corequisite coursework, many institutions are scrambling to pair college-level math courses with corequisite developmental supports. Corequisite models can include several different structural components: Colleges must determine the timing of the corequisite support course, how to assign faculty to teach paired courses, instructional modality, whether to include college-ready students in the college-level course, and which math pathways (e.g., algebra, statistics) to prioritize.

Timing of Developmental Support

Many corequisite advocates envision that colleges will provide "just-in-time" support for the college-level course, with dev-ed course material concurrently supplementing college-level material; however, this is not always the case (Daugherty et al., 2018). Some corequisite courses are organized sequentially: The dev-ed component is taken first—serving as an embedded prerequisite—and the college-level second within the same term (Daugherty et al., 2018; Meiselman & Schudde, 2020). Currently, little evidence exists about how timing the corequisite support course predicts student outcomes. Meiselman and Schudde (2020) offered preliminary evidence that students in "embedded prerequisites" were slightly more likely to pass college-level math and persist in college than "true corequisite" students, but their identification strategy did not fully account for selection into the embedded prerequisite model.

Instructor Structure and Characteristics

Another structural component concerns whether the college-level course and dev-ed support course are taught by the same instructor. If two instructors teach the courses, they must collaborate and communicate to maintain similar pacing and align content. The extent of the alignment between the two courses can improve the student experience; using the same instructor may facilitate alignment (Daugherty et al., 2021).

Non-tenure-track (NTT) faculty have traditionally taught the bulk of developmental coursework (Datray et al., 2014; Grubb & Cox, 2005), but corequisite reforms may shift some of that responsibility to tenure-track (TT) faculty. Faculty with different contractual forms often face different responsibilities and levels of job security (Conley et al., 2002; Ran & Xu, 2018). In a public two-year college system with no TT faculty, Ran and Xu (2018) found that students in introductory courses with short-term NTT instructors (i.e., non-tenure-track faculty with temporary adjunct contracts)—compared with long-term NTTs (those with longer term contracts)—experienced higher grades but lower probabilities of taking and passing additional courses in the sequence. Research suggests that contextual and institutional factors related to part-time employment rather than instructor characteristics (e.g., race/ethnicity, gender, and highest degree earned) explain the association between NTT faculty status and student outcomes (Ran & Sanders, 2020).

Instruction Modality and Type

Research suggests that taking an introductory college-level math course online, as opposed to face-to-face, is associated with a 10-percentage-point decrease in the probability of passing it and a 15-percentage-point increase in the probability of course withdrawal (Xu & Jaggars, 2011). Taking developmental courses online is also negatively associated with student outcomes, including enrolling in and passing subsequent gateway courses (Jaggars & Xu, 2010), although research on hybrid developmental courses offers more optimistic findings. Research from Kentucky suggests that public two-year college students in a hybrid developmental math course—a mix of in-person and online sessions— were more likely to persist to the following semester than were those in a face-to-face class (Davidson & Petrosko, 2015). Identifying the effects of instructional modality is challenging because students select course modality aligned with their preferences, where students with the greatest external obligations (working for pay, caring for dependents) are more likely to select online options (Dutton et al., 2002).

The dev-ed support course can be structured in several ways. It can be course-based—structured primarily as a lecture in a traditional course format—or non-course-based, where the supports are offered outside of traditional classroom instruction (Daugherty et al., 2018). A non-course-based dev-ed section has the potential to align content with student needs; for example, it can include sections offered at a tutoring center with modularized computer-adaptive instruction or with an instructor who supports students with various levels of needs at their own pace. To date, no studies have explored the roles instructional modality or type play in student outcomes within a corequisite model.

Class Composition and Size

In structuring corequisite coursework, practitioners must decide whether to include both college-ready and dev-ed students in the college-level course. The mixed-ability model has some support in K–12 math settings, where research indicates that students with lower prior achievement benefit the most from collaborating with peers on math problems (Boaler, 2008; Fuchs et al., 1997; Fuchs et al., 2001). Some evidence suggests that similar peer effects occur in college STEM classrooms, although the only work in this area examines students at an elite university (Ost, 2010). In the only study (to our knowledge) on peer effects on course outcomes at community colleges, Liu and Xu (2021) found that the percentage of dual-enrollment students (those taking college coursework for credit during high school) enrolled in a community college course was negatively correlated with academic performance among non-dual-enrollment students (Liu & Xu, 2021). Parallels may exist with mixed-ability classrooms in which students who need developmental support take college-level math with college-ready peers, but because those students are also college students, their presence may not evoke the same response. Mixed-ability classes may also increase teacher expectations for students with the lowest prior achievement, as teachers tend to teach to the middle-range ability group when confronted with varied student ability (Tomlinson, 2014).

Class size is also linked with student outcomes, where K-12 research suggests that smaller classes improve students' academic performance, perhaps through shifts in teacher's instructional strategies or increased social and academic engagement compared with larger classes (Finn et al. 2003). Class size has not been focal in higher education research, though some studies in university settings link larger class sizes to fewer interactions with faculty and peers and lower grades (Beattie & Thiele, 2016; Johnson, 2010; Kokkelenberg et al., 2008).

Math Pathways

Dev-ed reforms have often coincided with math pathways reforms, which reconsider the status quo algebra-for-all approach to college math requirements. Under math pathways, students can select quantitative reasoning (QR), statistics, or algebra depending on their desired major (Bryk & Treisman, 2010). Math pathways reforms focus on changing both the content and instruction of math in college, offering options for math content and shifting instructional approaches for how they learn it (Zachry Rutschow et al., 2019). In a randomized controlled trial in Texas, Zachry Rutschow and colleagues (2019) illustrated that the Dana Center Math Pathways model, which accelerated dev-ed course sequences and reformed math curricula across three math pathways, positively impacted college-level math course completion and number of math credits earned.

Research on the link between math pathway—which type of math course students take—and student outcomes is limited. Extant experimental research on corequisite math in the CUNY system (Logue et al., 2016, 2019) targeted students whose majors did not require algebra. The experiment identified stronger effects of corequisite statistics coursework on several long-term academic outcomes, including transfer and degree attainment, compared with studies focused on corequisites in contexts with a mix of math pathways or primarily algebra (Ran & Lin, 2019; Meiselman & Schudde, 2020); it is difficult to know whether the differences in findings result from math pathways or different study contexts. Ran and Lin (2019) found that there were differential effects of corequisite math coursework across math pathways, where the positive effects of corequisite math coursework on completing college-level math were largely driven by students taking non-algebra college math rather than college algebra.

Although interest in corequisite models has increased, little research has explored the efficacy of different approaches and how students in corequisite coursework respond to corequisite course structures and characteristics. College personnel implementing corequisite reforms need this information to build efficient, effective math pipelines for students.

Research Questions

To help meet the pressing need for information about the link between corequisite coursework characteristics and student outcomes, we address the following research questions (RQs):

1. As colleges worked to implement a statewide corequisite mandate, how did they structure corequisite math coursework, including timing of course pairings, instructional modalities, math pathway offerings, and instructor assignments?
2. How do corequisite course structures and characteristics predict student outcomes?

Policy Contexts

Half of all first-time college students at Texas public two-year institutions do not meet college readiness standards in math—a score of 350 on the math Texas Success Initiative (TSI) assessment, a placement test taken at college entrance (Texas Higher Education Coordinating Board [THECB], 2016). Seeking stronger student outcomes, some colleges implemented corequisite coursework as early as 2014 but enrolled only a small fraction of students in corequisite math offerings (Meiselman & Schudde, 2020). In 2017, Texas's 85th Texas Legislature passed House Bill 2223 (HB2223), a mandate for colleges to scale corequisites for students who do not meet college-readiness standards. HB2223 required colleges to enroll at least 25% of all developmental students in each subject (i.e., math and English) in corequisite coursework by fall 2018, 50% by fall 2019, and 75% by fall 2020 (THECB, 2018). Using rulemaking authority, the THECB recently amended the policy to require that colleges move to 100% corequisites by fall 2021 (THECB, 2020).

HB2223 allowed colleges to determine how to structure corequisite math coursework. The recently enacted policy allows for sequential corequisite models as long as the dev-ed and college-level courses are offered within the same term. State policy requires that faculty with appropriate credentials teach the college-level component; this standard may shape colleges' decisions to assign the same instructor across paired courses, because dev-ed instructors may lack the credential needed to teach college-level courses.

Methods

To answer our research questions, we used statewide administrative data provided through a restricted-use agreement with the Texas Education Research Center (ERC), a research center and data clearinghouse at the University of Texas at Austin. We defined corequisite math coursework as enrolling in dev-ed and introductory college-level math courses in the same semester. Our analytic sample includes community college students who enrolled in corequisite math in a fall or spring term between fall 2018 and spring 2020. We relied on descriptive statistics to capture the structure and characteristics of corequisite math coursework. We used regression to explore the relationship between course characteristics and student outcomes, such as course passing, persistence in college, and vertical transfer.

Data

The ERC data includes student-level data for the entire population of secondary and postsecondary students in Texas. We used student-level data collected by the THECB, including files capturing student demographics, college enrollment, course enrollment and grades, placement test scores, and financial aid information, along with demographic and occupational information on course instructors.

To create the analytic sample, we first identified community college students who enrolled in dev-ed and college-level math within the same semester in the period after HB2223 was enacted (fall 2018–spring 2020) (N = 103,260). We restricted the analytic sample to students who had placement test scores (N = 69,301), so that we could include the TSI score as a proxy for math ability.[1] In the final analytic sample, 1% of students took module-based dev-ed math or multiple corequisite math courses in the same term, which resulted in two or more dev-ed math attempts in the same semester as the college-level course. Thus, the final analytic sample captured 70,026 corequisite dev-ed course enrollments among 69,301 students between fall 2018 and spring 2020.

Variables

Our main independent variables of interest capture corequisite math course structures and characteristics. For the college-level math course, we included class size, instructional modality, an indicator of mixed-ability composition (mix of developmental and college-ready students), and math pathway—college algebra, math for business, quantitative reasoning, and statistics. For

[1] About one-third of the population of interest lacked TSI scores, a result that aligns with prior research (e.g., Schudde & Keisler, 2019; Meiselman & Schudde, 2020). These scores may be missing because students did not plan to enroll in any math courses in their first semester or their initial degree plan did not require math (e.g., certificates or technical associate degrees). For a further discussion of placement score missingness in Texas, see Schudde and Meiselman (2019). We ran supplemental models on the restricted sample (those with test scores) and full sample (those with and without TSI scores) and present the results in Appendix C.

the developmental-level math course, we used measures of class size, semester credit hours, instructional modality, whether the course was lecture-based[2] (as opposed to a lab or independent study), and whether the college-level course was taught by the same instructor as the developmental course. We also captured four categories of dev-ed support courses based on the timing and duration of support: full-term concurrent, compressed concurrent, embedded prerequisite, and boot camp prerequisite (where the boot camp prerequisite is shorter than the embedded prerequisite, but both occur before the college-level course).

We also capture characteristics of developmental math course instructors,[3] including gender, race/ethnicity, age, faculty type (NTT vs. TT) and employment intensity, educational attainment, and 9-month salary. Our regression models include student characteristics and academic and financial background information as statistical controls. For example, we used math placement scores as a proxy for student ability. Because some students had non-TSI placement scores, we calculated each student's z-score on the placement test taken. Appendix A includes definitions and descriptive statistics for variables used in our main and supplemental analytic models.

We focus on five separate outcome measures that capture student performance in the college-level course and subsequent college outcomes. We created measures for passing the college-level math course (as opposed to either failing or withdrawing) and withdrawing from it (as opposed to persisting to the end of the course). To measure academic progress, we captured

[2] We relied on an indicator of instruction type, capturing whether a section is lecture-based (vs. lab or tutoring), instead of course prefixes suggesting a section is a non-course-based-option (NCBO) because several colleges designated all their dev-ed courses with NCBO prefixes despite variation in the instruction type measure. We spoke with faculty at some of the departments to confirm that instruction type varied, informing our decision not rely on the NCBO course prefix.

[3] In supplemental analyses (available upon request), we captured college-level instructor characteristics. Given that the majority of paired courses are taught by the same instructor (see Table 1), we focus on characteristics of developmental faculty in our descriptives and regression models.

whether students persisted into the subsequent semester and into the subsequent year, and whether they transferred to a four-year institution within 1 year. We ran analyses for several additional outcomes, including dev-ed math course outcomes, subsequent math course enrollment, and major switching, and present them in Appendix B.

Analytic Approach

To understand the structure and characteristics of corequisite coursework implemented at Texas community colleges (RQ1), we leveraged descriptive statistics. We then used logistic regression, given the dichotomous nature of our dependent variables, to examine which variables predict student outcomes while controlling for student background (RQ 2).

We used the following model for student *i* at college *j* in semester *t*:

$$Logit\ (p_{ijt}) = b_0 + b_1X_1 + b_2X_2 + \ldots. + b_nX_n + \xi_j + \lambda_t$$

where p_{ijt} is the probability of a discrete outcome's occurring, b_0 is the intercept, X_1–X_n are the independent variables, b_1–b_n are the associated regression weights, ξ_j is a college fixed effect, and λ_t is a semester fixed effect. The logit transformation ensures that the predicted probability of the outcome's occurring lies within the 0–1 bound. This approach allows for a more realistic representation of the curvilinear association because of the dichotomous outcome variable, and it tends to linearize the association between the predicted outcome and the set of predictors (Raudenbush & Bryk, 2002). We included college and semester fixed effects to control for other sources of between-college variation and factors changing each semester.

Because we rely on regression, the results do not represent causal relationships. When we use observational data, a regression with rich covariates is our strongest analytic strategy for examining which course features predict student success. We included a variety of control variables capturing student and instructor background; nevertheless, the estimated relationships could still partially be explained by unobserved factors. Several factors we expect to predict course selection and student outcomes, such as student motivation, social networks, and instructional quality, are unobservable in the data. Thus, the results are correlations that partially reflect sorting into specific courses (i.e., some students are more inclined to enter a given math course type than others, and those unobserved characteristics may also predict subsequent academic outcomes). Despite these limitations, the results stand to inform the extant literature on corequisite implementation.

Results

Description of Corequisite Math Coursework

We begin by describing, in Table 1, course and instructor characteristics for the developmental and college-level courses within community colleges' corequisite offerings since HB2223. The average developmental-support course was larger than the college-level course (by about 1.5 students) and worth fewer credits. Both courses were predominantly lecture based (95% of college-level courses and 77% of dev-ed courses) and taught in person. Over one-half of the paired college-level and developmental-support courses were taught by the same instructor. Colleges primarily offered dev-ed math corequisite courses that ran concurrently with the college-level course. Most—88%—of the dev-ed support courses were run as full-term concurrent courses: Students co-enrolled in the support course and college-level math course throughout the semester. The remaining dev-ed support courses were structured as compressed concurrent dev-ed (6% coincided with the college-level course but were shorter in duration) and embedded prerequisites (5% of dev-ed courses preceded the college-level course within the same term). Very few courses (approximately 1%) were set up as "boot camp" prerequisites, where the developmental course occurred before the college-level course and lasted under 2 weeks. Nearly one-half of the college-level courses were college algebra, with the remainder offered as QR and statistics and, less often, math for business.

In addition to corequisite course structures and characteristics, Table 1 describes instructor characteristics. Over one-half of all courses were taught by female instructors, and the racial-ethnic representations looked fairly similar across both course types, with White faculty teaching approximately 61% of courses. The age of instructors was also similar, with an average age of 50. Only 17–18% of instructors were TT or tenured in either course type. The majority of instructors for both courses were NTT, where the bulk of instructors were full-time NTT (48.3% for dev-ed and 52.5% for college-level). A larger portion of dev-ed instructors than of college-level instructors were part-time NTT (27% and 20%, respectively). The educational backgrounds of instructors differed across college-level and dev-ed courses. A smaller portion of dev-ed instructors held a graduate degree (about 80%) compared with college-level instructors (about 95%). On average, college-level instructors earned more, by about $4,000, than dev-ed instructors per academic year.

Regression Results: Course and College Outcomes

Table 2 presents the results for a series of logistic regression models predicting college-level course outcomes and subsequent college outcomes. For ease of interpretation, we present results using average marginal effects (AMEs) rather than log-odds or odd ratios; AMEs can be interpreted as the change in predicted probability for a one-unit change in the independent variable (holding other independent variables at their mean). The first and second columns present results from regressions on passing or withdrawing from the college-level math course, while the final three columns present results for persistence into next semester, persistence into the next year, and transferring to a university within 1 year.

Predictors of College-Level Math Course Passing and Withdrawal

Looking at predictors of college-level course outcomes, we note several patterns. The class size of the college-level course appeared to have a small positive association with passing and negative association with withdrawal—the larger the class size, the more likely students were to pass and less likely they were to withdraw. Taking a mixed-ability college-level math section was associated with a three-percentage-point increase in the probability of passing compared with taking a section where all students did not meet college-readiness standards. In terms of instructional modality, students in an online college-level course were eight percentage points less likely to pass the course than students in a face-to-face course. Students in hybrid courses, however, appeared less likely to withdraw than those in face-to-face courses. Finally, the math pathway of the college-level course was associated with both passing and withdrawal. Compared with the students taking college algebra, taking QR was associated with a 10.7-percentage-point increase in the probability of passing the course. Taking either QR or statistics—as opposed to algebra—negatively predicted course withdrawal.

Several developmental course characteristics also predicted college-level course outcomes. Increased credit hours of the dev-ed section positively predicted passing the college-level math course (and negatively predicted withdrawal), possibly indicating that students benefit from more time-intensive developmental support courses. Enrolling in a lecture-based dev-ed course—as opposed to a lab or independent study—predicted a decrease in withdrawal from the college-level course. Instructional modality of developmental courses also predicted college math course outcomes, where taking online or hybrid developmental courses, compared with face-to-face courses, was associated with a decreased probability of passing college-level math and an increased probability of course withdrawal. Taking corequisite coursework where the same instructor taught the college-level math and the dev-ed math support courses was associated with a 3.7-percentage-point increase in the probability of passing college-level math and 1.9-percentage-point decrease in the probability of withdrawing, compared with a corequisite model in which the paired courses were taught by different instructors. Finally, the timing and duration of the developmental support course (dev-ed math course type) did not appear to predict passing college-level math, but enrolling in a boot camp–style prerequisite dev-ed course was associated with a somewhat lower probability of withdrawing from the college-level course than was enrolling in a full-term concurrent dev-ed support course.

Regarding developmental instructors' characteristics, we found that those taking the dev-ed support course with a full-time NTT experienced a 4.7-percentage-point boost in the probability of passing college math compared with those taking the course with a tenured professor. (We similarly see a decrease in their probability of withdrawal.) The "unknown" faculty category was also associated with improved passing and decreased course withdrawals. Although we cannot avow that all the faculty in that category are full-time NTTs, we suspect that they are—that group largely comprises faculty at a handful of colleges that do not classify faculty and have no tenure (although we can see that most "unknown" instructors work full time).

Predictors of Persistence and Transfer

As we turn to longer-term outcomes, a prominent predictor of student success was whether the student had passed their college-level math course. Passing the college-level math course was associated with a 30- and 34-percentage-point increase in the probability of persisting into the subsequent semester and the following year, respectively, and with a 3.8-percentage-point increase in the probability of transferring to a university within a year.

Although several college-level math and developmental course characteristics that predicted short-term success in college-level math did not predict persistence and transfer, the math pathway of the college-level course and the timing of the dev-ed course appeared consequential for those outcomes. Taking QR or statistics—compared with algebra—negatively predicted persistence and vertical transfer, though the observed pattern for statistics was significant only for persistence into the next year. Students in math for business were more likely to persist into the subsequent year than algebra students, but the relationship was no longer significant a year out. The timing of the developmental support course appeared to predict persistence in college, where the embedded prerequisite and compressed concurrent models positively predicted persistence into the next term, compared with a full-term concurrent dev-ed course structure. The relationships are no longer significant (and, for compressed concurrent, actually reverse direction) for the outcome capturing persistence into the next year. Boot camp-style prerequisites appeared more negatively related to transferring to a four-year institution within 1 year, compared with full-term concurrent dev-ed.

We also examined whether developmental course instructor characteristics were associated with the probabilities of persistence and transfer, but the results yielded no notable significant patterns. In Appendix B we present results for additional outcomes, including developmental course outcomes, math course taking, and major choice.

Discussion

Over the past few years, colleges across the country began to revise decades-old approaches to dev-ed. Faced with pressure to implement corequisite reforms, college administrators and faculty need evidence for how to build effective course pairings of introductory college-level math and corequisite developmental support. In this paper, we used administrative data from Texas to illustrate how colleges structured corequisite coursework in response to a statewide mandate and how different corequisite course characteristics and structures predict student outcomes.

For the most part, our results suggest that, among students taking corequisite coursework, some course design decisions moderately improve passing rates of college-level math but do not trickle down to longer term outcomes like persistence and transfer. Our results suggest that mixed-ability college-level math classes boost pass rates for students who tested as not college-ready, which presents an actionable approach colleges might consider when designing corequisite coursework. Other characteristics, like course modality, are also linked improvements in course outcomes, though it is unclear whether those results are driven by selection (i.e., students in face-to-face vs. online courses, or in different math pathways, likely differ systematically in a way that may not be captured in our models). Experiencing the college-level math course face-to-face is associated with higher pass rates than taking the course online, although hybrid modality may boost course retention (though we should note that hybrid courses made up a very small proportion in our sample and may not be representative of hybrid courses generally).

The math pathway of the college-level course significantly predicts course outcomes and subsequent college outcomes, whereas other college-level course characteristics do not appear to explain the longer-term college outcomes, but we anticipate that students' differential selection into math pathway may also play a role in these observed relationships. Taking QR—compared with taking algebra—is positively associated with passing college math but negatively associated with persistence and vertical transfer. Taking statistics is also associated with a decrease in the probability of persistence into the subsequent year. Students in math for business, however, are more likely to persist into the next term than those who take algebra, though the relationship diminishes by the subsequent term. Overall, our results suggest that students in the college algebra pathway are more likely to persist in college than those in other pathways. Our supplemental analyses (see Appendix B) suggest they are also more likely to switch into STEM majors and to enroll in advanced math coursework. Ran and Lin (2019) similarly reported that students in non-algebra corequisite coursework experienced a larger boost in passing college-level math than those in algebra, with minimal long-term impacts. In their study of corequisite statistics coursework, Logue and colleagues (2016, 2019) observed both greater short-term improvements in course outcomes and longer-term benefits for credit accrual and degree attainment than in the traditional prerequisite algebra course. Although our results suggest that non-algebra corequisite coursework is correlated with higher passing rates than algebra corequisites, it is possible that the statistical model does not fully capture selection into math pathways; we also expect there could be differences in student support structures and subsequent course sequences across math pathways that are correlated with persistence and transfer. Selection into and impacts of math pathways are beyond the scope of our study, but we hope these results spur relevant future research.

Our regression results suggest that developmental supports also shape student outcomes in the college-level course. The number of credits for the dev-ed support course is positively associated with passing the college-level course. Likewise, face-to-face instruction and taking a lecture-based course also appear to boost success in the college-level math course.

Structuring corequisite coursework to use the same instructor across both courses positively predicts passing and persisting in the college-level course. Although we cannot know the mechanism driving this result, it is possible that when the two courses have the same instructor, the content is better aligned (Daugherty et al., 2018). Taking the developmental course with a full-time NTT instructor appears to positively predict passing the college-level course and course retention. Although we cannot discern experience teaching dev-ed from the administrative data we have access to, prior research (e.g., Datray et al., 2014; Daugherty et al., 2018) and our ongoing interviews in the field suggest that NTTs, especially those appointed at full time, have historically taught dev-ed courses. We hope that future research can capture the role teaching experience plays in student outcomes and can delineate between how prior experience teaching dev-ed intersects with conditions of having paired instructors.

Corequisite course design decisions appear to shape immediate student outcomes, such as persisting in and passing their required college-level math course. Our study offers a first look at how Texas community colleges—which educate 12% of the nation's public two-year college students (Snyder et al., 2019)—implemented a statewide mandate for corequisites. By fall 2019 (the second fall cohort in our analytic sample), one-half of all developmental math students were enrolled in the corequisite courses we examined. Our results suggest that some course design elements, such as mixed-ability classes for the college-level course, higher credit loads (as opposed to 1-credit courses) for the dev-ed corequisite support course, and using the same instructor across both the college-level and dev-ed course, improve immediate outcomes for students. The relationships we illuminate offer insights for policymakers, administrators, and practitioners seeking evidence for how to put corequisite models into practice.

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Tables

Table 1

Descriptive Statistics of Corequisite Math Coursework: Developmental and College-Level Course Characteristics

	Math Course Level	
Variable	Dev-Ed (% or M)	College-Level (% or M)
Course *N*	6,671	7,290
Course characteristics		
Class size	15.7	14.2
Number of credits	2.3	3.0
Lecture section	76.65%	94.84%
Instruction modality		
Face-to-face	88.01%	84.65%
Online	10.54%	13.47%
Hybrid	1.45%	1.88%
Same-instructor for paired courses	55.81%	51.59%
Dev-ed course type		
Boot camp prerequisite	1.09%	—
Embedded prerequisite	4.96%	—
Compressed concurrent	6.09%	—
Full-term concurrent	87.86%	—
College-level composition		
Mixed ability	—	43.61%
All dev-ed students	—	56.39%
College-level math pathway		
Algebra	—	49.97%
Math for business	—	12.04%
Quant reasoning	—	19.22%
Statistics	—	18.77%
Instructor characteristics		
Female	57.40%	53.40%
Race		
White	60.58%	61.32%
Black	10.03%	8.55%
Hispanic	18.33%	18.74%
Asian	7.99%	8.68%
Other	3.07%	2.72%
Age	50.2	49.9
Faculty type		

	Math Course Level	
Variable	Dev-Ed (% or M)	College-Level (% or M)
Tenured	13.58%	14.10%
Tenure-track	3.42%	4.36%
Full-time non-tenure-track	48.34%	52.47%
Part-time non-tenure-track	26.47%	19.56%
Unknown	8.18%	9.51%
Highest education level		
Doctoral degree	9.29%	11.21%
Master's degree	70.47%	83.48%
Bachelor's degree	17.45%	2.95%
Associate degree or certificate	<1%	<1%
No degree	2.07%	2.13%
Full-time employed	73.36%	80.26%
Calculated 9-month salary	$44,910	$48,770

Note. The table describes characteristics of corequisite math courses and instructors (reported at the course level, where column 1 and 2 show results for the dev-ed support course and college-level course, respectively). We provide means for continuous variables and percentages for categorical measures. The measures of college-level course instructor characteristics are not included in the regression models because the majority of corequisites were taught by same instructor.

Table 2

Regression Model Predicting Student Outcomes

	College-Level Math Course		Persistence and Transfer		
	Passed the course	Withdrew from the course	Persistence into the subsequent semester	Persistence into the subsequent year	Transfer to a 4-year institution within 1 year
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Passed the college-level math course[a]			0.298*** (0.006)	0.342*** (0.007)	0.038 *** (0.003)
College-level course characteristics					
Class size	0.002** (0.001)	-0.002*** (0.001)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
Mixed ability	0.029* (0.013)	-0.012 (0.007)	0.006 (0.009)	0.014 (0.014)	-0.002 (0.005)
Instruction modality (Ref. Face-to-face)					
Online	-0.080** (0.029)	0.014 (0.014)	-0.011 (0.012)	-0.014 (0.017)	0.009 (0.007)
Hybrid	0.070 (0.043)	-0.085** (0.021)	0.019 (0.024)	0.017 (0.030)	0.001 (0.017)
Math pathway (Ref. Algebra)					
Math for business	-0.003 (0.016)	0.004 (0.017)	0.014* (0.006)	0.005 (0.008)	0.007 (0.005)

	College-Level Math Course		Persistence and Transfer		
	Passed the course	Withdrew from the course	Persistence into the subsequent semester	Persistence into the subsequent year	Transfer to a 4-year institution within 1 year
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Quantitative reasoning	0.107*** (0.013)	-0.080*** (0.006)	-0.048*** (0.008)	-0.066*** (0.011)	-0.014*** (0.004)
Statistics	0.005 (0.015)	-0.016* (0.008)	-0.012 (0.007)	-0.028*** (0.008)	-0.001 (0.004)
Dev-ed support course characteristics					
Class size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of credits	0.016* (0.008)	-0.011** (0.004)	-0.013 (0.008)	-0.014 (0.008)	0.000 (0.003)
Lecture section	0.017 (0.024)	-0.037* (0.018)	-0.002 (0.012)	-0.015 (0.014)	0.002 (0.006)
Instruction modality (Ref. Face-to-face)					
Online	-0.054* (0.026)	0.028* (0.014)	0.014 (0.012)	0.009 (0.017)	0.006 (0.007)
Hybrid	-0.127*** (0.032)	0.112*** (0.034)	-0.012 (0.019)	0.040 (0.027)	0.019 (0.019)
Same instructor	0.037* (0.015)	-0.019* (0.009)	-0.010 (0.012)	-0.008 (0.014)	-0.001 (0.003)

	College-Level Math Course		Persistence and Transfer		
	Passed the course	Withdrew from the course	Persistence into the subsequent semester	Persistence into the subsequent year	Transfer to a 4-year institution within 1 year
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Dev-ed course type (Ref. Full-term concurrent)					
Boot camp prerequisite	0.039 (0.041)	-0.064* (0.026)	0.028 (0.026)	-0.012 (0.042)	-0.033* (0.009)
Embedded prerequisite	-0.007 (0.050)	-0.032 (0.031)	0.085* (0.033)	0.003 (0.024)	-0.015 (0.006)
Compressed concurrent	0.013 (0.022)	-0.014 (0.016)	0.129** (0.032)	-0.036* (0.015)	-0.008 (0.005)
Dev-ed support course instructor characteristics					
Female	0.015 (0.011)	-0.006 (0.007)	0.006 (0.004)	0.009 (0.005)	0.001 (0.002)
Race (Ref. White)					
Black	-0.003 (0.017)	0.000 (0.012)	0.000 (0.007)	0.004 (0.008)	0.000 (0.005)
Hispanic	0.024 (0.017)	-0.016 (0.011)	-0.009 (0.006)	-0.008 (0.009)	-0.007 (0.004)
Asian	-0.017 (0.016)	0.005 (0.007)	0.002 (0.007)	0.010 (0.009)	-0.008 (0.007)
Other	-0.064*** (0.018)	0.031* (0.015)	-0.016 (0.011)	0.001 (0.010)	-0.016 (0.012)

Variable	College-Level Math Course		Persistence and Transfer		
	Passed the course	Withdrew from the course	Persistence into the subsequent semester	Persistence into the subsequent year	Transfer to a 4-year institution within 1 year
	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
Faculty type (Ref. Tenured)					
Tenure-track	0.041 (0.036)	-0.035 (0.022)	-0.009 (0.011)	0.011 (0.014)	-0.011 (0.007)
Full-time non-tenure-track	0.047** (0.018)	-0.037** (0.012)	-0.005 (0.008)	-0.011 (0.011)	0.009 (0.006)
Part-time non-tenure-track	0.048 (0.026)	-0.025 (0.017)	-0.021 (0.014)	-0.015 (0.016)	-0.007 (0.011)
Unknown	0.058* (0.027)	-0.049** (0.017)	-0.005 (0.010)	0.006 (0.013)	0.003 (0.006)
Highest education level (Ref. No degree)					
Doctoral degree	0.004 (0.029)	0.005 (0.023)	0.005 (0.024)	-0.019 (0.028)	-0.002 (0.008)
Master's degree	0.002 (0.023)	-0.001 (0.022)	0.004 (0.023)	-0.012 (0.023)	0.002 (0.006)
Bachelor's degree	0.002 (0.026)	0.002 (0.023)	0.010 (0.023)	0.000 (0.025)	0.000 (0.007)
Associate degree	0.014 (0.035)	0.005 (0.054)	-0.050 (0.042)	-0.015 (0.035)	-0.013 (0.016)

	College-Level Math Course		Persistence and Transfer		
	Passed the course	Withdrew from the course	Persistence into the subsequent semester	Persistence into the subsequent year	Transfer to a 4-year institution within 1 year
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Calculated 9-month salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Sample Size	70,026	70,019	70,026	52,307	52,029

Notes. Table presents full logistic regression results, where each column represents a separate logistic regression model. All models included the following student characteristics: gender, race/ethnicity, age, major, financial aid application, Pell grant recipient, enrollment intensity, first time in college, and a z-score for their math placement test score. All models also included semester and college fixed effects and used robust standard errors clustered by semester and college. We present average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. For statistical significance tests, we rely on raw p values in the table. To adjust for multiple comparisons across regression models, we also estimated Benjamini et al.'s (2006) sharpened q values, following guidance from Anderson (2008), and present the results in Appendix D. The first three analyses included the entire sample, and the subsequent analyses excluded students in spring 2020 from the analytic sample because the follow-up data has not yet been released to capture outcomes after 1 year. The sample size across outcomes varies slightly because of the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome (e.g., course withdrawal and transfer) during a given term were dropped from those analyses. For ease of interpretation, the sample means for the outcomes of interest in each of the five regressions are: passed college math: 0.613; withdrew from college math: 0.171; persistence next semester: 0.741; persistence next year: 0.558; transfer: 0.047.
[a] "Passed the college-level math course" is included as an independent variable only in regressions on persistence and transfer outcomes.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix A: Description of Variables and Samples

Table A1. Description of Variables

Variable	Description	Analytic Sample: All Students [1]	Analytic Sample: Students Who Passed College Math [2]
Dependent Variables			
College-level math course			
Passed the course	Indicates whether the student passed college-level math, including grades of A, B, C, D, or P (for Pass)	0.613 (0.487)	
Withdrew from the course	Indicates whether the student withdrew from college-level math	0.171 (0.377)	
Grade	Numerical grade on a 4-point scale, college math	1.943 (1.423)	2,607 (0.993)
Dev-ed math course			
Passed the course	Indicates whether the student passed dev-ed math (A, B, C, D, or P)	0.649 (0.477)	0.934 (0.249)
Withdrew from the course	Indicates whether the student withdrew from dev-ed math	0.154 (0.361)	0.001 (0.032)
Numerical grade	Numerical grade on a 4-point scale, dev-ed math	2.218 (1.493)	2.850 (1.106)
Course enrollment in the subsequent semester			
Enrolled in any college-level math	Indicates whether the student enrolled in any college-level math in the following term	0.143 (0.351)	0.147 (0.354)
Enrolled in entry-level math	Indicates whether the student enrolled in entry-level math in the following term	0.087 (0.282)	0.058 (0.233)
Enrolled in advanced math	Indicates whether the student enrolled in advanced-level math in the following term	0.055 (0.228)	0.088 (0.283)
Persistence and transfer			
Persistence into the subsequent semester	Indicates whether the student continued to enroll in any courses in the following term	0.741 (0.438)	0.858 (0.349)

Variable	Description	Analytic Sample All Students [1]	 Students Who Passed College Math [2]
Persistence into the subsequent year	Indicates whether the student continued to enroll in any courses throughout the following year	0.558 (0.497)	0.691 (0.462)
Transfer to a 4-year institution within 1 year	Indicates whether the student transferred to a 4-year institution within the following year	0.047 (0.212)	0.061 (0.240)
Major switching in the subsequent semester			
Switched out of a broad major field	Indicates whether the student changed a broad major field in the following term	0.116 (0.321)	0.114 (0.318)
Entered STEM	Indicates whether the student changed from a non-STEM major filed to a STEM major field in the following term	0.017 (0.490)	0.017 (0.129)
Independent Variables			
Student characteristics			
Female	Identifies as female	0.598 (0.490)	0.630 (0.483)
Race			
White	Identifies as White, non-Hispanic	0.284 (0.451)	0.294 (0.456)
Black	Identifies as Black, non-Hispanic	0.147 (0.354)	0.126 (0.332)
Hispanic	Identifies as Hispanic	0.494 (0.500)	0.501 (0.500)
Asian	Identifies as Asian, non-Hispanic	0.021 (0.144)	0.025 (0.155)
Other	Identifies as Other race, non-Hispanic	0.054 (0.225)	0.055 (0.227)
Age	Age at corequisite course enrollment	21.250 (5.871)	21.411 (6.068)
Broad major field	Eight classification for broad major fields		
Humanities, Liberal Arts, and General Studies	Majors in Humanities, Liberal Arts, and General Studies	0.493 (0.500)	0.497 (0.500)
Social and Behavior Sciences	Majors in Social and Behavior Sciences	0.049 (0.215)	0.051 (0.220)
STEM	Majors in STEM	0.126 (0.332)	0.127 (0.333)

Variable	Description	Analytic Sample All Students [1]	 Students Who Passed College Math [2]
Education	Majors in Education	0.070 (0.254)	0.070 (0.254)
Business	Majors in Business	0.094 (0.292)	0.088 (0.283)
Health	Majors in Health	0.081 (0.272)	0.082 (0.275)
Industry/Agriculture/ Manufacturing/ Construction	Majors in Industry/Agriculture/Manufacturing/ Construction	0.038 (0.191)	0.039 (0.194)
Service Oriented	Majors in Service Oriented	0.049 (0.216)	0.046 (0.209)
Financial aid applicant	Indicates whether the student ever filed for federal or state student aid	0.819 (0.385)	0.821 (0.383)
Pell grant recipient	Indicates whether the student ever received Pell Grant	0.576 (0.494)	0.569 (0.495)
Full-time enrollment	Indicates whether the student enrolled full time in the current semester	0.597 (0.490)	0.611 (0.488)
First year of college	Indicates whether the student was in the first year of college	0.458 (0.498)	0.458 (0.498)
Math placement test z-score (any test)	Constructed z-score by test type (e.g., TSI, ACCUPLACER, COMPASS) and semester of student's test results among all students in all Texas public postsecondary institutions	0.000 (1.000)	0.070 (0.985)
College-level course characteristics			
Class size	The number of students enrolled in the college-level math course	20.658 (7.930)	20.729 (7.883)
Mixed ability	Indicates whether class included students assessed as college ready and below college ready	0.244 (0.430)	0.245 (0.430)
Instruction modality			
Face-to-face	The college-level math course was taught in person	0.900 (0.300)	0.910 (0.286)
Online	The college-level math course was taught online	0.086 (0.281)	0.076 (0.265)
Hybrid	The college-level math course was taught hybrid	0.014 (0.116)	0.014 (0.118)

Variable	Description	Analytic Sample All Students [1]	 Students Who Passed College Math [2]
Math pathway			
Algebra	College algebra course	0.508 (0.500)	0.507 (0.500)
Math for business	Math for business course	0.119 (0.324)	0.109 (0.312)
Quant reasoning	Quantitative reasoning course	0.215 (0.411)	0.236 (0.425)
Statistics	Introductory statistics course	0.159 (0.365)	0.148 (0.355)
Dev-ed support course characteristics			
Class size	The number of students enrolled, dev-ed math	22.827 (15.640)	22.847 (15.497)
Number of credits	Credit hours, dev-ed math	2.234 (0.984)	2.222 (1.002)
Lecture section	The dev-ed math support course is lecture-based	0.826 (0.379)	0.824 (0.381)
Instruction modality			
Face-to-face	The dev-ed math course was taught in person	0.907 (0.290)	0.917 (0.275)
Online	The dev-ed math course was taught online	0.081 (0.272)	0.071 (0.257)
Hybrid	The dev-ed math course was taught hybrid (mix of in-person and online)	0.012 (0.108)	0.012 (0.108)
Same-instructor	The dev-ed math course taught by same instructor as college-level math course	0.629 (0.483)	0.633 (0.482)
Dev-ed course type			
Boot camp prerequisite	Less-than-2-week dev-ed course taken within same semester as, but before, students enroll in the college-level course	0.001 (0.035)	0.001 (0.035)
Embedded prerequisite	Dev-ed math that occurs within the same semester as, but before, students enroll in the college-level course	0.032 (0.176)	0.036 (0.186)
Compressed concurrent	Dev-ed math course taken at same time as college-level course but duration is under 12 weeks	0.043 (0.202)	0.045 (0.207)
Full-term concurrent	Dev-ed math course taken at same time and more same duration as college-level course	0.924 (0.265)	0.918 (0.275)

Variable	Description	Analytic Sample All Students [1]	 Students Who Passed College Math [2]
Dev-ed support course instructor characteristics			
Female	Identifies as female	0.589 (0.492)	0.593 (0.491)
Race			
White	Identifies as White, non-Hispanic	0.634 (0.482)	0.629 (0.483)
Black	Identifies as Black, non-Hispanic	0.073 (0.260)	0.075 (0.263)
Hispanic	Identifies as Hispanic	0.182 (0.386)	0.192 (0.394)
Asian	Identifies as Asian, non-Hispanic	0.078 (0.268)	0.074 (0.262)
Other	Identifies as Other race, non-Hispanic	0.033 (0.179)	0.030 (0.170)
Age	Age at the time of teaching	49.803 (12.247)	49.805 (12.104)
Faculty type			
Tenured	Full or associate professor with tenure	0.105 (0.307)	0.103 (0.304)
Tenure-track	Assistant professor, tenure-track	0.043 (0.204)	0.044 (0.204)
Full-time non-tenure-track	Full-time non-tenure-track faculty	0.541 (0.498)	0.546 (0.498)
Part-time non-tenure-track	Part-time non-tenure-track faculty	0.203 (0.403)	0.203 (0.402)
Unknown	Faculty in colleges without ranking system and no other information on faculty type	0.107 (0.309)	0.105 (0.306)
Highest education level			
Doctorate degree	Doctoral degree or equivalent	0.073 (0.261)	0.072 (0.258)
Master's degree	Master's degree	0.756 (0.429)	0.754 (0.431)
Bachelor's degree	Bachelor's degree	0.157 (0.364)	0.162 (0.368)
Associate degree	Associate degree or certificate	0.002 (0.042)	0.002 (0.044)
No degree	No college degree	0.011 (0.105)	0.010 (0.101)
Calculated 9-month salary	The calculated 9-month salary based on the length of employment contract and total salary	$47,415.24 ($22,019.57)	$47,287.47 ($22,051.62)

Notes. All student $N = 69{,}301$; Students who passed college-level math $N = 42{,}482$. The table describes analytic variables and presents means and standard deviations (SD), reported at the student level. It includes several additional outcome variables (aligned with those in Appendix B), including dev-ed course, subsequent math course, and major switching outcomes. Columns [1] and [2] show results for all students and students who passed college-level math, respectively, where [1] corresponds to the analytic sample in the main paper and [2] corresponds to the results for the restricted analytic sample used to examine subsequent math course-taking outcomes in Appendix B (Table B2).

Appendix B: Regression Results from Additional Outcomes

In our main results, we presented logistic regression estimating the relationship between corequisite math coursework characteristics and student outcomes, such as college-level course completion patterns, continued college attendance, and vertical transfer. Here, we include regression results from several additional outcomes, including dev-ed math course outcomes, subsequent math course enrollment, and major switching in the following semester. Table B1 presents regression results from additional corequisite course-level outcomes: college-level math course grade, dev-ed course passing, dev-ed course withdrawal, and dev-ed course grade. For the course grade outcomes, students earned whole letter grades ranging from 0 (F) to 4 (A). We fitted OLS regression models and ordered logistic regression models (because the outcome was ultimately in 5 ordinal categories) to examine how corequisite course structures predict course grades. We found very similar results across the two approaches and ultimately present those from the OLS regression modeling (an approach referred to as a linear probability model) for ease of interpretability. In Table B2, we present additional logistic regression results for math course taking and major-switching patterns in the subsequent semester. In our analyses across additional outcomes, we used the same predictive variables as in the main results tables.

Table B1. Regression Model Predicting Additional Course-Level Outcomes

	College-Level Math Course	Dev-Ed Math Course		
	Grade	Grade	Passed the course	Withdrew from the course
Variable	Coefficient (*SE*)	Coefficient (*SE*)	AME (*SE*)	AME (*SE*)
College-level course characteristics				
Class size	0.006**	0.006	-0.001	-0.001
	(0.002)	(0.004)	(0.001)	(0.001)
Mixed ability	0.074	0.080	0.023*	-0.006
	(0.044)	(0.060)	(0.011)	(0.007)
Instruction modality (Ref. Face-to-face)				
Online	-0.179*	0.041	-0.042	0.024
	(0.085)	(0.090)	(0.025)	(0.018)
Hybrid	-0.050	0.386*	0.103**	-0.069**
	(0.104)	(0.151)	(0.035)	(0.021)
Math pathway (Ref. Algebra)				
Math for business	0.040	-0.039	0.003	0.000
	(0.045)	(0.049)	(0.012)	(0.017)
Quant reasoning	0.233***	0.095	0.084***	-0.073***
	(0.047)	(0.049)	(0.011)	(0.007)
Statistics	0.002	0.031	0.009	-0.016
	(0.051)	(0.036)	(0.012)	(0.008)
Dev-ed support course characteristics				
Class size	-0.001	-0.005	0.002*	0.000
	(0.001)	(0.003)	(0.001)	(0.000)
Number of credits	0.027	0.212	0.030***	-0.010*
	(0.024)	(0.120)	(0.007)	(0.004)
Lecture section	-0.064	0.011	-0.039	0.003
	(0.068)	(0.084)	(0.037)	(0.014)

Variable	College-Level Math Course Grade Coefficient (*SE*)	Dev-Ed Math Course Grade Coefficient (*SE*)	Dev-Ed Math Course Passed the course AME (*SE*)	Dev-Ed Math Course Withdrew from the course AME (*SE*)
Instruction modality (Ref. Face-to-face)				
Online	-0.232**	-0.253**	-0.080***	0.023
	(0.075)	(0.094)	(0.024)	(0.017)
Hybrid	-0.229**	-0.574***	-0.203***	0.099**
	(0.076)	(0.111)	(0.054)	(0.038)
Same-instructor	0.125**	0.219**	0.011	0.002
	(0.041)	(0.073)	(0.010)	(0.007)
Dev-ed course type (Ref. Full-term concurrent)				
Boot camp prerequisite	0.023	-2.149***	0.213	-0.141***
	(0.180)	(0.358)	(0.084)	(0.010)
Embedded prerequisite	-0.163	-0.011	0.160	-0.159***
	(0.105)	(0.135)	(0.079)	(0.002)
Compressed concurrent	-0.019	-0.135*	0.010	-0.035**
	(0.088)	(0.067)	(0.030)	(0.011)
Dev-ed support course instructor characteristics				
Female	0.033	0.020	0.020	-0.002
	(0.033)	(0.039)	(0.012)	(0.006)
Race (Ref. White)				
Black	-0.028	-0.012	0.000	-0.004
	(0.046)	(0.064)	(0.015)	(0.010)
Hispanic	0.117*	-0.009	0.017	-0.014
	(0.052)	(0.059)	(0.017)	(0.010)
Asian	-0.045	-0.036	-0.030**	0.012
	(0.058)	(0.058)	(0.010)	(0.008)

Variable	College-Level Math Course Grade Coefficient (*SE*)	Dev-Ed Math Course Grade Coefficient (*SE*)	Dev-Ed Math Course Passed the course AME (*SE*)	Dev-Ed Math Course Withdrew from the course AME (*SE*)
Other	-0.176**	-0.139*	-0.041*	0.039**
	(0.054)	(0.061)	(0.018)	(0.015)
Age	0.001	0.001	0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Faculty type (Ref. Tenured)				
Tenure-track	0.168	0.019	0.039	-0.027
	(0.121)	(0.114)	(0.032)	(0.023)
Full-time non-tenure-track	0.159*	0.027	0.042*	-0.040***
	(0.063)	(0.051)	(0.019)	(0.013)
Part-time non-tenure-track	0.208*	0.006	0.032	-0.036*
	(0.093)	(0.075)	(0.027)	(0.017)
Unknown	0.264**	0.067	0.059*	-0.054***
	(0.086)	(0.110)	(0.026)	(0.016)
Highest education level (Ref. No degree)				
Doctorate degree	0.154	0.083	0.024	0.018
	(0.085)	(0.104)	(0.036)	(0.021)
Master's degree	0.114	0.073	0.017	0.012
	(0.064)	(0.071)	(0.032)	(0.019)
Bachelor's degree	0.132	0.120	0.020	0.008
	(0.078)	(0.088)	(0.034)	(0.020)
Associate degree	0.203	0.270	0.077	-0.024
	(0.180)	(0.140)	(0.050)	(0.057)
Calculated 9-month salary	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Sample Size	57,396	42,743	68,482	68,672

Notes. Table presents regression results, where each column represents a separate regression model. We used OLS regression for numerical letter grades captured on a 4-point scale (The top grade is an A which equals 4, the lowest grade is a F which equals 0, and the other grades are B, C, and

D.) and logistic regression for course passing and withdrawing. All models included the following student characteristics: gender, race/ethnicity, age, major, financial aid application, Pell grant recipient, enrollment intensity, first time in college, and a z-score for their math placement test score. All models also included semester and college fixed effects and used robust standard errors clustered by semester and college. We present average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. The first two analyses included students who earned numerical course grades and the subsequent analyses included the entire sample. The sample size across outcomes varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome during a given term were dropped from those analyses. For ease of interpretation of the sample mean for the outcomes of interest in each of the four regressions are: Grade in college math: 1.943; grade in dev-ed math: 2.218; passed dev-ed math: 0.649; withdrew from dev-ed math: 0.154.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table B2. Regression Model Predicting Course Enrollment and Major Switching in the Subsequent Semester

	Course Enrollment in the Subsequent Semester			Major Switching in the Subsequent Semester	
	Enrolled in any college-level math	Enrolled in entry-level math	Enrolled in advanced math	Switched out of a broad major field	Entered STEM
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Passed the college-level math course[a]				-0.009* (0.004)	0.001 (0.002)
College-level course characteristics					
Class size	0.000 (0.001)	0.000 (0.000)	0.000 (0.001)	-0.001* (0.000)	0.000 (0.000)
Mixed ability	0.003 (0.009)	0.002 (0.005)	0.001 (0.007)	-0.003 (0.006)	0.003 (0.003)
Instruction modality (Ref. Face-to-face)					
Online	-0.015 (0.022)	-0.019* (0.007)	0.002 (0.017)	0.001 (0.010)	0.002 (0.004)
Hybrid	0.106 (0.081)	0.035 (0.027)	0.074 (0.081)	0.012 (0.024)	0.006 (0.019)
Math pathway (Ref. Algebra)					
Math for business	0.053 (0.037)	-0.021** (0.007)	0.072 (0.044)	-0.011 (0.006)	-0.016*** (0.003)
Quant reasoning	-0.112*** (0.012)	-0.006 (0.007)	-0.109*** (0.007)	-0.012 (0.006)	-0.013*** (0.002)
Statistics	-0.109*** (0.010)	-0.006 (0.004)	-0.109*** (0.006)	-0.006 (0.006)	-0.010* (0.004)
Dev-ed support course characteristics					
Class size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

	Course Enrollment in the Subsequent Semester			Major Switching in the Subsequent Semester	
	Enrolled in any college-level math	Enrolled in entry-level math	Enrolled in advanced math	Switched out of a broad major field	Entered STEM
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Number of credits	-0.002 (0.005)	0.000 (0.002)	-0.003 (0.004)	0.003 (0.004)	0.001 (0.002)
Lecture section	0.001 (0.025)	0.012* (0.006)	-0.004 (0.024)	-0.020 (0.014)	-0.002 (0.003)
Instruction modality (Ref. Face-to-face)					
Online	0.035 (0.026)	0.048*** (0.016)	-0.001 (0.015)	0.000 (0.011)	-0.003 (0.003)
Hybrid	-0.001 (0.026)	-0.009 (0.015)	0.010 (0.023)	-0.031* (0.014)	-0.008 (0.008)
Same-instructor	0.004 (0.010)	-0.004 (0.004)	0.004 (0.007)	-0.002 (0.005)	-0.001 (0.002)
Dev-ed course type (Ref. Full-term concurrent)					
Boot camp prerequisite	0.067 (0.054)	-0.025 (0.022)	0.101** (0.046)	-0.010 (0.022)	0.018 (0.022)
Embedded prerequisite	0.079 (0.048)	0.001 (0.005)	0.074* (0.042)	-0.022 (0.017)	0.000 (0.005)
Compressed concurrent	0.006 (0.018)	-0.010* (0.004)	0.015 (0.015)	0.012 (0.017)	0.000 (0.004)
Dev-ed support course instructor characteristics					
Female	0.003 (0.004)	-0.003 (0.003)	0.003 (0.002)	-0.004 (0.004)	-0.001 (0.001)
Race (Ref. White)					
Black	0.010 (0.009)	0.000 (0.005)	0.013 (0.008)	-0.009 (0.008)	-0.003 (0.002)

Variable	Course Enrollment in the Subsequent Semester			Major Switching in the Subsequent Semester	
	Enrolled in any college-level math	Enrolled in entry-level math	Enrolled in advanced math	Switched out of a broad major field	Entered STEM
	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Hispanic	-0.009 (0.008)	-0.001 (0.003)	-0.005 (0.007)	0.006 (0.006)	-0.001 (0.002)
Asian	0.001 (0.008)	0.001 (0.005)	0.003 (0.005)	-0.010 (0.008)	-0.002 (0.002)
Other	0.010 (0.011)	-0.006 (0.009)	0.019 (0.011)	-0.015 (0.014)	0.004 (0.007)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Faculty type (Ref. Tenured)					
Tenure-track	0.013 (0.014)	-0.007 (0.012)	0.026 (0.020)	-0.013 (0.011)	0.001 (0.005)
Full-time non-tenure-track	-0.021*** (0.006)	-0.020*** (0.007)	-0.007 (0.006)	0.010 (0.006)	-0.001 (0.003)
Part-time non-tenure-track	-0.027** (0.010)	-0.030*** (0.009)	-0.004 (0.010)	-0.004 (0.011)	0.003 (0.006)
Unknown	-0.018 (0.010)	-0.020* (0.008)	-0.009 (0.014)	0.008 (0.009)	0.001 (0.004)
Highest education level (Ref. No degree)					
Doctorate degree	-0.019 (0.016)	-0.006 (0.012)	-0.025 (0.021)	-0.052** (0.021)	-0.012 (0.011)
Master's degree	-0.008 (0.014)	-0.006 (0.010)	-0.015 (0.019)	-0.051** (0.021)	-0.010 (0.010)
Bachelor's degree	-0.002 (0.015)	-0.006 (0.011)	-0.011 (0.019)	-0.051** (0.022)	-0.012 (0.010)
Associate degree	-0.089* (0.033)	-0.033 (0.030)	-0.070* (0.025)	-0.014 (0.021)	-0.013 (0.012)

	Course Enrollment in the Subsequent Semester			Major Switching in the Subsequent Semester	
	Enrolled in any college-level math	Enrolled in entry-level math	Enrolled in advanced math	Switched out of a broad major field	Entered STEM
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Calculated 9-month salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Sample Size	42,896	42,876	42,851	51,891	44,668

Notes. Table presents logistic regression results, where each column represents a separate logistic regression model. All models included the following student characteristics: gender, race/ethnicity, age, major, financial aid application, Pell grant recipient, enrollment intensity, first time in college, and a z-score for their math placement test score. All models also included semester and college fixed effects and used robust standard errors clustered by semester and college. We present average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. The first three analyses included a subset of the main analytic sample comprised of students who passed college math (these students were most appropriate for examining subsequent math course enrollment). The fourth and fifth analyses included only students who continued to enroll in college in the subsequent semester, where the fifth analysis also focuses only on students who initially majored in non-STEM fields (most appropriate for capturing major movement from non-STEM to STEM). The sample size across outcomes also varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome during a given term were dropped from those analyses. For ease of interpretation of the sample mean for the outcomes of interest in each of the five regressions are: Enrolled in any college math: 0.143; enrolled in entry-level college math: 0.087; Enrolled in advanced math: 0.055; switched out of a broad major field: 0.116; entered STEM: 0.017.

[a] "Passed the college-level math course" is included as an independent variable only in regressions on major switching outcomes.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix C: Regression Results Without Conditioning on Test Scores

In the paper, we presented the regression results for the main analytic sample, where inclusion in the analytic sample was conditional on students having placement test scores in math. In Table C1 and C2, we present the results for both the main analytic sample (those with test scores, which allowed us to include test score in the regression model) and the full sample (those with and without test scores) to inform readers of how the exclusion of students without test scores from the analysis might change the estimated relationship between corequisite math coursework characteristics and student outcomes. The results show some differences in results obtained using our preferred analytic sample and model (sample inclusion conditional on having a placement test score and model specification controls for test score) and the full analytic sample, which is not conditional on having a placement test and therefore does not control for test scores.

When we no longer restrict the sample to students with a placement test score, the sample size increases from 70,026 to 104,179 (note that analytic samples differ slightly across models/outcomes). In Table C1 and C2, we highlight in green the differences in statistically significant results across models performed on the conditional and full sample. In some cases, results that appeared significant in the preferred conditional sample are not significant in the full sample. For example, for the passing college math outcome, the credit hours of the dev-ed section were associated with an increased probability of passing the college-level math course in our preferred model, but the relationship was not significant in the results for the full sample. It is difficult to say whether the differences in the observed relationship are due to the change in the sample or because the variable of interest—in this case, credits in dev-ed—is correlated with an omitted variable that would otherwise capture individual ability (in our preferred model, test score is a proxy for math ability/performance). Both explanations seem plausible because removing the inclusion criteria increased the sample size by a third (and students without test scores likely systematically differ from those with scores, though we cannot say precisely how) and the number of credits in dev-ed support are likely determined by students' performance on the math placement test.

Because restricting the sample to only students with math placement scores substantially reduces the sample, we anticipate it may reduce our statistical power compared with capturing the full sample. Some of the differences in results suggest that could be the case. For example, in predicting both persistence into the next semester and vertical transfer, the results for the full sample suggest that taking hybrid and online courses—compared with face-to-face courses—positively predict the outcomes, whereas the results from the analytic sample conditional on test scores yield no significant relationship. Both the hybrid and online sections had smaller cell sizes, so it does seem plausible that increasing the sample size by approximately a third could improve our power to detect a statistically significant results. Unfortunately, since we do not have another proxy of individual ability or prior achievement in math to use as a statistical control in the full sample, we prefer to focus on the more comprehensive model, which includes the placement test score (and necessitates restricting the sample base on having a test score). Ultimately, despite the sacrifice in sample size and statistical power, we prefer to capture a measure of prior math ability, as it is important for predicting the outcomes, particularly immediate outcomes in the college-level math course.

Table C1. Comparison of Regression Models Predicting Outcomes of Corequisite College-Level Math Course: Preferred Analytic Sample Conditional on Math Placement Test Scores Versus Full Sample (No Test Scores)

	College-Level Math Course Outcomes			
	Passed the course		Withdrew from the course	
	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
College-Level Course Characteristics				
Class size	0.002** (0.001)	0.001 (0.001)	-0.002*** (0.001)	-0.001* (0.000)
Mixed ability	0.029* (0.013)	0.030** (0.012)	-0.012 (0.007)	-0.014 (0.007)
Instruction modality (Ref. Face-to-face)				
Online	-0.080** (0.029)	-0.086*** (0.025)	0.014 (0.014)	0.022 (0.013)
Hybrid	0.070 (0.043)	0.057 (0.037)	-0.085** (0.021)	-0.082*** (0.017)
Math pathway (Ref. Algebra)				
Math for Business	-0.003 (0.016)	-0.007 (0.015)	0.004 (0.017)	0.006 (0.014)
Quant reasoning	0.107*** (0.013)	0.089*** (0.012)	-0.080*** (0.006)	-0.070*** (0.005)
Statistics	0.005 (0.015)	-0.011 (0.012)	-0.016* (0.008)	-0.007 (0.007)
Dev-Ed Support Course Characteristics				
Class size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of credits	0.016* (0.008)	0.010 (0.008)	-0.011** (0.004)	-0.008* (0.004)
Lecture section	0.017 (0.024)	0.019 (0.019)	-0.037* (0.018)	-0.024 (0.015)

	College-Level Math Course Outcomes			
	Passed the course		Withdrew from the course	
	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Instruction modality (Ref. Face-to-face)				
Online	-0.054* (0.026)	-0.049* (0.024)	0.028* (0.014)	0.035* (0.016)
Hybrid	-0.127*** (0.032)	-0.122*** (0.029)	0.112*** (0.034)	0.132*** (0.030)
Same-instructor for paired courses	0.037* (0.015)	0.043** (0.015)	-0.019* (0.009)	-0.020* (0.009)
Dev-ed course type (Ref. Full-term concurrent dev-ed)				
Boot camp prerequisite	0.039 (0.041)	0.007 (0.039)	-0.064* (0.026)	-0.010 (0.023)
Embedded prerequisite	-0.007 (0.050)	-0.013 (0.039)	-0.032 (0.031)	-0.026 (0.028)
Compressed concurrent dev-ed	0.013 (0.022)	0.005 (0.025)	-0.014 (0.016)	-0.016 (0.016)
Dev-Ed Support Course Instructor Characteristics				
Female	0.015 (0.011)	0.008 (0.010)	-0.006 (0.007)	0.001 (0.007)
Race (Ref. White, non-Hispanic)				
Black, non-Hispanic	-0.003 (0.017)	-0.005 (0.012)	0.000 (0.012)	0.004 (0.009)
Hispanic	0.024 (0.017)	0.023 (0.015)	-0.016 (0.011)	-0.013 (0.009)
Asian, non-Hispanic	-0.017 (0.016)	-0.022 (0.012)	0.005 (0.007)	0.010 (0.007)
Other races, non-Hispanic	-0.064*** (0.018)	-0.057*** (0.016)	0.031* (0.015)	0.028* (0.012)

	College-Level Math Course Outcomes			
	Passed the course		Withdrew from the course	
	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Faculty type (Ref. Tenured)				
Tenure-track	0.041 (0.036)	0.037 (0.029)	-0.035 (0.022)	-0.031 (0.018)
Full-time non-tenure-track	0.047** (0.018)	0.033* (0.015)	-0.037** (0.012)	-0.025** (0.010)
Part-time non-tenure-track	0.048 (0.026)	0.024 (0.020)	-0.025 (0.017)	-0.010 (0.014)
Unknown	0.058* (0.027)	0.035 (0.022)	-0.049** (0.017)	-0.031* (0.014)
Highest education level (Ref. No degree)				
Doctorate degree	0.004 (0.029)	-0.035 (0.023)	0.005 (0.023)	0.018 (0.016)
Master’s degree	0.002 (0.023)	-0.040* (0.018)	-0.001 (0.022)	0.018 (0.013)
Bachelor’s degree	0.002 (0.026)	-0.037 (0.020)	0.002 (0.023)	0.017 (0.015)
Associate degree	0.014 (0.035)	-0.014 (0.052)	0.005 (0.054)	-0.001 (0.037)
Calculated 9-month salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Sample Size	70,026	104,179	70,019	104,169

Notes. Table presents full logistic regression results, where each column represents a separate logistic regression model. All models included semester and college fixed effects and used robust standard errors clustered by semester and college. We present average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. For each outcome, we present results from our preferred model run on a restricted sample, conditional on students’ having a placement test score (which aligns with results from Table 2), and a full sample, with no such restrictions. The first and third analyses—performed on the restricted sample—include z-scores for students' math placement test score and the second and fourth analyses do not include students' math placement test score (because not all students had a test score). The sample size across outcomes varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome (e.g., course withdrawal) during a given term were dropped from those analyses. Differences in significant results across the restricted and full analytic samples are highlighted in green. For ease of interpretation, the sample means for the outcomes of interest in each of the five regressions are: passed college math – with test scores: 0.613, without test scores: 0.609; withdrew from college math – with test scores: 0.171, without test scores: 0.172.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table C2. Comparison of Regression Models Predicting Persistence and Transfer Outcomes: Preferred Analytic Sample Conditional on Math Placement Test Scores Versus Full Sample (No Test Scores)

	Persistence				Transfer	
	Persistence into the subsequent semester		Persistence into the subsequent year		Transfer to a 4-year institution within 1 year	
	Conditional on test score	Full Sample, no test score	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Passed the college-level math course	0.298*** (0.006)	0.293*** (0.006)	0.342*** (0.007)	0.335*** (0.007)	0.038 *** (0.003)	0.040*** (0.002)
College-Level Course Characteristics						
Class size	0.000 (0.000)	0.001 (0.000)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
Mixed ability	0.006 (0.009)	-0.002 (0.009)	0.014 (0.014)	0.009 (0.012)	-0.002 (0.005)	-0.001 (0.003)
Instruction modality (Ref. Face-to-face)						
Online	-0.011 (0.012)	-0.004 (0.009)	-0.014 (0.017)	-0.017 (0.013)	0.009 (0.007)	0.012** (0.005)
Hybrid	0.019 (0.024)	0.036* (0.016)	0.017 (0.030)	0.012 (0.027)	0.001 (0.017)	-0.011 (0.012)
Math pathway (Ref. Algebra)						
Math for Business	0.014* (0.006)	0.012* (0.006)	0.005 (0.008)	0.010 (0.007)	0.007 (0.005)	0.009* (0.004)
Quant reasoning	-0.048*** (0.008)	-0.044*** (0.007)	-0.066*** (0.011)	-0.064*** (0.009)	-0.014*** (0.004)	-0.013*** (0.004)
Statistics	-0.012 (0.007)	-0.005 (0.006)	-0.028*** (0.008)	-0.020** (0.007)	-0.001 (0.004)	-0.004 (0.003)
Dev-Ed Support Course Characteristics						
Class size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

	Persistence				Transfer	
	Persistence into the subsequent semester		Persistence into the subsequent year		Transfer to a 4-year institution within 1 year	
	Conditional on test score	Full Sample, no test score	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Number of credits	-0.013 (0.008)	-0.015* (0.007)	-0.014 (0.008)	-0.013 (0.007)	0.000 (0.003)	-0.003 (0.002)
Lecture section	-0.002 (0.012)	0.013 (0.011)	-0.015 (0.014)	-0.002 (0.012)	0.002 (0.006)	0.001 (0.005)
Instruction modality (Ref. Face-to-face)						
Online	0.014 (0.012)	0.014 (0.010)	0.009 (0.017)	0.017 (0.013)	0.006 (0.007)	0.003 (0.005)
Hybrid	-0.012 (0.019)	-0.011 (0.017)	0.040 (0.027)	0.034 (0.026)	0.019 (0.019)	0.023 (0.019)
Same-instructor for paired courses	-0.010 (0.012)	-0.017 (0.010)	-0.008 (0.014)	-0.008 (0.011)	-0.001 (0.003)	-0.002 (0.003)
Dev-ed course type (Ref. Full-term concurrent dev-ed)						
Boot camp prerequisite	0.028 (0.026)	0.067 (0.033)	-0.012 (0.042)	0.055 (0.033)	-0.033* (0.009)	-0.036** (0.005)
Embedded prerequisite	0.085* (0.033)	0.102** (0.033)	0.003 (0.024)	0.021 (0.023)	-0.015 (0.006)	-0.011* (0.004)
Compressed concurrent dev-ed	0.129** (0.032)	0.140*** (0.031)	-0.036* (0.015)	-0.022 (0.012)	-0.008 (0.005)	-0.002 (0.004)
Dev-Ed Support Course Instructor Characteristics						
Female	0.006 (0.004)	0.004 (0.004)	0.009 (0.005)	0.006 (0.005)	0.001 (0.002)	0.000 (0.002)
Race (Ref. White, non-Hispanic)						
Black, non-Hispanic	0.000 (0.007)	-0.009 (0.006)	0.004 (0.008)	-0.004 (0.007)	0.000 (0.005)	-0.001 (0.004)

	Persistence				Transfer	
	Persistence into the subsequent semester		Persistence into the subsequent year		Transfer to a 4-year institution within 1 year	
	Conditional on test score	Full Sample, no test score	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Hispanic	-0.009 (0.006)	-0.010 (0.006)	-0.008 (0.009)	-0.005 (0.008)	-0.007 (0.004)	-0.005 (0.003)
Asian, non-Hispanic	0.002 (0.007)	-0.004 (0.006)	0.010 (0.009)	-0.003 (0.009)	-0.008 (0.007)	-0.009 (0.006)
Other races, non-Hispanic	-0.016 (0.011)	-0.018* (0.009)	0.001 (0.010)	-0.001 (0.011)	-0.016 (0.012)	-0.017 (0.008)
Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001* (0.000)	0.000* (0.000)	0.000* (0.000)
Faculty type (Ref. Tenured)						
Tenure-track	-0.009 (0.011)	-0.010 (0.012)	0.011 (0.014)	0.007 (0.011)	-0.011 (0.007)	-0.009 (0.007)
Full-time non-tenure-track	-0.005 (0.008)	-0.009 (0.006)	-0.011 (0.011)	-0.009 (0.008)	0.009 (0.006)	0.008 (0.005)
Part-time non-tenure-track	-0.021 (0.014)	-0.025** (0.010)	-0.015 (0.016)	-0.014 (0.011)	-0.007 (0.011)	-0.005 (0.008)
Unknown	-0.005 (0.010)	-0.011 (0.008)	0.006 (0.013)	0.004 (0.008)	0.003 (0.006)	0.000 (0.005)
Highest education level (Ref. No degree)						
Doctorate degree	0.005 (0.024)	0.007 (0.015)	-0.019 (0.028)	-0.003 (0.016)	-0.002 (0.008)	-0.007 (0.005)
Master's degree	0.004 (0.023)	0.011 (0.013)	-0.012 (0.023)	0.005 (0.014)	0.002 (0.006)	-0.004 (0.004)
Bachelor's degree	0.010 (0.023)	0.012 (0.014)	0.000 (0.025)	0.011 (0.015)	0.000 (0.007)	-0.004 (0.004)

	Persistence				Transfer	
	Persistence into the subsequent semester		Persistence into the subsequent year		Transfer to a 4-year institution within 1 year	
	Conditional on test score	Full Sample, no test score	Conditional on test score	Full sample, no test score	Conditional on test score	Full sample, no test score
Variable	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)	AME (*SE*)
Associate degree	-0.050 (0.042)	-0.024 (0.037)	-0.015 (0.035)	0.012 (0.044)	-0.013 (0.016)	-0.021 (0.013)
Calculated 9-month salary	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Sample Size	70,026	104,179	52,307	76,423	52,029	76,189

Notes. Table presents full logistic regression results, where each column represents a separate logistic regression model. All models included semester and college fixed effects and used robust standard errors clustered by semester and college. We present average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. For each outcome, we present results from our preferred model run on a restricted sample, conditional on students' having a placement test score (which aligns with results from Table 2), and a full sample, with no such restrictions. The first, third, and fifth analyses—performed on the restricted sample—include z-scores for students' math placement test score and the second, fourth, and sixth analyses do not include the math placement test score (because not all students had a test score). The sample size across outcomes varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome (e.g., transfer) during a given term were dropped from those analyses. Differences in significant results across the restricted and full analytic samples are highlighted in green. For ease of interpretation, the sample means for the outcomes of interest in each of the five regressions are: persistence next semester – with test scores: 0.741, without test scores: 0.733; persistence next year – with test scores: 0.558, without test scores: 0.545; transfer – with test scores: 0.047, without test scores: 0.046.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Appendix D: Regression Results with Adjustment for Multiple Comparisons

In our main results presented in Table 2 of the paper, we presented logit model estimates for the various outcomes regressed on a large number of corequisite course characteristic variables. Given the large number of predictors and multiple outcome variables across our regression models, we anticipate that performing multiple comparisons (or multiple statistical testing) could increase the probability of false rejections where our significant findings might be due to chance. To address the possible concern about over-rejection of the null hypothesis, we computed sharpened *q* values, which control for the false discovery rate (FDR) (i.e., the expected proportion of rejections which are Type I errors), using a two-stage procedure proposed by Benjamini et al. (2006)[1] and following Anderson's (2008)[2] guidance for implementation in Stata. The sharpened *q* values—which are an analog to the original *p* values—represent the probabilities of type I errors after adjustment for multiple testing, allowing us to offer a significance level to describe the likelihood of a false statistically significant result. We present the results of our analyses here, with *q* values for our models presented side by side with the original *p* values.

For the primary models presented in the paper, we identified two groups of analyses that used distinct model specifications and outcome types; adjusting for multiple comparisons requires adjusting the *p* values within those two groups. Group 1 includes college-level math course outcomes (passed or withdrew from the course), where analyses for both outcomes used the same model specification. We adjusted the *p* values for multiple comparisons and present the results—including the original AMEs, SEs, and *p* values, and the newly calculated *q* values—in Table D1. Group 2 includes the models for the persistence and transfer outcomes, where the regression model was distinct from the specification in Group 1 because it included "passed the college-level math course" as an additional independent variable. For Group 2 models, Table D2 present unadjusted and adjusted *p* values (i.e., sharpened *q* values) along with AMEs and SEs.

We find our results are relatively robust to the adjustment. All estimates significant at $p < .01$ in Table 2 of the main paper have sharpened *q* values below .05, but some estimates significant at $p < .05$ do not have sharpened *q* values below .05 (though most are marginally significant with *q* values below .1). For example, the class size of the college-level course was positively associated with passing the college-level math course ($AME = .002$, $SE = .001$, $p = .004$) and the sharpened *q* value for the class size remains significant at the 5 percent test level. The credit hours of the dev-ed section also appeared to have a positive association with passing the college-level math course ($AME = .016$, $SE = .008$, $p = .039$), but the association did not persist after FDR adjustment (sharpened *q* value = .097). In Table D1 and D2, we highlight differences in statistically significant results across unadjusted and adjusted *p* values in green, for readers' convenience.

[1] Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika, 93*(3), 491–507.
[2] Anderson M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American statistical Association, 103*(484), 1481–1495.

Table D1. Comparison of *P* Values in Regression Analyses for Outcomes of Corequisite College-Level Math Course: Unadjusted *P* Value Versus Sharpened *Q* Value

	College-Level Math Course					
	Passed the course			Withdrew from the course		
Variable	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value
College-level course characteristics						
Class size	0.002 (0.001)	0.004	0.022	-0.002 (0.001)	<0.001	0.007
Mixed ability	0.029 (0.013)	0.021	0.075	-0.012 (0.007)	0.091	0.155
Instruction modality (Ref. Face-to-face)						
Online	-0.080 (0.029)	0.005	0.023	0.014 (0.014)	0.333	0.443
Hybrid	0.070 (0.043)	0.122	0.202	-0.085 (0.021)	0.003	0.017
Math pathway (Ref. Algebra)						
Math for Business	-0.003 (0.016)	0.844	0.852	0.004 (0.017)	0.830	0.852
Quant reasoning	0.107 (0.013)	<0.001	0.001	-0.080 (0.006)	<0.001	0.001
Statistics	0.005 (0.015)	0.731	0.791	-0.016 (0.008)	0.049	0.107
Dev-ed support course characteristics						
Class size	0.000 (0.000)	0.916	0.852	0.000 (0.000)	0.608	0.683
Number of credits	0.016 (0.008)	0.039	0.097	-0.011 (0.004)	0.002	0.016
Lecture section	0.017 (0.024)	0.498	0.532	-0.037 (0.018)	0.030	0.093
Instruction modality (Ref. Face-to-face)						
Online	-0.054 (0.026)	0.033	0.094	0.028 (0.014)	0.043	0.102
Hybrid	-0.127 (0.032)	<0.001	0.002	0.112 (0.034)	<0.001	0.002
Same-instructor for paired courses	0.037 (0.015)	0.016	0.058	-0.019 (0.009)	0.046	0.104
Dev-ed course type (Ref. Full-term concurrent dev-ed)						
Boot camp prerequisite	0.039 (0.041)	0.343	0.443	-0.064 (0.026)	0.039	0.097

	College-Level Math Course					
	Passed the course			Withdrew from the course		
Variable	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value
Embedded prerequisite	-0.007 (0.050)	0.888	0.852	-0.032 (0.031)	0.337	0.443
Compressed concurrent dev-ed	0.013 (0.022)	0.575	0.645	-0.014 (0.016)	0.393	0.458
Dev-ed support course instructor characteristics						
Female	0.015 (0.011)	0.152	0.231	-0.006 (0.007)	0.380	0.457
Race (Ref. White, non-Hispanic)						
Black, non-Hispanic	-0.003 (0.017)	0.848	0.852	0.000 (0.012)	0.983	0.852
Hispanic	0.024 (0.017)	0.174	0.252	-0.016 (0.011)	0.162	0.239
Asian, non-Hispanic	-0.017 (0.016)	0.275	0.391	0.005 (0.007)	0.466	0.507
Other races, non-Hispanic	-0.064 (0.018)	<0.001	0.005	0.031 (0.015)	0.034	0.094
Age	0.000 (0.000)	0.727	0.791	0.000 (0.000)	0.970	0.852
Faculty type (Ref. Tenured)						
Tenure-track	0.041 (0.036)	0.260	0.381	-0.035 (0.022)	0.128	0.203
Full-time non-tenure-track	0.047 (0.018)	0.009	0.037	-0.037 (0.012)	0.002	0.014
Part-time non-tenure-track	0.048 (0.026)	0.064	0.125	-0.025 (0.017)	0.144	0.225
Unknown	0.058 (0.027)	0.030	0.093	-0.049 (0.017)	0.004	0.022
Highest education level (Ref. No degree)						
Doctorate degree	0.004 (0.029)	0.881	0.852	0.005 (0.023)	0.818	0.852
Master’s degree	0.002 (0.023)	0.946	0.852	-0.001 (0.022)	0.978	0.852
Bachelor’s degree	0.002 (0.026)	0.949	0.852	0.002 (0.023)	0.941	0.852
Associate degree	0.014 (0.035)	0.688	0.767	0.005 (0.054)	0.921	0.852
Calculated 9-month salary	0.000 (0.000)	0.378	0.457	0.000 (0.000)	0.222	0.321
Sample Size	70,026			70,019		

Notes. Table presents full logistic regression results, where each column represents a separate logistic regression model. All models included semester and college fixed effects and used robust standard errors clustered by semester and college. We present unadjusted *p* values and sharpened *q* values together with average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. The sample size across outcomes varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome (e.g., course withdrawal) during a given term were dropped from those analyses. Differences in significant results across unadjusted *p* values and sharpened *q* values are highlighted in green. For ease of interpretation, the sample means for the outcomes of interest in each of the two regressions are: passed college math: 0.613; withdrew from college math: 0.171.

Table D2. Comparison of *P* Values in Regression Analyses for College Outcomes: Unadjusted *P* Value Versus Sharpened *Q* Value

	Persistence and Transfer								
	Persistence into the subsequent semester			Persistence into the subsequent year			Transfer to a 4-year institution within 1 year		
Variable	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value
Passed the college-level math course	0.298 (0.006)	<0.001	0.001	0.342 (0.007)	<0.001	0.001	0.038 (0.003)	<0.001	0.001
College-level course characteristics									
Class size	0.000 (0.000)	0.333	1.000	0.000 (0.001)	0.761	1.000	0.000 (0.000)	0.772	1.000
Mixed ability	0.006 (0.009)	0.469	1.000	0.014 (0.014)	0.338	1.000	-0.002 (0.005)	0.728	1.000
Instruction modality (Ref. Face-to-face)									
Online	-0.011 (0.012)	0.348	1.000	-0.014 (0.017)	0.406	1.000	0.009 (0.007)	0.146	0.777
Hybrid	0.019 (0.024)	0.436	1.000	0.017 (0.030)	0.582	1.000	0.001 (0.017)	0.965	1.000
Math pathway (Ref. Algebra)									
Math for Business	0.014 (0.006)	0.020	0.182	0.005 (0.008)	0.478	1.000	0.007 (0.005)	0.120	0.777
Quant reasoning	-0.048 (0.008)	<0.001	0.001	-0.066 (0.011)	<0.001	0.001	-0.014 (0.004)	<0.001	0.012
Statistics	-0.012 (0.007)	0.065	0.567	-0.028 (0.008)	<0.001	0.009	-0.001 (0.004)	0.759	1.000
Dev-ed support course characteristics									
Class size	0.000 (0.000)	0.410	1.000	0.000 (0.000)	0.435	1.000	0.000 (0.000)	0.288	1.000
Number of credits	-0.013 (0.008)	0.092	0.719	-0.014 (0.008)	0.096	0.719	0.000 (0.003)	0.947	1.000

	Persistence and Transfer								
	Persistence into the subsequent semester			Persistence into the subsequent year			Transfer to a 4-year institution within 1 year		
Variable	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value
Lecture section	-0.002 (0.012)	0.864	1.000	-0.015 (0.014)	0.305	1.000	0.002 (0.006)	0.787	1.000
Instruction modality (Ref. Face-to-face)									
Online	0.014 (0.012)	0.262	1.000	0.009 (0.017)	0.605	1.000	0.006 (0.007)	0.367	1.000
Hybrid	-0.012 (0.019)	0.514	1.000	0.040 (0.027)	0.144	0.777	0.019 (0.019)	0.254	1.000
Same-instructor for paired courses	-0.010 (0.012)	0.441	1.000	-0.008 (0.014)	0.597	1.000	-0.001 (0.003)	0.673	1.000
Dev-ed course type (Ref. Full-term concurrent dev-ed)									
Boot camp prerequisite	0.028 (0.026)	0.307	1.000	-0.012 (0.042)	0.768	1.000	-0.033 (0.009)	0.043	0.379
Embedded prerequisite	0.085 (0.033)	0.021	0.182	0.003 (0.024)	0.900	1.000	-0.015 (0.006)	0.053	0.458
Compressed concurrent dev-ed	0.129 (0.032)	0.001	0.016	-0.036 (0.015)	0.015	0.177	-0.008 (0.005)	0.143	0.777
Dev-ed support course instructor characteristics									
Female	0.006 (0.004)	0.155	0.777	0.009 (0.005)	0.079	0.686	0.001 (0.002)	0.632	1.000
Race (Ref. White, non-Hispanic)									
Black, non-Hispanic	0.000 (0.007)	0.983	1.000	0.004 (0.008)	0.656	1.000	0.000 (0.005)	0.956	1.000
Hispanic	-0.009 (0.006)	0.162	0.777	-0.008 (0.009)	0.398	1.000	-0.007 (0.004)	0.104	0.733

	Persistence and Transfer								
	Persistence into the subsequent semester			Persistence into the subsequent year			Transfer to a 4-year institution within 1 year		
Variable	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value	AME (*SE*)	Unadjusted *p* value	Sharpened *q* value
Asian, non-Hispanic	0.002 (0.007)	0.773	1.000	0.010 (0.009)	0.311	1.000	-0.008 (0.007)	0.280	1.000
Other races, non-Hispanic	-0.016 (0.011)	0.135	0.777	0.001 (0.010)	0.896	1.000	-0.016 (0.012)	0.242	1.000
Age	0.000 (0.000)	0.590	1.000	0.000 (0.000)	0.192	0.977	0.000 (0.000)	0.020	0.182
Faculty type (Ref. Tenured)									
Tenure-track	-0.009 (0.011)	0.419	1.000	0.011 (0.014)	0.427	1.000	-0.011 (0.007)	0.138	0.777
Full-time non-tenure-track	-0.005 (0.008)	0.530	1.000	-0.011 (0.011)	0.303	1.000	0.009 (0.006)	0.162	0.777
Part-time non-tenure-track	-0.021 (0.014)	0.126	0.777	-0.015 (0.016)	0.364	1.000	-0.007 (0.011)	0.518	1.000
Unknown	-0.005 (0.010)	0.619	1.000	0.006 (0.013)	0.613	1.000	0.003 (0.006)	0.608	1.000
Highest education level (Ref. No degree)									
Doctorate degree	0.005 (0.024)	0.847	1.000	-0.019 (0.028)	0.499	1.000	-0.002 (0.008)	0.800	1.000
Master’s degree	0.004 (0.023)	0.864	1.000	-0.012 (0.023)	0.609	1.000	0.002 (0.006)	0.685	1.000
Bachelor’s degree	0.010 (0.023)	0.667	1.000	0.000 (0.025)	0.990	1.000	0.000 (0.007)	0.965	1.000
Associate degree	-0.050 (0.042)	0.225	1.000	-0.015 (0.035)	0.661	1.000	-0.013 (0.016)	0.473	1.000
Calculated 9-month salary	0.000 (0.000)	0.786	1.000	0.000 (0.000)	0.098	0.719	0.000 (0.000)	0.641	1.000
Sample Size	70,026			52,307			52,029		

Notes. Table presents full logistic regression results, where each column represents a separate logistic regression model. All models included semester and college fixed effects and used robust standard errors clustered by semester and college. We present unadjusted p values and sharpened q values together with average marginal effects (AME) and standard errors (SE) for each covariate included in the binary logistic regression models. The sample size across outcomes varies slightly due to the inclusion of both semester and college fixed effects, where some colleges with no variation in a given outcome (e.g., course withdrawal) during a given term were dropped from those analyses. Differences in significant results across unadjusted p values and sharpened q values are highlighted in green. For ease of interpretation, the sample means for the outcomes of interest in each of the three regressions are: persistence next semester: 0.741; persistence next year: 0.558; transfer: 0.047.