Evaluation of Los Angeles City College's STEM Pathways Program

Impacts of the STEM Learning Center on student outcomes

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Introduction

Los Angeles City College (LACC) launched the STEM Pathways (STEMP) program in 2016 with funding from the U.S. Department of Education.[1] The college conceived the STEMP program as a comprehensive suite of evidence-based supports working together to improve STEM outcomes for Hispanic or Latinx (Latinx) and low-income students. LACC engaged SRI Education as the independent evaluator for this grant to assess its impact on student outcomes. This report focuses on the STEM Learning Center (SLC), one of the grant's most used supports. The SLC is a STEM-specialized tutoring center situated within the college that provides students with the academic support to succeed in their STEM courses. This report describes SLC participation from fall 2017 through fall 2019 and presents results from a quasi-experimental research study to estimate the impact of SLC participation on STEM course success and continuation in STEM.

The report begins with a description of the study context, including an overview of LACC and the SLC. We then describe prior research on effective STEM supports and present our research questions and data sources. Next, we discuss results from a descriptive analysis of SLC participation, including an examination of proportionality for students in the demographic groups targeted by the grant—Latinx students and students from low-income families. Last, we describe the methods used for the impact analysis and summarize findings regarding the impacts of SLC participation on students' STEM outcomes.

Study Context and SLC Overview

LACC is a public community college in Los Angeles, California. It is one of the nine community colleges that make up the Los Angeles Community College District (LACCD) and one of 116 community colleges in the California community college system.

LACC serves a large and diverse student population, enrolling over 15,000 students in fall 2018, over half of whom were Latinx (54%) (Los Angeles City College, 2018). Thus, LACC easily meets the federal definition for a Hispanic-Serving Institution, which requires that undergraduate enrollment is composed of at least 25% Latinx students (U.S. Department of Education, n.d.). In addition, 6% of LACC students were Black/African American, 12% were Asian/Pacific Islander, 45% were first-generation, 57% received financial aid, and 58% were female. Because Latinx students are underrepresented in STEM fields, Hispanic-Serving Institutions have high potential to increase degree completion in STEM fields for this population (Santiago et al., 2015). Although nationally Latinx students declare STEM majors at similar rates as White students, they are less likely to stay in the STEM major and less likely to complete a degree at all.

[1] In 2016, the U.S. Department of Education awarded Los Angeles City College (LACC) a 5-year, $6 million grant to develop a program aimed at increasing STEM degree completion and transfer for low-income and Hispanic/Latinx students.

Programs like the STEMP program seek to attract Latinx students to the STEM field and retain them by offering supports to address common barriers (Riegle-Crumb et al., 2019).

During the period of the study, students at LACC had access to several supports to help them succeed in STEM coursework. Students could seek tutoring from LACC's Pi Shoppe, which provided tutoring to help students succeed in introductory math courses that had low pass rates. Failure to pass these introductory courses can prevent students from enrolling in higher-level STEM courses. To complement the Pi Shoppe's support for introductory math classes, the STEMP program offered supports for higher-level math courses, many of which are required for a STEM degree. In addition to the SLC, the program began offering supplemental instruction for select sections of STEM gateway courses in fall 2017. Supplemental instruction is an evidence-based model that gives students access to a knowledgeable peer outside of class hours. The supplemental instructor, typically a peer who has already succeeded in the focal course, participates in the course alongside other students and offers supplemental sections to support students as they progress through the course (Dawson et al., 2014).

The focus of this study, however, was the SLC. During the period of the study, the SLC employed student tutors to provide academic support in math (Math 240 and above), chemistry, biology, physics, and computer science. Tutoring offerings varied by semester, depending on the availability of experienced peer tutors. From spring 2017 to fall 2019, the SLC offered free, optional, drop-in tutoring support for these courses 10 a.m.–6 p.m. Monday–Thursday and 9 a.m.–1 p.m. Fridays during the spring and fall semesters.

The content and frequency of the SLC tutoring was driven by students' needs and course requirements—sample activities included concept review, test preparation, or homework help. Participation numbers and intensity varied by term. Many students visited the SLC just once or twice during a focal term, while others visited multiple times per week and attended as often as 50–70 times in a given term. The SLC typically had more visitors in the spring and fall terms than in the shorter winter and summer terms (134 students on average visited in the fall or spring terms, as compared with 31 visitors in the winter or summer terms), and the average number of visits was also higher during these terms (an average of 9.0 visits in fall and spring, compared with 5.3 visits in winter and summer).

SLC tutors received an introductory training from STEMP program staff. This training focused on best practices for working with students, policies, and procedures. Per LACC requirements, a STEMP program staff member supervised the SLC sessions. Program staff did not provide academic support, but they made sure that students signed in upon entry. They also provided learning resources to students (e.g., textbooks, computers, writing materials, and workstations).

There are a few important contextual factors to consider when interpreting the analysis. In fall 2019, LACC began implementing new requirements to comply with California Assembly Bill (AB) 705. AB 705 required that all California community college districts and colleges streamline the pathway toward graduation by reducing credit-bearing developmental coursework for students, instead aiming for all students to enter and complete transfer-level coursework in English and math within 1 year (California Community Colleges, 2018). It is possible that the population of students seeking support from the STEMP program changed in fall 2019 as students who would have previously been placed into developmental coursework attained access to transfer-level courses.

LACC also expanded the supplemental instruction (SI) program in fall 2019. In fall 2019, LACC began offering SI in additional sections of chemistry. Students in these sections who may have previously sought support from the SLC may have instead sought support from their supplemental instructor.

Finally, in March 2020, the COVID-19 pandemic prompted LACC to shift to remote learning for the remainder of the 2019−20 academic year and for the 2020−21 academic year. To continue meeting students’ needs, the STEMP program began providing SLC virtually. Due to the abrupt shifts in STEMP programming and increased course withdrawal rates at LACC during remote instruction, the research team did not calculate impacts for terms beyond fall 2019.

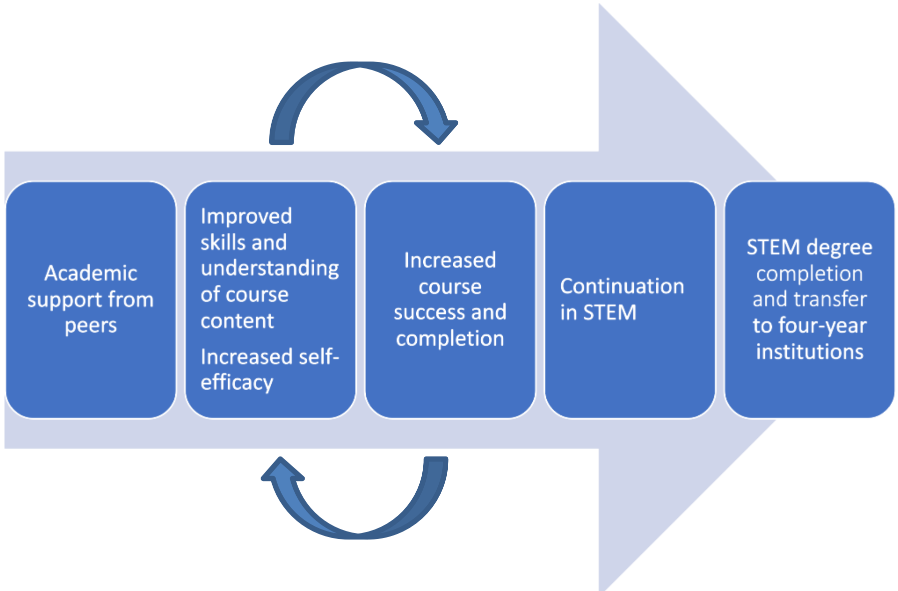
Study Purpose

The purpose of this analysis is to examine the extent to which the SLC reached the target student population, and to determine whether SLC participation helped students succeed in completing STEM coursework and continuing in STEM, setting the stage for improved STEM degree completion and transfer.

Conceptual Model

The goal of the STEMP program is to improve STEM degree completion and transfer to 4-year colleges, particularly for low-income and Latinx students. One way the SLC may increase these long-term outcomes is through improving short-term academic performance and STEM persistence (Exhibit 1). Targeted, academic tutoring support from peers helps students improve their skills and understanding of course content as well as their sense of self-efficacy. The improved skills and understanding enable greater course success. Practically, increased course success means students earn more credits toward their degree, and may also increase their commitment to STEM, thereby making them more likely to eventually complete a degree or certificate and transfer (Dawson et al., 2014). This analysis focused on the shorter-term SLC outcomes, specifically course success and continuation in STEM.

Exhibit 1. SLC Conceptual Framework



Research Questions

SRI conducted a rigorous, quasi-experimental analysis to understand the impact of SLC participation on students' course success. The following research questions guided this analysis:

(1) To what extent did the SLC reach the target population of low-income students and Latinx students?

(2) What is the impact of attending the SLC on STEM course success?

(3) Does SLC participation increase the likelihood that students continue in STEM?

Data Sources

This evaluation report draws on two sources of data. The first is student enrollment, demographic, and historical and current coursetaking data from LACC's administrative data system. The college provided these data for all students enrolled at LACC between spring 2017 and fall 2019 who met the STEM student definition: any student who declared a STEM major or took Math 240 or a higher math course by fall 2019.[2] The second data source is SLC participation records, gathered directly from the STEMP program. SLC participants were asked to log in using their student ID when they arrived for drop-in tutoring. The STEMP program staff assigned pseudo identifiers to these SLC usage data that enabled linking to the data from the

[2] Math 240 is a trigonometry course and a "gateway" math course, meaning that it is a prerequisite for many other STEM courses.

college's administrative data system. SRI combined these SLC program participation data with extant administrative data from LACC to examine program participation and impact.

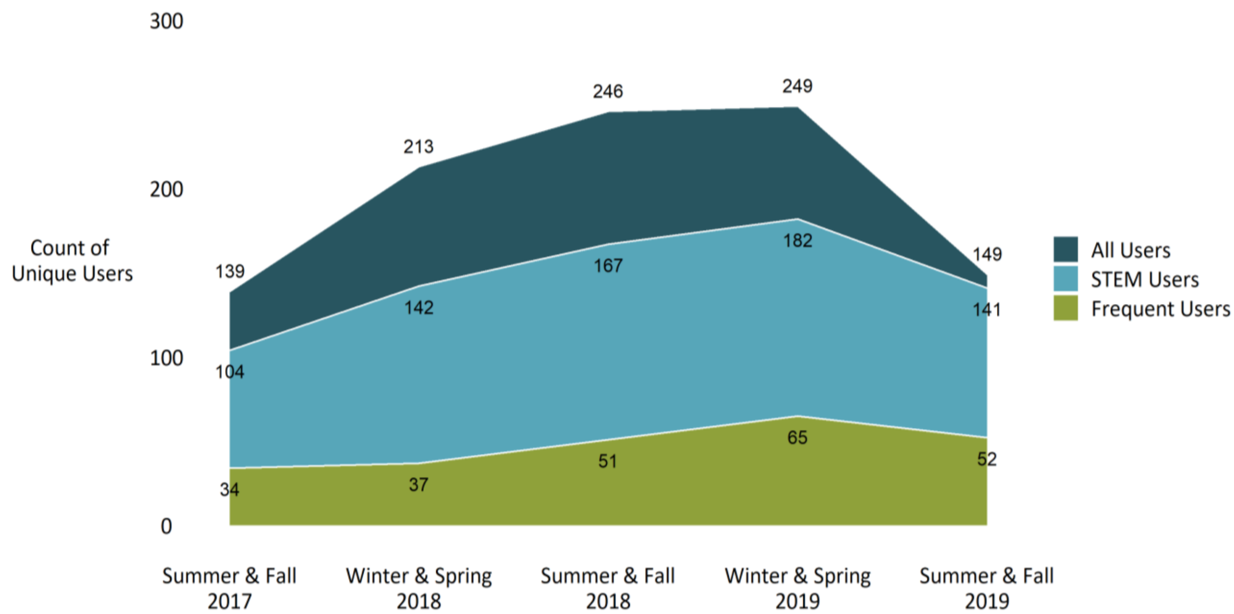
Program Participation

Together, the student enrollment data and SLC participation data enabled us to examine both the number of students who took advantage of the SLC tutoring and the extent to which these students were representative of the broader population of STEM students at LACC.

SLC Participation

The descriptive analysis of user participation shows that usage of the SLC was trending upward from summer 2017 through spring 2019 for all groups, including STEM students, frequent users of the SLC (defined as 10 or more visits in a term), and all users (including non-STEM students, i.e., students who do not meet our STEM student definition) (Exhibit 2). After spring 2019, there was a sharp decline in participation, particularly for non-STEM students. We combine the number of unique users by term and year for main terms (fall and spring) with adjacent intercessions (summer and winter) to clearly display trends. For example, 249 unique users visited the SLC in winter and spring 2019. That number fell to 149 unique users by summer and fall 2019. Although we do not know for certain the reason for the decline in SLC participation in spring 2019, LACC noted two potential contextual factors that contributed to this change, discussed above. First, the program expanded SI in this term, adding new sections in chemistry, so some students who previously sought help through the SLC may have instead received support through SI. Second, the college's placement policies changed in fall 2019, making it easier for students to enter directly into transfer-level coursework. Anticipating an increase in students who might need additional support in math in response to this policy change, the college added support classes in math as well. Together, the expansion of the SI and support classes may have reduced some of the demand for SLC support.

Exhibit 2. SLC Participation, Summer 2017 to Fall 2019



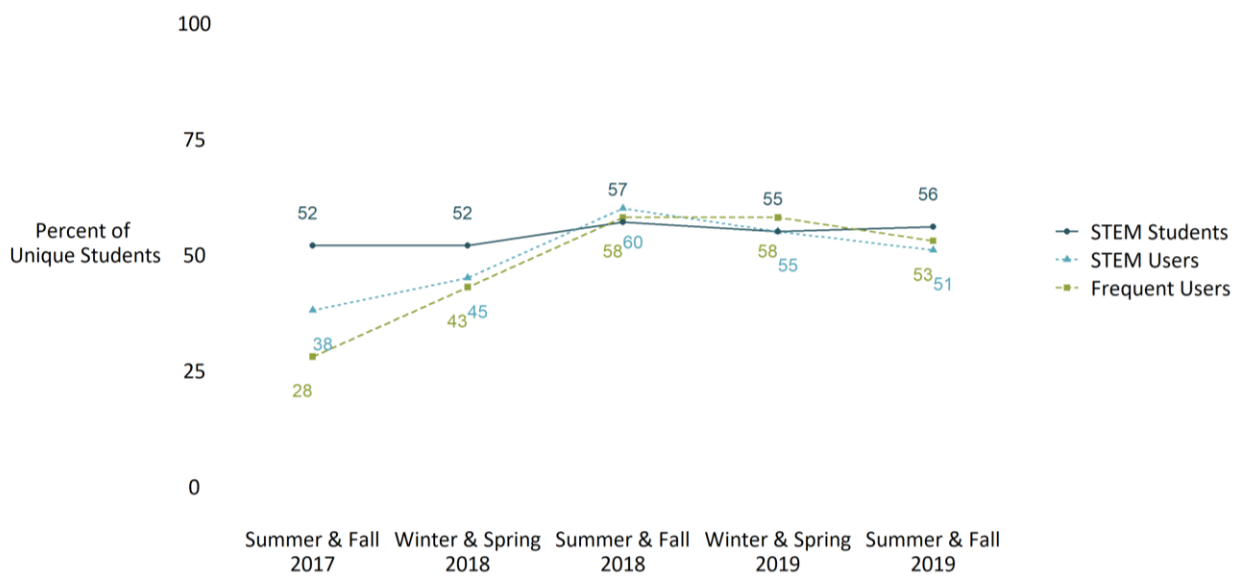
SLC Proportionality

In addition to exploring trends in participation over the study period, we also examined the extent to which the SLC was reaching students of the target demographics.

Proportionality for Latinx Students

Exhibit 3 shows the proportion of SLC users who are Latinx relative to the proportion of Latinx STEM students at LACC as a whole. From this figure, we see that representation of Latinx students in the SLC grew to match the STEM student population over time, even as the proportion of Latinx STEM students increased. In summer and fall 2017, the STEM student population at LACC was 52% Latinx, while STEM users of the SLC were just 38% Latinx and frequent users of the SLC were 28% Latinx. The differences between these groups reversed by late 2018, when 60% and 58% of STEM users and frequent users of the SLC, respectively, were Latinx, compared with 57% of STEM students at LACC. In the final terms examined (summer and fall 2019), when SLC participation dropped overall, we also see a slight drop in Latinx representation among STEM users and frequent users of the SLC while the proportion of Latinx STEM students at LACC increased just slightly.

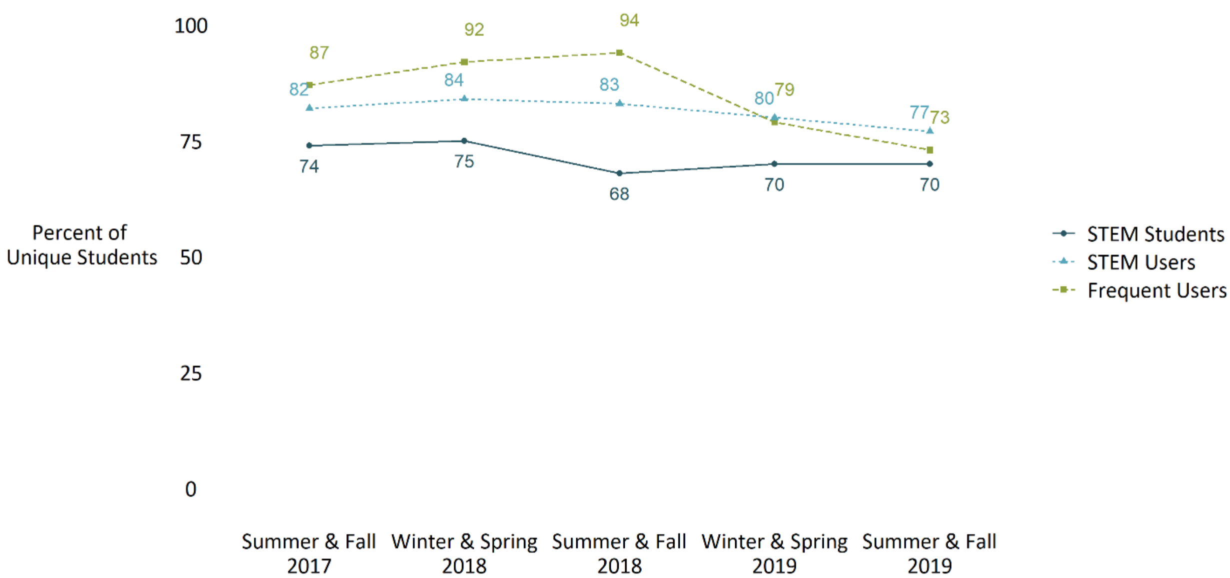
Exhibit 3. Proportionality of Participation for Latinx Students



Proportionality for Low-Income Students

In contrast to Latinx participation, the proportion of students who are low-income (defined as Pell Grant or California Promise Grant recipients) was consistently higher among SLC users than among STEM students at LACC, though that difference narrowed in 2019 (Exhibit 4). For example, in summer and fall 2017, 82% of STEM users and 87% of frequent users of the SLC were low-income relative to 74% of STEM students at LACC. Though the difference narrows by summer and fall 2019 to 77% and 73% for STEM users and frequent users of the SLC, respectively, compared with 70% of LACC STEM students, the proportion of low-income students remains higher for the SLC population.

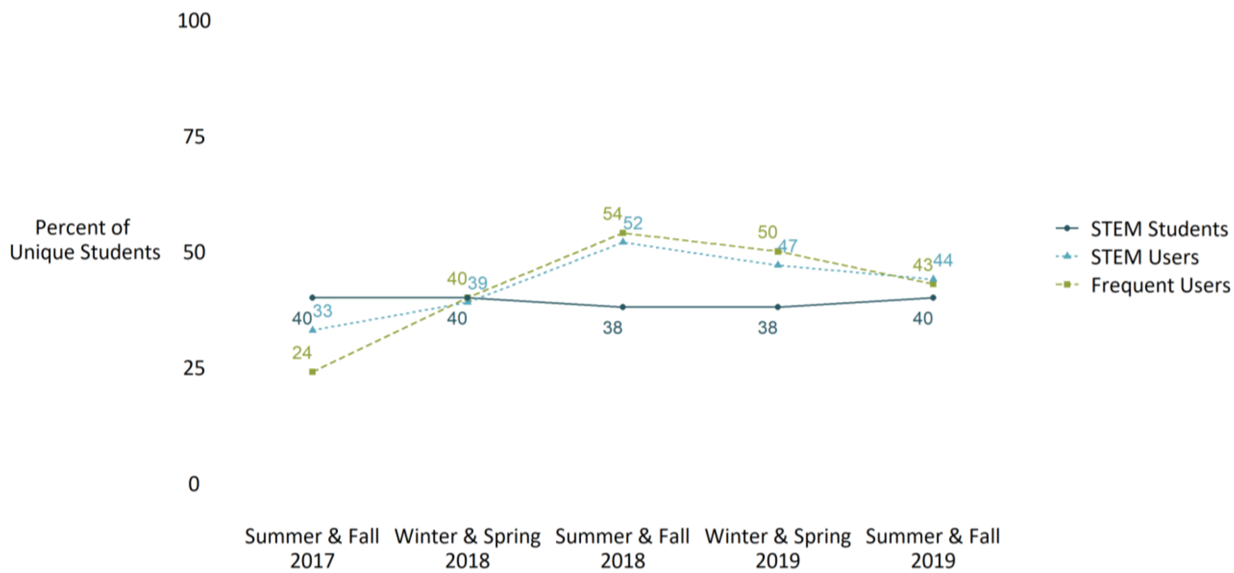
Exhibit 4. Proportionality of Participation for Pell or California Promise Grant Students



Proportionality for Low-Income Latinx Students

Finally, we examine student participation for those at the intersection of the two target demographic groups: Latinx students who are low-income. Exhibit 5 shows the proportion of STEM users of the SLC who are both Latinx and low-income relative to all STEM students at LACC. Trends are somewhat similar to those for Latinx participation—representation among STEM users of the SLC lags behind the STEM student population as a whole in 2017 but differences narrow quickly. By late 2018, students who are both Latinx and low-income are better represented among STEM users of the SLC than among the LACC STEM student population.

Exhibit 5. Proportionality of Participation for Latinx Pell or California Promise Grant Students



Taken together, these results suggest that while the SLC may not have started out reaching its targeted student population, representation of students who are Latinx and/or low-income improved over time. However, summer and fall 2019 saw a narrowing of the differences between SLC and STEM student demographics as SLC use dropped. This might be the start of a downward trend, a leveling off, or simply a singular year resulting from broader policy changes that impact demographics in the student population. Next, we turn to a discussion of the estimated impacts of the SLC on the students served.

Impact Analysis

We estimated the effects of SLC participation using propensity score weighted regression.

Methods

We used propensity score weighting to estimate the impact of SLC participation on three student outcomes tied to the focal term: STEM GPA, STEM credits earned, and continuation in STEM, defined as enrollment in a STEM course in either of the subsequent two terms (including intersession terms). We did not consider the continuation in STEM outcome for fall 2019 because of the global pandemic; the college extended the withdrawal period when instruction became abruptly remote in spring 2020, resulting in unusual observed course withdrawal patterns in this term.

We defined the intervention as SLC participation within a given term rather than the combined terms used in the participation analysis to ensure tight alignment between SLC use and the outcomes examined. We defined the treatment group as any STEM student enrolled at the college who attended the SLC at least once within a given fall or spring term from fall 2017 through fall 2019.[3] The comparison group was any STEM student who did not attend the SLC in the given term.

The propensity score weighting ensured that the treatment and comparison groups were equivalent on observed student characteristics, including gender, race and ethnicity, and eligibility for a California Promise Grant, as well as prior coursetaking and GPA, both overall and in STEM. This methodology reduces bias due to these observable characteristics; it does not, however, eliminate bias due to unobserved differences in treatment and comparison groups, such as differences in prior educational opportunities, access to outside supports, or the nature of peer relationships. We estimated the impact of SLC participation in each term separately, and then combined these estimates using meta-analysis (Appendix A). Some students who used the SLC also participated in SI in the same term (between 24% and 41% by term). To better understand the unique impact of SLC participation on student outcomes, we also conducted a sensitivity analysis excluding these students from the sample (Appendix B).

SLC Impact by Term

The weighted regressions estimating the impact of SLC participation on STEM outcomes result in positive and significant effects on STEM credits earned, STEM GPA, and continuation in STEM. For each term and outcome, we show weighted means and standard deviations for treatment and comparison groups, the coefficient (and standard error) on the SLC indicator from the weighted regression models, and the effect size (Exhibit 6). The effects were most consistent for STEM credits earned (significant in all five terms), followed by STEM GPA (significant in three out of five terms) and continuation in STEM (significant in two out of four terms). Estimated effect sizes for significant coefficients range from 0.09–0.40 for STEM credits earned, 0.13–1.16 for STEM GPA, and 0.19–0.47 for continuation in STEM.[4] Effect sizes provide useful standardized measures of magnitude that allow for comparisons across different metrics. However, for outcomes such as credits earned and GPA, it is also useful to consider impacts on the scale of their original measurement. On average, SLC participants earned between 0.42 and 1.42 more credits each semester than similar peers who did not visit the SLC, and STEM grade point averages that were between 0.17 and 1.19 higher. In fall 2018, the predicted probability of continuing in STEM for the typical low-income female Latinx California resident student was 85.8% for SLC participants versus 73.4% for non-SLC participants.[5]

[3] SRI excluded the summer and winter terms from the analysis due to low SLC participation during those periods and consequently unstable estimates (n of SLC participants in summer and winter terms during the study period ranged from 6 to 38).

[4] Cohen (1988) suggested that 0.20 be considered a “small” effect size, 0.50 represents a “medium” effect size and 0.80 a “large” effect size. The results of the sensitivity analysis, which excludes students who also participated in SI in the focal term, were similar, though the estimated impact on STEM credits earned was positive and significant in only four of the five terms and on continuation in STEM in only one of the four terms.

[5] These predicted probabilities are for a student without AB540 status, who is not in her first term at LACCD, and who has no dual enrollment credits, prior math, prior transfer credits, prior non-transfer credits, prior SI/SLC use, or prior STEMP support.

Exhibit 6. Outcomes by Term

	Fall 2017				Spring 2018				Fall 2018			
	C mean (sd)	**T mean (sd)**	**β (SE)**	**Effect Size**	**C mean (sd)**	**T mean (sd)**	**β (SE)**	**Effect Size**	**C mean (sd)**	**T mean (sd)**	**β (SE)**	**Effect Size**
STEM credits earned	6.01 (0.78)	6.63 (4.48)	0.42*** (0.12)	.09	6.02 (0.94)	7.23 (3.39)	1.35*** (0.10)	.40	5.96 (1.14)	6.57 (4.23)	0.68*** (0.13)	.16
STEM GPA	2.56 (0.26)	2.54 (1.31)	0.05 (0.04)	.04	2.47 (0.3)	3.00 (1.03)	1.19*** (0.10)	1.16	2.25 (0.38)	2.56 (1.19)	0.34*** (0.05)	.28
Continuation in STEM	.80 (0.08)	.85 (0.36)	0.33 (0.54)	.20	.62 (0.11)	.74 (0.44)	0.55*** (0.04)	.33	.73 (0.12)	.84 (0.36)	0.78* (0.32)	.47
N	*2019*	*79*			*2038*	*110*			*2063*	*141*		

	Spring 2019				Fall 2019			
	C mean (sd)	**T mean (sd)**	**β (SE)**	**Effect Size**	**C mean (sd)**	**T mean (sd)**	**β (SE)**	**Effect Size**
STEM credits earned	5.39 (1.07)	6.26 (3.99)	0.48*** (0.12)	.12	5.00 (0.93)	6.03 (4.36)	1.42*** (0.14)	.32
STEM GPA	2.33 (0.38)	2.49 (1.28)	0.17*** (0.05)	.13	2.41 (0.34)	2.30 (1.39)	0.10 (0.05)	.05
Continuation in STEM	.69 (0.12)	.74 (0.44)	0.30 (0.30)	.19	NA NA	NA NA	NA NA	NA
N	*2102*	*144*			*2396*	*103*		

*p < .05; **p < .01; ***p < .001

Note. Effect size for dichotomous outcomes is Cox's index.

Combined Estimate of SLC Participation

The meta-analysis results show the average impact of SLC participation across five terms for STEM credits earned and STEM GPA and across four terms for continuation in STEM (Exhibit 7). The overall effect is an average of the distribution of the effects of SLC participation in the population. Students who participated in the SLC earned, on average, 0.22 more STEM credits in a term than their similar peers who did not participate in the SLC. Further, SLC participants were more likely to continue enrolling in STEM classes than their peers who did not participate in the SLC. After combining the estimates across the terms, however, the effect of SLC participation on STEM GPA was not statistically significant. Further, the results of the sensitivity analysis are not statistically significant when combined across the terms using meta-analysis, though continuation in STEM is positive and marginally significant (p=.07) (see Exhibit B-3).

Exhibit 7. Meta-Analysis Impact Estimate Across Terms

Outcome	Effect Size	SE	p
STEM credits earned	0.22	0.06	0.02
STEM GPA	0.33	0.21	0.19
Continuation in STEM*	0.30	0.06	0.02

**Excludes fall 2019 term due to change in withdrawal policy with pandemic-related shift to remote learning in spring 2020.*

Limitations

The goal of this analysis is to estimate the impact of SLC participation on student outcomes. Because we are unable to observe outcomes for the same students with and without the SLC support and SLC participation was not randomized, we have attempted to approximate this impact by employing a statistically equivalent comparison group. By weighting the comparison group to be similar to the group of SLC participants in each term, we have reduced any differences in the outcomes that are due to differences in the composition of the treatment and comparison groups themselves rather than SLC participation. For example, by ensuring the two groups have similar prior STEM GPAs, we minimize the extent to which any observed differences in the STEM GPA earned in the focal terms result from prior achievement rather than SLC support. As with any observational study employing propensity score methodologies, a key limitation is effectively accounting for all factors associated with selection into the SLC intervention. There may still be unobservable characteristics that drive differences between the treatment and comparison groups. We are only able to ensure equivalence on observed characteristics, including student demographics and STEM preparation, but cannot account for other potentially important and unobserved characteristics. Some examples include access to resources outside of LACC, peer networks, or a standardized measure of prior achievement. If SLC participants and nonparticipants vary based on these unobserved characteristics, the impact estimates may be biased, i.e., they may overestimate or underestimate program impact.

Discussion

These findings suggest that visiting the SLC has positive effects on students' progression in STEM, both in terms of increase in STEM credits earned and their likelihood of continuing in STEM. The results from the sensitivity analysis, which excludes students who accessed SI in the same term, are consistently positive though lesser in magnitude than these main effects and not consistently statistically significant at conventional levels; these analyses have a very small treatment group size (n=55−109) and thus may not be adequately powered. In addition, if part of the effect of visiting the SLC is an increased likelihood to seek out other programs in the suite of STEM student supports provided by LACC, then including students who accessed more than one program component better captures the effect of the SLC. Additional reports examine the impacts of SI participation and of participation in any STEMP program component.

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Appendix A: Impact Analysis Methodology

Data Elements

The administrative and SLC program participation data enabled us to create the outcome measures and the demographic, enrollment, and coursetaking metrics used in the analysis.

Outcome Measures

The goal of the SLC was to provide students with academic support to help them succeed in STEM courses, allowing them to proceed to higher-level STEM coursework in pursuit of a degree or certificate, if they chose. To capture the impact of SLC participation on course success and continuation in STEM, we examined three outcomes: STEM credits earned during the focal term, STEM GPA during the focal term, and a student's continued enrollment in STEM courses in the subsequent two terms (Exhibit A-1). We examined course success outcomes in the focal term when a student sought help because we expected the SLC to have the largest impacts on concurrent coursework. Because of the increase in course withdrawals in spring 2020 due to the COVID-19 pandemic, we do not examine continuation in STEM for the fall 2019 term.

Exhibit A-1. Outcomes in the Focal Term

Variable	Description
STEM credits earned	Total number of STEM credits earned during the focal term.
STEM GPA	Student's STEM GPA in the focal term only. STEM GPA was calculated as the total grade points earned in STEM courses (A = 4, B = 3, C = 2, D = 1, F = 0) divided by the total number of credits attempted in STEM courses, excluding withdrawals and courses taken pass/fail.
Continuation in STEM	STEM course enrollment in one or more of the two subsequent terms following the focal term (binary indicator).

Demographic, Enrollment, and Coursetaking Measures

Exhibit A-2 defines all demographic, enrollment, and coursetaking measures used in the impact analysis. We included measures that would reasonably be associated with both a student's likelihood of taking up the SLC programming and their STEM course success and progress toward degree attainment. These include demographic indictors of race/ethnicity, gender, socioeconomic status, and residency as well as academic performance prior to the focal term.

Some students were associated with multiple race/ethnicity values across data requests—in all of these instances, students were identified by the college as "unknown" in addition to another race/ethnicity. A response of "unknown" means that a student did not self-identify their race/ethnicity, or that they self-identified as “other” race/ethnicity. In these cases, we assigned students the non-unknown values for race/ethnicity. When calculating course grades, some students had multiple enrollments in the same course section that were associated with multiple grades. In these instances, the highest grade was kept (A > B > C > D > F and P > NP). Duplicates where one grade was a “W” (withdrawal) or missing had that record dropped.

Exhibit A-2. Enrollment, Demographic, and Coursetaking Data Elements

Variable	Description
Student demographics	
Black[a]	Student self-identifies as “Black or African American” (binary indicator).
Latinx[a]	Student self-identifies as “Hispanic/Latino” (binary indicator).
Asian[a]	Student self-identifies as “Asian” (binary indicator).
Female	Student self-identifies as “Female” (binary indicator).
Age	Student’s age as of beginning of focal semester, calculated from birth date.
Pell	Student received a Pell grant (binary indicator). Note—undocumented students are not eligible for federal financial aid.
Promise grant	Student is eligible for California Promise Grant to waive enrollment fees (binary indicator).
Non-resident	Student is not a California resident (i.e., out-of-state or out-of-country) (binary indicator).
AB540	Student has a special residency status of “AB540” (binary indicator), indicating that they are eligible to pay in-state tuition despite being classified as a non-resident.[b] To be eligible, a student must have attended a California educational institution for 3+ years, attained a diploma, degree, or fulfilled minimum transfer requirements from a California educational institution, and have a signed exemption request.
Prior enrollment and coursetaking	
First term	Focal term is the student’s first term enrolled at LACCD (binary indicator).
N terms enrolled	Total number of terms (winter, spring, summer, fall) in which student was enrolled in at least one course across all LACCD campuses prior to the focal semester, including enrollments during high school (dual credit).
Credits earned	Total number of credits student earned across all LACCD campuses prior to the focal term. Credits are considered earned if the student earned a grade “C” or better, or earned a grade of “P”, “CR”, or “CRX” in the course.
Any dual enrollment credits	Student earned LACCD credits while in high school (prior to focal term) through dual enrollment (binary indicator).
Prior GPA	Student’s GPA across all courses prior to the focal semester. GPA was calculated as the total grade points earned (A = 4, B = 3, C = 2, D = 1, F = 0) divided by the total number of credits attempted.
Focal term coursetaking	
Credits attempted (att.)	Total credits attempted during focal term.
STEM credits att.	STEM credits attempted during focal term.
Prior STEM coursetaking	
Highest math	Tier of highest-level math course taken at any LACCD campus prior to the focal term (e.g., Tier 1 includes intermediate algebra and pre-statistics; Tier 2 includes statistics and college algebra; Tier 3 includes pre-calculus; Tier 4 includes Calculus I; Tier 5 includes Calculus II; and Tier 6 includes Calculus III and ordinary differential equations). Equal to 0 if student had no prior math course. Missing for students whose highest prior math course could not be classified into a tier.
No prior math	Student was not enrolled in a math course at any LACCD campus prior to the focal term (binary indicator).

Variable	Description
Prior transfer-level (TL) STEM credits	Total number of transfer-level STEM credits the student earned prior to the focal term. STEM courses were identified based on eligible Taxonomy of Programs (TOP) codes.[c] STEM courses were considered transfer-level if they have a transfer code of A – transferable to UC/CSU or B – transferable to CSU only.
Prior non-transfer level (NTL) STEM credits	Total number of below-transfer-level STEM credits the student earned prior to the focal semester. STEM courses were identified based on eligible TOP codes. STEM courses were considered below transfer-level if they have a transfer code of "C – non-transferable."
Prior TL STEM GPA	Student's GPA across transfer-level STEM courses taken prior to the focal term. GPA was calculated as the total grade points earned (A = 4, B = 3, C = 2, D = 1, F = 0) divided by the total number of credits attempted. STEM courses were identified based on eligible TOP codes. STEM courses were considered transfer-level if they have a transfer code of A – transferable to UC/CSU or B – transferable to CSU only. Equal to 0 if student had no prior transfer-level STEM credits attempted.
Prior NTL STEM GPA	Student's GPA across below-transfer-level STEM courses taken prior to the focal term. GPA was calculated as the total grade points earned (A = 4, B = 3, C = 2, D = 1, F = 0) divided by the total number of credits attempted. STEM courses were identified based on eligible TOP codes. STEM courses were considered below transfer-level if they have a transfer code of C – non-transferable. Equal to 0 if student had no prior below-transfer-level STEM credits attempted.
No prior NTL STEM credits	Student had no below-transfer-level STEM credits attempted prior to the focal semester (binary indicator).
No prior TL STEM credits	Student had no transfer-level STEM credits attempted prior to the focal semester (binary indicator).
Prior program participation	
Prior SI or SLC	Student attended an SLC or SI session in the previous two terms (binary indicator).
Prior STEMP Program (STEMPP) support	Student ever accessed another program component (counseling, undergraduate research program, book loan program, math boot camp, mentor group) prior to focal term (beginning fall 2017) (binary indicator).

[a] Other race/ethnicity variables included American Indian/Alaskan Native, Pacific Islander, two or more races, and White.

[b] Students may be classified as non-residents for a variety of reasons, including being undocumented.

[c] The Taxonomy of Programs (TOP) is a California state-level system to organize and equate course and program information across multiple institutions that may use a variety of names for similar courses or programs.

Analytic Approach

This study used propensity score weighting to test the effect of SLC participation on student outcomes. Propensity score techniques are quasi-experimental approaches developed to approximate findings obtained from randomized controlled trials (Becker & Ichino, 2002). They have been increasingly used in observational studies with cohort designs to reduce selection bias in estimating treatment or intervention effects when randomized controlled trials are not feasible or ethical (Rosenbaum & Rubin, 1983, 1984, 1985).

Propensity Score Methodology

The propensity score is the predicted probability of participating in a treatment (for example, SLC participation) based on a set of potentially confounding covariates (i.e., student demographic characteristics, prior term coursetaking, and academic achievement). In this analysis, we estimated propensity scores using a logistic regression model with the predictors defined in Exhibit A-2.

Propensity score techniques attempt to equalize the mean values of potentially confounding observed covariates in the treatment and comparison groups, assuring that differences in outcomes between the treatment and comparison groups are not the result of differences in mean values of those covariates. These approaches aim to generate rigorous and unbiased estimates of the effects of a treatment on the outcome of interest; however, propensity score techniques cannot account for unobserved confounders such as student motivation in seeking tutoring support.

Weighting

This study estimated the average treatment effect on the treated (ATT) of SLC participation for each term. These ATT analyses adjusted for confounding factors using inverse propensity score estimators (Rosenbaum & Rubin, 1983). Specifically, the weight for treated students was 1.0, and the weight for comparison students was equal to $p_i/(1-p_i)$, where p_i is the propensity score for the i-th comparison student (Harder et al., 2010; Hirano et al., 2003). Comparison students with a high estimated propensity score will be assigned a large weight, which may contribute to unstable estimates (Austin & Stuart, 2015). This instability may particularly be an issue when there are few students with high propensities in the sample. To address this issue, we trimmed the sample to exclude students with propensity scores in the 99th percentile (p = 0.62-0.83). After applying the weights to the comparison sample, we examined the standardized mean difference (SMD) score (the difference in means for the treatment and comparison groups divided by a treatment standard deviation; Stuart et al., 2013) to ensure that they were less than 0.25, thereby assuring covariate balance (What Works Clearinghouse, 2017).

Impact Analysis Modeling

After establishing that the weights achieved baseline equivalence on observables, the study team used weighted multiple regression to estimate the impact of SLC participation on the two continuous outcomes (STEM credits earned and STEM GPA) and used weighted logistic regression models for the binary outcome (continuation in STEM). The regression coefficients from each weighted regression model can be interpreted as the measure of association between SLC participation and the STEM outcome, adjusted for the estimated propensity of SLC participation.

All the models also controlled for student demographic characteristics and prior enrollment, coursetaking, program participation, and academic achievement. We estimated a separate weighted regression model for each outcome and each term.

The weighted regression model is as follows.

$$\eta_i = \beta_0 + \beta_1(SLC_i) + X_i B + e_i$$

In the multiple regression model η_i denotes the i-th student's STEM credits earned or STEM GPA. For the logistic regression model with the dichotomous outcome of continuation in STEM, η_i is the logit link function $\eta_i = ln\left(\frac{\pi_i}{1-\pi_i}\right)$, with π_i denoting the probability that the i-th student enrolled in a STEM course in the next two terms. SLC_i is the treatment indicator variable, where 1 indicates participation in SLC and 0 indicates no SLC participation. X_i is the vector of student-level prior achievement and demographic characteristics defined in Exhibit A-2. The regression coefficient β_1 indicates the difference between SLC and non-SLC students in the outcome. B represents the vector of regression coefficients for demographic and prior academic achievement variables included as controls. The study team calculated effect size as the estimated difference in the outcome between treatment and comparison groups, divided by the standard deviation in the treated group (Stuart et al., 2013).

Meta-Analytic Approach

After estimating separate models for each term and outcome, we combined estimates using meta-analysis to provide a single estimate of the treatment effect for each outcome. We performed a random-effects meta-analysis that calculates the average effect of SLC participation on STEM learning outcomes across terms (all five terms for STEM GPA and credits earned; only four terms for continuation in STEM). A random-effects model is more appropriate than a fixed-effects model because of the observed variation in the effect sizes across different terms (Hox et al., 2018). We conducted the multilevel meta-analysis of the by-term estimates using the empty "intercept-only" model using SAS PROC MIXED restricted maximum likelihood estimation.

Handling Missing Data

Less than 5% of students have missing data; therefore, the study team did not impute any missing data. Only complete case analyses were used for the impact analysis.

Descriptive Statistics for Analytic Sample

Exhibit A-3 provides the unweighted descriptive statistics for the enrollment, demographic, and coursetaking data elements used in the impact analyses for students in each term who participated in the SLC and their peers who did not; Exhibit A-4 presents the unweighted outcomes before propensity score weighting. These descriptive statistics are for the trimmed sample, excluding students with propensity scores in the 99th percentile. In Exhibits A-3 and A-4, "C" columns show values for the comparison group—STEM students who did not use the

SLC in the focal term. “T” columns show values for the treatment group—STEM students who used the SLC at least once during the focal term. In addition to mean values, tables also show the standard deviation (“sd”) and standardized mean difference (“SMD”) between the treatment and comparison groups .

SLC participants across all five terms were less likely to be female than non-users and were less likely to be Latinx in all terms except fall 2018; SLC participants had also been enrolled for more terms, on average, than non-users and had more credits and higher overall and STEM GPAs coming into the focal term (Exhibit A-3). Consistent with this higher average prior achievement, SLC participants had, on average, more positive STEM outcomes in the focal term than non-users, earning more STEM credits and higher STEM GPAs, and exhibiting a greater likelihood of continuing in STEM (Exhibit A-4).

Exhibit A-3. Descriptive Statistics Before Propensity Score Weighting

	Fall 2017			Spring 2018			Fall 2018			Spring 2019			Fall 2019		
	C mean (sd)	T mean (sd)	SMD	C mean (sd)	T mean (sd)	SMD	C mean (sd)	T mean (sd)	SMD	C mean (sd)	T mean (sd)	SMD	C mean (sd)	T mean (sd)	SMD
Demographics															
Black	.05 (0.22)	.05 (0.22)	.00	.05 (0.23)	.06 (0.25)	-.04	.05 (0.22)	.07 (0.26)	-.07	.05 (0.21)	.08 (0.27)	-.11	.05 (0.22)	.04 (0.19)	.07
Latinx	.50 (0.50)	.38 (0.49)	.24	.50 (0.5)	.45 (0.50)	.10	.52 (0.50)	.56 (0.50)	-.09	.52 (0.50)	.51 (0.50)	.03	.54 (0.50)	.50 (0.50)	.08
Asian	.21 (0.41)	.24 (0.43)	-.08	.21 (0.41)	.17 (0.38)	.10	.20 (0.40)	.15 (0.36)	.15	.18 (0.39)	.17 (0.38)	.02	.18 (0.39)	.20 (0.40)	-.06
Female	.40 (0.49)	.35 (0.48)	.10	.42 (0.49)	.41 (0.49)	.02	.44 (0.50)	.35 (0.48)	.19	.44 (0.50)	.36 (0.48)	.17	.46 (0.50)	.42 (0.50)	.08
Age	25.74 (8.32)	26.81 (6.84)	-.16	26.16 (8.92)	27.93 (8.95)	-.20	25.81 (8.53)	25.50 (7.57)	.04	26.12 (8.65)	25.67 (7.06)	.06	25.90 (8.32)	26.19 (8.81)	-.03
Pell	.43 (0.49)	.43 (0.50)	-.01	.47 (0.50)	.53 (0.50)	-.12	.46 (0.50)	.53 (0.50)	-.15	.48 (0.50)	.55 (0.50)	-.13	.48 (0.50)	.55 (0.50)	-.14
Promise grant	.75 (0.43)	.82 (0.38)	-.19	.77 (0.42)	.82 (0.39)	-.12	.76 (0.42)	.79 (0.41)	-.05	.75 (0.43)	.78 (0.42)	-.06	.77 (0.42)	.75 (0.44)	.05
Non-resident	.13 (0.34)	.13 (0.33)	.02	.11 (0.32)	.15 (0.35)	-.09	.11 (0.31)	.16 (0.37)	-.14	.11 (0.31)	.15 (0.36)	-.11	.11 (0.31)	.17 (0.38)	-.17
AB540	.08 (0.27)	.06 (0.25)	.06	.07 (0.25)	.11 (0.31)	-.14	.07 (0.25)	.09 (0.29)	-.09	.07 (0.25)	.10 (0.30)	-.10	.07 (0.25)	.08 (0.27)	-.04
Prior coursetaking															
First term	.16 (0.36)	.03 (0.16)	.84	.08 (0.27)	.05 (0.21)	.15	.14 (0.35)	.14 (0.35)	.00	.08 (0.28)	.03 (0.16)	.34	.12 (0.32)	.05 (0.22)	.32
N terms enrolled	6.69 (5.86)	9.81 (5.31)	-.59	7.44 (6.32)	9.44 (5.76)	-.35	6.94 (6.46)	7.60 (5.77)	-.12	7.21 (6.2)	8.12 (5.45)	-.17	6.90 (6.38)	8.10 (5.30)	-.23
Credits earned	38.67 (33.64)	64.05 (29.11)	-.87	43.54 (35.89)	61.49 (36.26)	-.50	39.49 (36.85)	50.07 (36.99)	-.29	41.09 (34.51)	54.71 (35.57)	-.38	37.75 (35.15)	52.83 (33.19)	-.45
Any dual enrollment credits	.23 (0.42)	.27 (0.44)	-.09	.23 (0.42)	.25 (0.44)	-.05	.25 (0.43)	.24 (0.43)	.01	.25 (0.43)	.22 (0.41)	.08	.25 (0.43)	.20 (0.40)	.12
Prior GPA	2.45 (1.21)	2.96 (0.81)	-.63	2.65 (1.06)	2.91 (0.86)	-.31	2.49 (1.19)	2.75 (1.11)	-.24	2.60 (1.08)	2.92 (0.89)	-.36	2.54 (1.2)	3.01 (0.83)	-.57
Focal term coursetaking															
Credits att.	10.56 (4.02)	11.61 (3.62)	-.29	10.64 (4.08)	10.90 (3.46)	-.07	10.42 (4.00)	12.40 (3.88)	-.51	10.25 (4.13)	11.39 (3.46)	-.33	14.41 (10.06)	16.76 (7.53)	-.31
STEM credits att.	6.11 (2.98)	8.96 (3.67)	-.78	6.26 (3.00)	8.35 (3.02)	-.69	5.96 (2.86)	9.12 (3.5)	-.90	5.97 (2.91)	8.78 (3.46)	-.81	7.45 (5.43)	11.87 (5.54)	-.80

	Fall 2017			Spring 2018			Fall 2018			Spring 2019			Fall 2019		
	C mean (sd)	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**
Prior STEM coursetaking															
Highest math	1.64 (1.84)	3.54 (1.90)	-1.00	1.81 (1.90)	3.14 (1.90)	-.70	1.59 (1.86)	2.97 (2.16)	-.64	1.71 (1.87)	3.58 (1.88)	-1.00	1.59 (1.81)	3.34 (1.92)	-.91
No prior math	.26 (0.44)	.05 (0.22)	.93	.17 (0.38)	.11 (0.31)	.20	.27 (0.44)	.21 (0.41)	.16	.21 (0.41)	.08 (0.27)	.50	.31 (0.46)	.14 (0.34)	.51
Prior TL STEM credits	9.70 (12.57)	25.04 (16.37)	-.94	11.36 (14.25)	23.85 (20.83)	-.60	9.53 (13.26)	21.01 (19.57)	-.59	10.37 (13.96)	23.07 (19.19)	-.66	9.37 (13.54)	23.20 (19.07)	-.73
Prior NTL STEM credits	3.65 (4.33)	5.91 (5.12)	-.44	3.82 (4.42)	6.43 (5.05)	-.52	3.48 (4.37)	4.55 (4.92)	-.22	3.68 (4.37)	4.79 (4.94)	-.22	3.08 (4.25)	4.98 (5.02)	-.38
Prior TL STEM GPA	1.81 (1.50)	2.69 (1.08)	-.82	1.91 (1.48)	2.60 (1.14)	-.60	1.66 (1.49)	2.35 (1.34)	-.52	1.82 (1.49)	2.65 (1.09)	-.76	1.65 (1.51)	2.73 (1.12)	-.96
Prior NTL STEM GPA	1.37 (1.55)	1.91 (1.58)	-.34	1.41 (1.54)	2.09 (1.53)	-.45	1.26 (1.51)	1.62 (1.62)	-.22	1.35 (1.53)	1.72 (1.65)	-.23	1.12 (1.49)	1.79 (1.66)	-.40
No prior NTL STEM credits	.48 (0.50)	.34 (0.48)	.30	.46 (0.50)	.29 (0.46)	.38	.51 (0.50)	.45 (0.50)	.10	.47 (0.50)	.44 (0.50)	.07	.56 (0.5)	.43 (0.50)	.27
No prior TL STEM credits	.31 (0.46)	.05 (0.22)	1.18	.28 (0.45)	.08 (0.28)	.72	.35 (0.48)	.19 (0.39)	.39	.29 (0.45)	.08 (0.27)	.81	.34 (0.48)	.08 (0.27)	.99
Prior program participation															
Prior SI or SLC	.01 (0.11)	.43 (0.50)	-.84	.04 (0.20)	.45 (0.50)	-.83	.03 (0.18)	.40 (0.49)	-.74	.04 (0.20)	.58 (0.50)	-1.08	.04 (0.19)	.69 (0.47)	-1.40
Prior STEMPP support	.02 (0.14)	.06 (0.25)	-.18	.02 (0.15)	.16 (0.37)	-.38	.03 (0.17)	.29 (0.46)	-.58	.03 (0.17)	.42 (0.50)	-.80	.03 (0.18)	.54 (0.50)	-1.02
N	*2019*	*79*		*2038*	*110*		*2063*	*141*		*2102*	*144*		*2397*	*103*	

Exhibit A-4. Outcomes Before Propensity Score Weighting

	Fall 2017			Spring 2018			Fall 2018			Spring 2019			Fall 2019		
	C mean (sd)	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**	**C mean (sd)**	**T mean (sd)**	**SMD**
Outcomes															
STEM credits earned	3.93 (3.38)	6.63 (4.48)	-.60	4.15 (3.46)	7.23 (3.39)	-.91	3.65 (3.35)	6.57 (4.23)	-.69	3.73 (3.37)	6.26 (3.99)	-.63	3.03 (3.36)	6.03 (4.36)	-.69
STEM GPA	2.21 (1.50)	2.54 (1.31)	-.26	2.24 (1.51)	3.00 (1.03)	-.74	2.08 (1.56)	2.56 (1.19)	-.41	2.16 (1.57)	2.49 (1.28)	-.25	1.70 (1.60)	2.30 (1.39)	-.43
Continuation in STEM	.66 (0.47)	.85 (0.36)	-.52	.60 (0.49)	.74 (0.44)	-.30	.63 (0.48)	.84 (0.36)	-.60	.61 (0.49)	.74 (0.44)	-.30	NA NA	NA NA	NA
N	*2019*	*79*		*2038*	*110*		*2063*	*141*		*2102*	*144*		*2397*	*103*	

Baseline Equivalence After Propensity Score Weighting

To ensure that the propensity score method successfully created balanced treatment and comparison groups in each term, we compared SMD after propensity score weighting for each observable characteristic. Balance on observable characteristics was greatly improved after applying the propensity score weights. Data presented in Exhibit A-5 show the baseline equivalence after weighting. To calculate SMD between treatment and comparison groups, the study team divided differences in each covariate by the treatment group standard deviations (Stuart et al., 2013). Prior to weighting, standardized differences ranged from -1.40 to 1.18 standard deviations (Exhibit A-3). After propensity score weighting, standardized differences ranged from -0.16 to 0.20 standard deviations (Exhibit A-5). These differences are lower than the What Works Clearinghouse 0.25 cutoff for baseline equivalence for quasi-experimental studies (What Works Clearinghouse, 2017). Therefore, participants and nonparticipants were very similar on all observed and potentially confounding covariates after propensity score weighting.

Exhibit A-5. Descriptive Statistics After Propensity Score Weighting

	Fall 2017					Spring 2018					Fall 2018					Spring 2019					Fall 2019				
	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD
Demographics																									
Black	.05	(0.04)	.05	(0.22)	.01	.07	(0.06)	.06	(0.25)	.03	.05	(0.06)	.07	(0.26)	-.09	.11	(0.08)	.08	(0.27)	.12	.03	(0.03)	.04	(0.19)	-.06
Latinx	.31	(0.09)	.38	(0.49)	-.15	.43	(0.11)	.45	(0.5)	-.02	.59	(0.13)	.56	(0.50)	.05	.46	(0.13)	.51	(0.50)	-.09	.42	(0.11)	.50	(0.50)	-.15
Asian	.27	(0.09)	.24	(0.43)	.06	.20	(0.09)	.17	(0.38)	.06	.14	(0.09)	.15	(0.36)	-.02	.18	(0.10)	.17	(0.38)	.03	.24	(0.09)	.20	(0.40)	.10
Female	.38	(0.09)	.35	(0.48)	.06	.42	(0.11)	.41	(0.49)	.02	.36	(0.13)	.35	(0.48)	.02	.43	(0.13)	.36	(0.48)	.15	.45	(0.11)	.42	(0.50)	.06
Age	27.84	(1.72)	26.81	(6.84)	.15	28.11	(2.32)	27.93	(8.95)	.02	25.60	(2.18)	25.50	(7.57)	.01	25.90	(1.93)	25.67	(7.06)	.03	27.24	(1.65)	26.19	(8.81)	.12
Pell	.45	(0.10)	.43	(0.50)	.05	.53	(0.11)	.53	(0.50)	.01	.51	(0.13)	.53	(0.50)	-.05	.58	(0.13)	.55	(0.50)	.06	.54	(0.11)	.55	(0.50)	-.03
Promise grant	.85	(0.07)	.82	(0.38)	.07	.81	(0.09)	.82	(0.39)	-.01	.77	(0.11)	.79	(0.41)	-.04	.76	(0.11)	.78	(0.42)	-.05	.80	(0.09)	.75	(0.44)	.12
Non-resident	.11	(0.06)	.13	(0.33)	-.06	.16	(0.08)	.15	(0.35)	.05	.17	(0.10)	.16	(0.37)	.02	.13	(0.09)	.15	(0.36)	-.05	.12	(0.07)	.17	(0.38)	-.14
AB540	.05	(0.04)	.06	(0.25)	-.07	.11	(0.07)	.11	(0.31)	.01	.08	(0.07)	.09	(0.29)	-.03	.07	(0.06)	.10	(0.30)	-.10	.07	(0.06)	.08	(0.27)	-.02
Prior coursetaking																									
First term	.03	(0.03)	.03	(0.16)	.01	.06	(0.05)	.05	(0.21)	.06	.13	(0.09)	.14	(0.35)	-.04	.03	(0.04)	.03	(0.16)	.03	.04	(0.04)	.05	(0.22)	-.03
N terms enrolled	9.32	(0.99)	9.81	(5.31)	-.09	9.11	(1.31)	9.44	(5.76)	-.06	7.67	(1.48)	7.60	(5.77)	.01	8.42	(1.48)	8.12	(5.45)	.05	8.34	(1.10)	8.10	(5.30)	.05
Credits earned	61.80	(6.52)	64.05	(29.11)	-.08	58.61	(7.68)	61.49	(36.26)	-.08	50.59	(9.41)	50.07	(36.99)	.01	54.92	(9.61)	54.71	(35.57)	.01	54.95	(8.00)	52.83	(33.19)	.06
Any dual enrollment credits	.23	(0.08)	.27	(0.44)	-.09	.24	(0.1)	.25	(0.44)	-.03	.25	(0.11)	.24	(0.43)	.03	.15	(0.09)	.22	(0.41)	-.15	.21	(0.09)	.20	(0.40)	.02
Prior GPA	2.97	(0.15)	2.96	(0.81)	.02	2.90	(0.2)	2.91	(0.86)	-.01	2.79	(0.28)	2.75	(1.11)	.03	2.94	(0.22)	2.92	(0.89)	.02	3.17	(0.19)	3.01	(0.83)	.20
Focal term coursetaking																									
Credits att.	11.28	(0.73)	11.61	(3.62)	-.09	11.03	(0.96)	10.90	(3.46)	.04	12.48	(1.03)	12.40	(3.88)	.02	11.12	(1.10)	11.39	(3.46)	-.08	17.77	(2.45)	16.76	(7.53)	.13
STEM credits att.	8.38	(0.69)	8.96	(3.67)	-.16	8.27	(0.86)	8.35	(3.02)	-.03	9.09	(0.86)	9.12	(3.5)	-.01	8.24	(0.96)	8.78	(3.46)	-.15	12.59	(1.75)	11.87	(5.54)	.13

	Fall 2017					Spring 2018					Fall 2018					Spring 2019					Fall 2019				
	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD
Prior STEM coursetaking																									
Highest math	3.80	(0.39)	3.54	(1.90)	.13	3.17	(0.47)	3.14	(1.90)	.02	3.15	(0.60)	2.97	(2.16)	.08	3.46	(0.53)	3.58	(1.88)	-.07	3.44	(0.42)	3.34	(1.92)	.05
No prior math	.05	(0.04)	.05	(0.22)	.01	.12	(0.07)	.11	(0.31)	.02	.19	(0.10)	.21	(0.41)	-.03	.09	(0.07)	.08	(0.27)	.05	.12	(0.07)	.14	(0.34)	-.05
Prior TL STEM credits	27.52	(4.02)	25.04	(16.37)	.15	23.06	(4.39)	23.85	(20.83)	-.04	22.05	(5.38)	21.01	(19.57)	.05	21.33	(4.68)	23.07	(19.19)	-.09	25.83	(4.91)	23.20	(19.07)	.14
Prior NTL STEM credits	5.11	(0.89)	5.91	(5.12)	-.15	6.15	(1.12)	6.43	(5.05)	-.05	4.48	(1.24)	4.55	(4.92)	-.01	5.24	(1.30)	4.79	(4.94)	.09	4.62	(1.05)	4.98	(5.02)	-.07
Prior TL STEM GPA	2.71	(0.20)	2.69	(1.08)	.02	2.58	(0.27)	2.60	(1.14)	-.01	2.43	(0.35)	2.35	(1.34)	.06	2.66	(0.29)	2.65	(1.09)	.01	2.94	(0.24)	2.73	(1.12)	.19
Prior NTL STEM GPA	1.81	(0.31)	1.91	(1.58)	-.06	2.11	(0.37)	2.09	(1.53)	.01	1.64	(0.44)	1.62	(1.62)	.01	1.77	(0.42)	1.72	(1.65)	.03	1.94	(0.37)	1.79	(1.66)	.09
No prior NTL STEM credits	.38	(0.09)	.34	(0.48)	.07	.31	(0.11)	.29	(0.46)	.03	.45	(0.13)	.45	(0.50)	-.01	.42	(0.13)	.44	(0.50)	-.04	.41	(0.11)	.43	(0.50)	-.04
No prior TL STEM credits	.05	(0.04)	.05	(0.22)	.01	.08	(0.06)	.08	(0.28)	.00	.17	(0.10)	.19	(0.39)	-.05	.07	(0.07)	.08	(0.27)	-.01	.07	(0.05)	.08	(0.27)	-.03
Prior program participation																									
Prior SI or SLC	.41	(0.10)	.43	(0.50)	-.03	.44	(0.11)	.45	(0.50)	-.04	.39	(0.13)	.40	(0.49)	-.02	.54	(0.13)	.58	(0.50)	-.07	.72	(0.10)	.69	(0.47)	.07
Prior STEMPP support	.08	(0.05)	.06	(0.25)	.07	.15	(0.08)	.16	(0.37)	-.03	.26	(0.12)	.29	(0.46)	-.06	.40	(0.12)	.42	(0.50)	-.05	.60	(0.11)	.54	(0.50)	.11
N	*2019*		*79*			*2038*		*110*			*2063*		*141*			*2102*		*144*			*2396*		*103*		

Appendix B: Sensitivity Analysis

In addition to the SLC, LACC offered SI during the terms examined for the impact analysis. Student who enrolled in a course with an SI section could seek support from an SI lead, peer tutors at the SLC, or both. Within our analytic sample of SLC students, 24%–41% of SLC participants also accessed SI in the same term. In an effort to disentangle the effects of SLC participation from SI participation, we conducted a sensitivity analysis to test whether the impact of SLC participation changed when we excluded concurrent SI users from the sample (both from the treatment and comparison groups). In this sensitivity analysis, we exclude students with concurrent SI usage and apply the same propensity score weights used in the main analysis for the remaining students. The resulting weighted treatment and comparison sample was similar for the observed demographic, enrollment, and coursetaking variables (Exhibit B-1), with standardized differences lower than the What Works Clearinghouse 0.25 cutoff for baseline equivalence for quasi-experimental studies (What Works Clearinghouse, 2017).

Results from the weighted regression models remain positive when significant for STEM credits earned, STEM GPA, and continuation in STEM. Since excluding concurrent SI users results in a smaller sample of SI participants, the standard errors for several terms and outcomes are larger than the main analysis and associated coefficients are no longer significant. However, results are broadly consistent with the patterns in the main analysis. Estimated effect sizes for significant results range from 0.09–0.35 for STEM credits earned, 0.12–0.57 for STEM GPA, and 0.67 for the single significant term for continuation in STEM (Exhibit B-2).

The meta-analysis results for the sensitivity analysis excluding concurrent SI participants are not significant at conventional levels (Exhibit B-3). The estimated magnitudes of the cross-term effects are smaller than the main estimates for both STEM credits earned (0.09 in the sensitivity analysis versus 0.22 in the main estimates) and STEM GPA (0.18 versus 0.33). The effect of SLC participation on continuation in STEM remains similar in magnitude, though only marginally significant. It may be the case that part of the positive effect of SLC participation was attributable to concurrent SI usage, though the term-specific estimates (Exhibit B-2) are still consistent with positive effects for those participating in SLC alone.

Exhibit B-1. Descriptives After Propensity Score Weighting, Excluding Students Who Took SI in the Focal Term

	Fall 2017					Spring 2018					Fall 2018					Spring 2019					Fall 2019				
	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD
Demographics																									
Black	.06	(0.04)	.05	(0.23)	.01	.08	(0.06)	.05	(0.23)	.09	.05	(0.06)	.07	(0.26)	-.09	.11	(0.08)	.08	(0.28)	.12	.02	(0.03)	.07	(0.25)	-.18
Latinx	.32	(0.09)	.36	(0.49)	-.09	.43	(0.11)	.47	(0.50)	-.08	.59	(0.13)	.56	(0.50)	.05	.46	(0.12)	.50	(0.50)	-.07	.40	(0.10)	.51	(0.50)	-.21
Asian	.26	(0.08)	.27	(0.45)	-.03	.20	(0.09)	.19	(0.40)	.02	.14	(0.09)	.15	(0.36)	-.02	.18	(0.10)	.17	(0.38)	.01	.25	(0.09)	.15	(0.36)	.30
Male	.64	(0.09)	.69	(0.47)	-.11	.57	(0.11)	.59	(0.50)	-.04	.64	(0.13)	.65	(0.48)	-.03	.55	(0.12)	.66	(0.48)	-.23	.54	(0.10)	.54	(0.50)	.00
Age	27.81	(1.71)	26.78	(6.88)	.15	28.07	(2.29)	28.70	(9.99)	-.06	25.60	(2.18)	25.50	(7.57)	.01	25.90	(1.91)	25.96	(7.47)	-.01	27.47	(1.66)	27.15	(10.33)	.03
Pell	.41	(0.09)	.36	(0.49)	.10	.54	(0.11)	.53	(0.50)	.02	.51	(0.13)	.53	(0.50)	-.05	.59	(0.12)	.52	(0.50)	.13	.51	(0.10)	.62	(0.49)	-.23
Promise grant	.84	(0.07)	.78	(0.42)	.14	.81	(0.09)	.84	(0.37)	-.06	.77	(0.11)	.79	(0.41)	-.04	.78	(0.10)	.73	(0.44)	.10	.79	(0.09)	.84	(0.37)	-.11
Non-resident	.11	(0.06)	.18	(0.39)	-.18	.16	(0.08)	.16	(0.37)	-.01	.17	(0.10)	.16	(0.37)	.02	.13	(0.08)	.17	(0.37)	-.09	.12	(0.07)	.20	(0.40)	-.19
AB540	.05	(0.04)	.09	(0.29)	-.16	.12	(0.07)	.12	(0.33)	-.01	.08	(0.07)	.09	(0.29)	-.03	.07	(0.06)	.09	(0.29)	-.07	.07	(0.06)	.10	(0.30)	-.08
Prior coursetaking																									
First term	.03	(0.03)	.02	(0.13)	.08	.06	(0.05)	.03	(0.16)	.22	.13	(0.09)	.14	(0.35)	-.04	.03	(0.04)	.04	(0.19)	-.02	.04	(0.04)	.05	(0.22)	-.03
N terms enrolled	9.34	(0.97)	10.09	(5.51)	-.14	9.16	(1.29)	9.44	(5.68)	-.05	7.67	(1.48)	7.60	(5.77)	.01	8.49	(1.48)	7.79	(5.74)	.12	8.48	(1.09)	7.85	(5.43)	.12
Credits earned	62.44	(6.41)	63.79	(29.47)	-.05	58.08	(7.32)	62.20	(35.58)	-.12	50.59	(9.41)	50.07	(36.99)	.01	55.14	(9.52)	52.56	(36.9)	.07	56.09	(7.96)	49.63	(34.10)	.19
Any dual enrollment credits	.21	(0.08)	.27	(0.45)	-.13	.26	(0.10)	.22	(0.42)	.09	.25	(0.11)	.24	(0.43)	.03	.16	(0.09)	.22	(0.42)	-.15	.20	(0.08)	.21	(0.41)	-.04
Prior GPA	2.97	(0.15)	2.93	(0.79)	.05	2.91	(0.20)	2.91	(0.83)	.00	2.79	(0.28)	2.75	(1.11)	.03	2.92	(0.22)	2.89	(0.95)	.03	3.17	(0.18)	2.98	(0.85)	.22
Focal term coursetaking																									
Credits att.	11.06	(0.71)	11.23	(3.41)	-.05	10.89	(0.94)	11.04	(3.49)	-.04	12.48	(1.03)	12.40	(3.88)	.02	11.11	(1.09)	11.42	(3.43)	-.09	18.13	(2.46)	16.18	(7.51)	.26
STEM credits att.	8.07	(0.66)	8.29	(3.23)	-.07	8.03	(0.81)	8.03	(3.05)	.00	9.09	(0.86)	9.12	(3.50)	-.01	8.21	(0.95)	8.68	(3.53)	-.13	12.62	(1.76)	11.15	(5.68)	.26

	Fall 2017					Spring 2018					Fall 2018					Spring 2019					Fall 2019				
	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD	C mean (sd)		T mean (sd)		SMD
Prior STEM coursetaking																									
Highest math	3.60	(0.37)	3.55	(1.88)	.03	3.04	(0.46)	2.99	(1.79)	.03	3.15	(0.60)	2.97	(2.16)	.08	3.42	(0.53)	3.45	(1.95)	-.01	3.37	(0.41)	3.10	(2.11)	.13
No prior math	.06	(0.04)	.05	(0.23)	.02	.12	(0.07)	.08	(0.28)	.15	.19	(0.10)	.21	(0.41)	-.03	.09	(0.07)	.09	(0.29)	.01	.12	(0.07)	.18	(0.39)	-.14
Prior TL STEM credits	27.66	(3.98)	24.96	(16.52)	.16	22.44	(4.24)	23.27	(21.5)	-.04	22.05	(5.38)	21.01	(19.57)	.05	21.32	(4.61)	22.59	(20.55)	-.06	26.26	(4.93)	21.98	(21.38)	.20
Prior NTL STEM credits	5.12	(0.86)	5.81	(5.16)	-.13	6.25	(1.07)	7.09	(4.98)	-.17	4.48	(1.24)	4.55	(4.92)	-.01	5.22	(1.28)	4.60	(5.01)	.12	4.67	(1.01)	5.23	(5.13)	-.11
Prior TL STEM GPA	2.69	(0.20)	2.66	(1.08)	.03	2.59	(0.27)	2.59	(1.09)	.00	2.43	(0.35)	2.35	(1.34)	.06	2.63	(0.28)	2.62	(1.12)	.01	2.93	(0.24)	2.57	(1.22)	.29
Prior NTL STEM GPA	1.76	(0.29)	1.77	(1.55)	.00	2.13	(0.35)	2.26	(1.41)	-.10	1.64	(0.44)	1.62	(1.62)	.01	1.75	(0.41)	1.52	(1.60)	.14	1.99	(0.36)	1.80	(1.67)	.11
No prior NTL STEM credits	.38	(0.09)	.36	(0.49)	.03	.30	(0.10)	.22	(0.42)	.18	.45	(0.13)	.45	(0.50)	-.01	.42	(0.12)	.48	(0.50)	-.12	.39	(0.10)	.43	(0.50)	-.07
No prior TL STEM credits	.06	(0.04)	.04	(0.19)	.12	.09	(0.06)	.07	(0.25)	.09	.17	(0.10)	.19	(0.39)	-.05	.08	(0.07)	.09	(0.29)	-.05	.07	(0.05)	.11	(0.32)	-.14
Prior program participation																									
Prior SI or SLC	.39	(0.09)	.47	(0.50)	-.17	.40	(0.11)	.47	(0.50)	-.13	.39	(0.13)	.40	(0.49)	-.02	.53	(0.12)	.53	(0.50)	-.01	.71	(0.10)	.66	(0.48)	.11
Prior STEMPP support	.09	(0.05)	.07	(0.26)	.06	.17	(0.08)	.19	(0.40)	-.06	.26	(0.12)	.29	(0.46)	-.06	.42	(0.12)	.42	(0.50)	-.01	.63	(0.10)	.52	(0.50)	.20
N	*1959*		*55*			*1966*		*73*			*2028*		*92*			*2068*		*109*			*2308*		*61*		

Exhibit B-2. Outcomes by Term, Excluding Students Who Took SI in the Focal Term

	Fall 2017							Spring 2018							Fall 2018						
	C mean (sd)		T mean (sd)		β (SE)		Effect Size	C mean (sd)		T mean (sd)		β (SE)		Effect Size	C mean (sd)		T mean (sd)		β (SE)		Effect Size
STEM credits earned	5.73	(0.73)	5.73	(3.87)	0.08	(0.12)	.02	5.91	(0.92)	6.95	(3.42)	1.21***	(0.11)	.35	5.89	(3.35)	6.24	(3.98)	0.3**	(0.13)	.09
STEM GPA	2.55	(0.25)	2.49	(1.43)	0.01	(0.05)	.01	2.48	(0.30)	2.98	(1.04)	0.59***	(0.05)	.57	2.24	(1.56)	2.54	(1.22)	0.23***	(0.05)	.19
Continuation in STEM	.77	(0.08)	.80	(0.40)	0.23	(0.57)	.14	.60	(0.11)	.74	(0.44)	0.74	(0.39)	.45	.72	(0.48)	.86	(0.35)	1.11**	(0.41)	.67
N	*1959*		*55*					*1966*		*73*					*2028*		*92*				

	Spring 2019							Fall 2019						
	C mean (sd)		T mean (sd)		β (SE)		Effect Size	C mean (sd)		T mean (sd)		β (SE)		Effect Size
STEM credits earned	5.29	(1.05)	6.22	(3.96)	0.53***	(0.13)	.13	4.82	(0.89)	5.30	(4.35)	-0.75	(1.04)	-.17
STEM GPA	2.31	(0.37)	2.48	(1.26)	0.15**	(0.05)	.12	2.43	(0.34)	2.15	(1.45)	-0.04	(0.06)	-.03
Continuation in STEM	.69	(0.12)	.72	(0.45)	0.25	(0.33)	.15	NA	NA	NA	NA	NA	NA	NA
N	*2068*		*109*					*2308*		*61*				

*p < .05; **p < .01; ***p < .001
Note. Effect size for dichotomous outcomes is Cox's index.

Exhibit B-3. Meta-Analysis Impact Estimate Across Terms

Outcome	Effect Size	SE	P
STEM credits earned	0.09	0.08	0.32
STEM GPA	0.18	0.10	0.17
Continuation in STEM*	0.35	0.13	0.07

**Excludes fall 2019 term due to change in withdrawal policy with pandemic-related shift to remote learning in spring 2020*