Evaluation of Los Angeles City College's STEM Pathways Program

Impacts of the Supplemental Instruction program on student outcomes

August 2021

Prepared for:
Jayesh Bhakta
Los Angeles City College
855 N. Vermont Ave.
Los Angeles, CA 90029
bhaktaj@lacitycollege.edu

Prepared by SRI International
Kyra Caspary, Allison Milby, Victoria Sosina, Xin Wei, and Rebecca Goetz
SRI Project Number:
100180.001.0000.0010

SRI Education™
A DIVISION OF SRI INTERNATIONAL

Suggested citation:

Caspary, K., Milby, A., Sosina, V., Wei, X., & Goetz, R. (2021). *Evaluation of Los Angeles City College's STEM Pathways program: Impacts of the Supplemental Instruction program on student outcomes*. SRI International.

Contents

Introduction 1
  Study Context and SI Overview 1
  Study Purpose 5
    Conceptual Model 5
    Research Questions 6
  Data Sources 6
Program Participation 7
  SI Participation 7
  SI Proportionality 8
    Proportionality for Latinx Students 8
    Proportionality for Low-Income Students 9
    Proportionality for Low-Income Latinx Students 10
Impact Analysis 11
  Methods 11
  SI Impact by Term 12
  Combined Estimate of SI Participation 16
  Limitations 16
  Discussion 17
References 18
Appendix: Impact Analysis Methodology A-1
  Sample and Data Elements A-1
    Analytic Sample A-1
    Outcome Measures A-3
    Demographic, Enrollment, and Coursetaking Measures A-3
  Analytic Approach A-6
    Propensity Score Methodology A-6
    Impact Analysis Modeling A-7
  Descriptive Statistics for Analytic Sample A-8
  Baseline Equivalence After Propensity Score Weighting A-12

List of Exhibits

Exhibit 1. Courses Which Offered SI and Number of SI Sections They Offered, by Term 4
Exhibit 2. Supplemental Instruction Conceptual Framework 6
Exhibit 3. SI Participation, Summer 2017 to Fall 2019 8
Exhibit 4. Proportionality of Participation for Latinx Students 9
Exhibit 5. Proportionality of Participation for Pell or California Promise Grant Recipients 10
Exhibit 6. Proportionality of Participation for Latinx Pell or California Program Grant Recipients 11
Exhibit 7. Outcomes by Term 15
Exhibit 8. Meta-Analysis Impact Estimate Across Terms 16
Exhibit A-1. Counts of Students Dropped from Analytic Sample A-2
Exhibit A-2. Outcomes in the Focal Term A-3
Exhibit A-3. Enrollment, Demographic, and Coursetaking Data Elements A-4
Exhibit A-4. Descriptive Statistics Before Propensity Score Weighting A-9
Exhibit A-5. Outcomes Before Propensity Score Weighting A-11
Exhibit A-6. Descriptive Statistics After Propensity Score Weighting A-13

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 implementation as well as the program's impact on student outcomes. This report focuses on the Supplemental Instruction (SI) program for STEM courses, one of the grant's most-used supports. SI 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). This report describes participation in SI from fall 2017 through fall 2019 and presents findings from a quasi-experimental study to estimate the impact of SI 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 SI. We then describe prior research on effective STEM supports and SI, and present our research questions and data sources. Next, we discuss results from a descriptive analysis of SI 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 SI participation on students' STEM outcomes.

Study Context and SI 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. 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. Thus, Hispanic-Serving

[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.

Institutions have high potential to increase degree completion in STEM fields for this population (Santiago et al., 2015). Programs like the STEMP program seek to attract Latinx students to the STEM field and retain them by offering supports to address common barriers to student persistence (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. The program offered drop-in tutoring support through the STEM Learning Center in math (Math 240 and above), chemistry, biology, physics, and computer science.

The focus of this report, however, is the SI program (also known as Peer-Assisted Study Sessions, or PASS). LACC included SI in the portfolio of STEM student supports because of evidence from the past 3 decades, conducted primary at 4-year institutions, suggesting that SI is an effective strategy for improving course performance for students of color and low-performing students. Martin and Arendale (1993) reviewed analyses, conducted over the course of a decade, of course success and continued college enrollment for SI participants compared with students who declared a strong interest in SI but did not participate, possibly due to schedule conflicts. They found positive effects from SI participation on course grades, course completion, and continued enrollment, overall and for students of color and students with high or low academic achievement. More recent studies have also found benefits from SI participation related to course performance (e.g., Peterfreund et al., 2008; Yue et al., 2018) and even graduation (Rath et al., 2007).[2] Peacock's (2008) study also provides evidence for positive effects specifically in a math gateway course in the community college setting. This study found that students participating in SI had higher grades and completion rates and were more likely to enroll in the subsequent semester compared with non-participants. Given the positive findings from studies like those summarized here, LACC chose to implement a STEM-specific SI program as a component of the larger STEM Pathways program.

LACC had an SI program that pre-dated the grant, but grant funds enabled the college to expand this support to STEM courses beginning in fall 2017. SI course offerings varied by term, depending upon which STEM courses were offered, instructor interest, and availability of qualified SI leaders (i.e., the students responsible for providing peer support and leading SI sessions); however, the program targeted prerequisite courses for STEM majors that had high

[2] The studies cited here use the term underrepresented minority (URM) to refer to students who have historically been underrepresented in higher education but operationalize the category differently. Peterfreund et al. (2008) and Rath et al. (2007), drawing on the same dataset, include within this category students identified in university records as American Indian, African American/Black, Chicano/Hispanic/Latino, or Pacific Islander (e.g., Guam, Native Hawaiian, and Filipino). Yue et al. (2018) also include students who were indicated as Asian because half of the Asian population in the study identified as Hmong, a historically underrepresented ethnic group in education.

failure rates. The courses in which SI was most frequently offered were Calculus I, II, and II, Introduction to General Chemistry, and Chemistry 101 (see Exhibit 1). In fall 2019, LACC expanded the SI program by more than doubling the number of chemistry sections offering SI. For our analysis we group courses offering SI into three main categories based on subject—math and computer science, advanced math, and biology and chemistry.

Exhibit 1. Courses Which Offered SI and Number of SI Sections They Offered, by Term

	Fall 2017		Spring 2018		Fall 2018		Spring 2019		Fall 2019		Totals	
	SI sections	Non-SI sections	SI sections	Non-SI sections	SI sections	Non-SI sections	SI sections	Non-SI sections	SI sections	Non-SI sections	Total SI sections	Total non-SI sections
Math and Computer Science course group[a]												
C++ Programming I	1	2	0	3	0	3	0	3	0	3	1	14
Math Workshop	1	0	0	1	0	1	0	1	0	1	1	4
Statistics	0	12	0	14	0	17	1	16	0	40	1	99
Trigonometry	1	2	0	4	0	3	1	2	0	0	2	11
Precalculus	1	3	0	4	2	2	0	4	0	11	3	24
Calculus I	0	5	4	1	4	1	5	0	5	0	18	7
Calculus II	1	1	1	1	0	3	2	1	3	0	7	6
Advanced Math course group												
Calculus III	2	0	2	0	2	0	3	0	2	1	11	1
Linear Algebra	2	0	2	0	2	0	2	0	1	1	9	1
Ordinary Differential Equations	2	0	2	0	2	0	0	2	2	0	8	2
Biology and Chemistry course group												
General Bio I	0	2	0	0	0	2	0	0	2	0	2	4
Intro to Gen Chem	3	7	4	1	5	6	1	4	10	0	23	18
Chemistry 101	2	2	3	1	2	2	1	4	5	0	13	9
Chemistry 102	0	2	1	1	0	2	1	1	2	0	4	6
Organic Chemistry	0	1	2	0	0	1	0	2	2	0	4	4
TOTAL	16	39	21	31	19	43	17	40	34	57	107	210

[a] The one computer science class that offered SI is grouped with the lower-level math courses because it was an introductory computer science course which had no math prerequisite.

The program had the following expectations for SI leaders:

- **In-class support:** SI leaders were responsible for attending all class sessions and completing coursework. The SI leader was also expected to model strong academic habits, including note-taking, active listening, and test preparation.
- **SI sessions:** SI leaders scheduled regular (at least weekly) sessions to support students enrolled in the course. Sample activities for SI sessions included reviewing concepts discussed in class, completing practice problems, and preparing for exams.

To prepare for SI, SI leaders and the instructors teaching the courses offering SI (also known as SI faculty) were each asked to participate in an initial orientation to the program and sign an agreement committing to complete the responsibilities associated with their role. Throughout the semester, SI faculty were expected to share curricular resources with SI leaders, and to check in as needed to discuss how to support students.

A few contextual factors are important to consider when interpreting the study findings. In fall 2019, LACC began implementing new course placement policies to comply with California Assembly Bill (AB) 705, effective January 2018. AB 705 required that 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.

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 SI 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

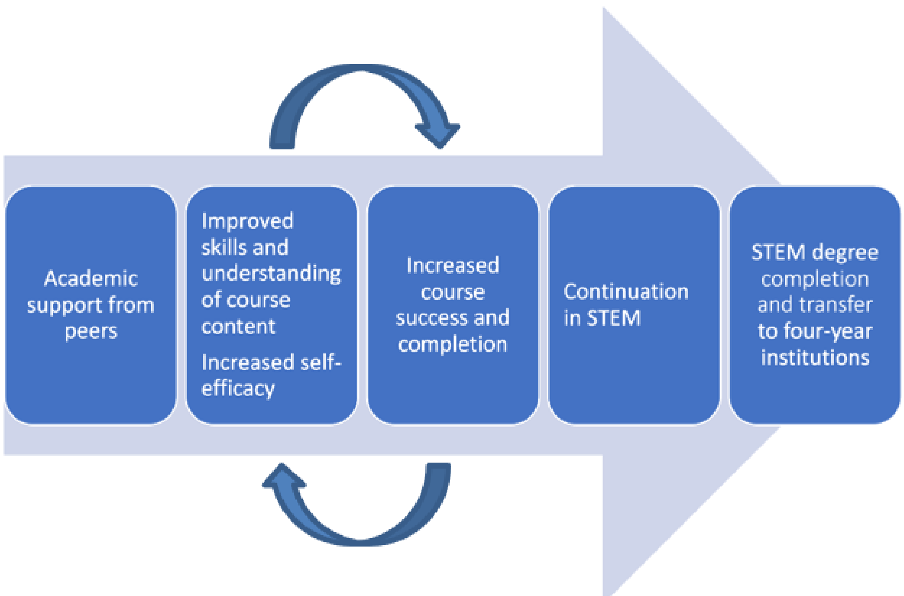
The purpose of this analysis is to examine the extent to which SI reached the target student population, and to determine whether SI participation helped students succeed in completing STEM coursework and continuing in STEM, setting the stage for improved STEM degree completion and transfer.

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 SI may increase these long-term outcomes is through improving short-term academic performance and STEM persistence

(Exhibit 2). Targeted academic 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 SI outcomes, specifically course success and continuation in STEM.

Exhibit 2. SI Conceptual Framework



Research Questions

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

1) To what extent did SI reach the target population of students who are low-income and Latinx?
2) What is the impact of participating in SI on course success?
3) Does SI 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.[3] The second data source is SI participation records, gathered directly from the STEMP program. SI participants were asked to sign into SI sessions using a Google form. The STEMP program staff compiled these participation data and assigned pseudo identifiers that enabled linking to the data from the college's administrative data system. SRI combined these SI program participation data with extant administrative data from LACC to examine program participation and impact.

Program Participation

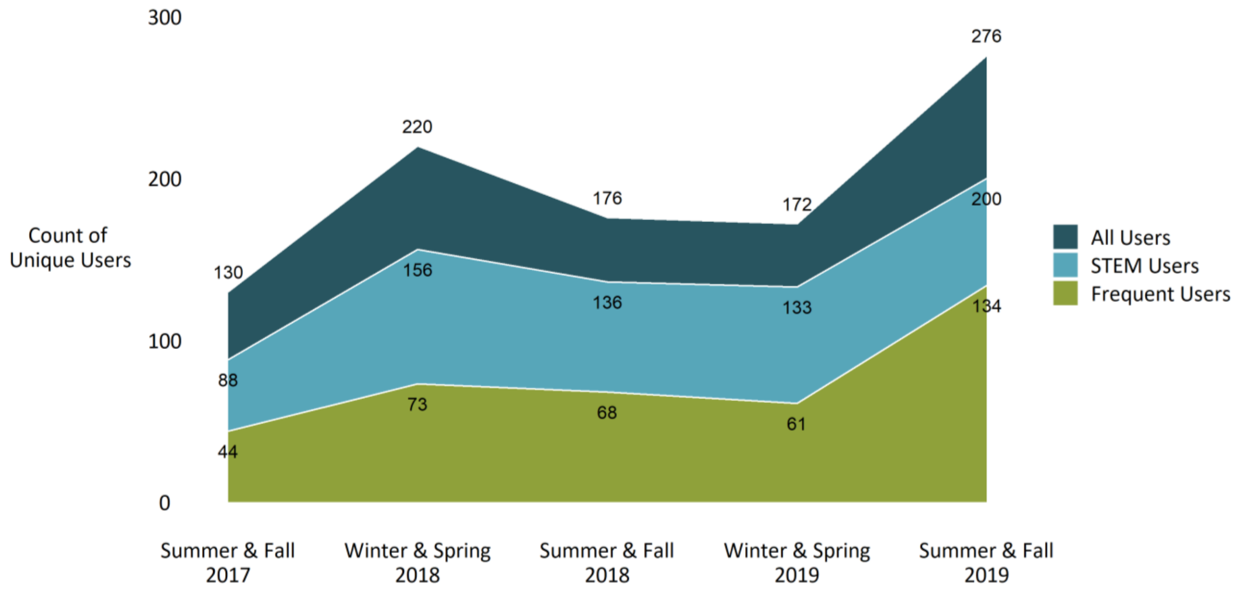
Together, the student enrollment data and SI participation data enabled us to examine both the number of students who took advantage of SI and the extent to which these students were representative of the broader population of STEM students at LACC.

SI Participation

The descriptive analysis of user participation shows that SI attendance increased from the beginning to the end of the study period for all groups, including frequent users of SI (defined as attending an SI session five or more times in the given term), STEM users, and all users (including students who do not meet our STEM student definition) (Exhibit 3). To examine participation, we combine the number of unique users by term and year for main terms (fall or spring) with adjacent intercessions (summer or winter) to clearly display trends. After an initial increase, SI participation dropped in summer and fall 2018, particularly for non-STEM students, although participation of all groups remained higher than in summer and fall 2017. Participation remained relatively consistent in winter and spring 2019, before increasing sharply in summer and fall 2019, reflecting the doubling in SI sections offered between spring and fall 2019 (from 17 to 34, see Exhibit 1). For example, 172 unique users participated in SI sessions in winter and spring 2019. That number increased to 276 unique users by summer and fall 2019.

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

Exhibit 3. SI Participation, Summer 2017 to Fall 2019



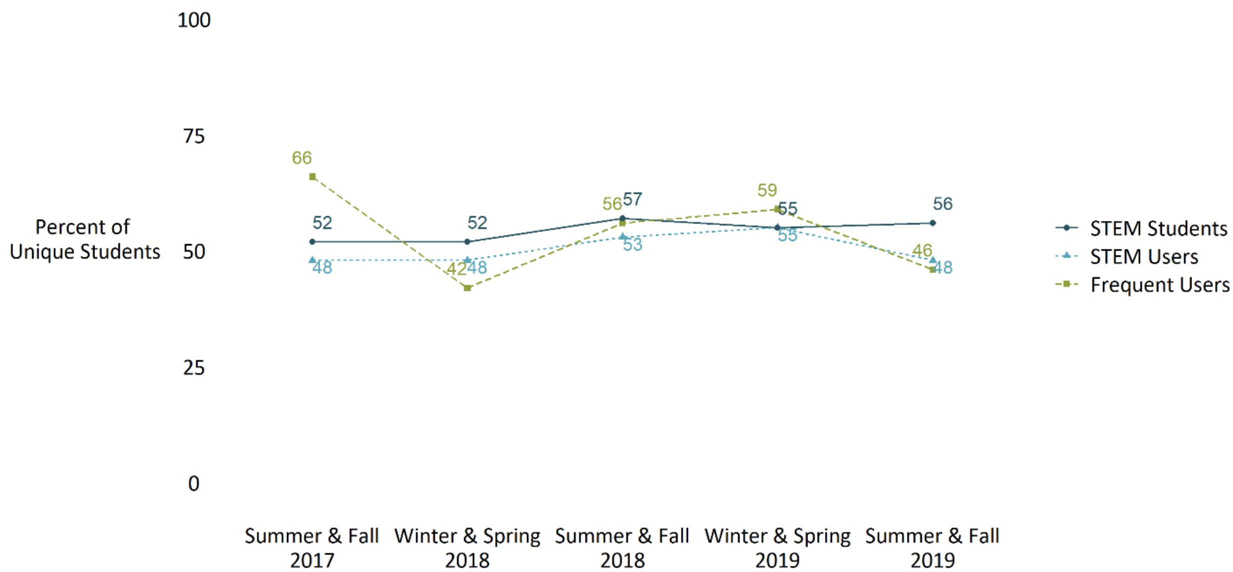
SI Proportionality

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

Proportionality for Latinx Students

Exhibit 4 shows the proportion of SI users who were Latinx relative to the proportion of Latinx STEM students at LACC as a whole. From this figure, we see that Latinx students were initially underrepresented among SI users relative to the overall STEM population by 4 percentage points. While Latinx SI users reached proportionality with the STEM population in winter/spring 2019, the percentage of SI users who were Latinx dropped in summer/fall 2019 with the expansion of SI chemistry offerings. The program ended up with an 8 percentage point gap between the proportion of Latinx SI users and the overall proportion of Latinx students in the STEM student population. The proportion of frequent users who were Latinx fluctuated throughout the analysis period (reflecting the smaller number of frequent users); initially in summer and fall 2017, the proportion of frequent users who were Latinx exceeded that of the overall STEM population before dipping in summer and fall 2019 with the expansion of SI sections.

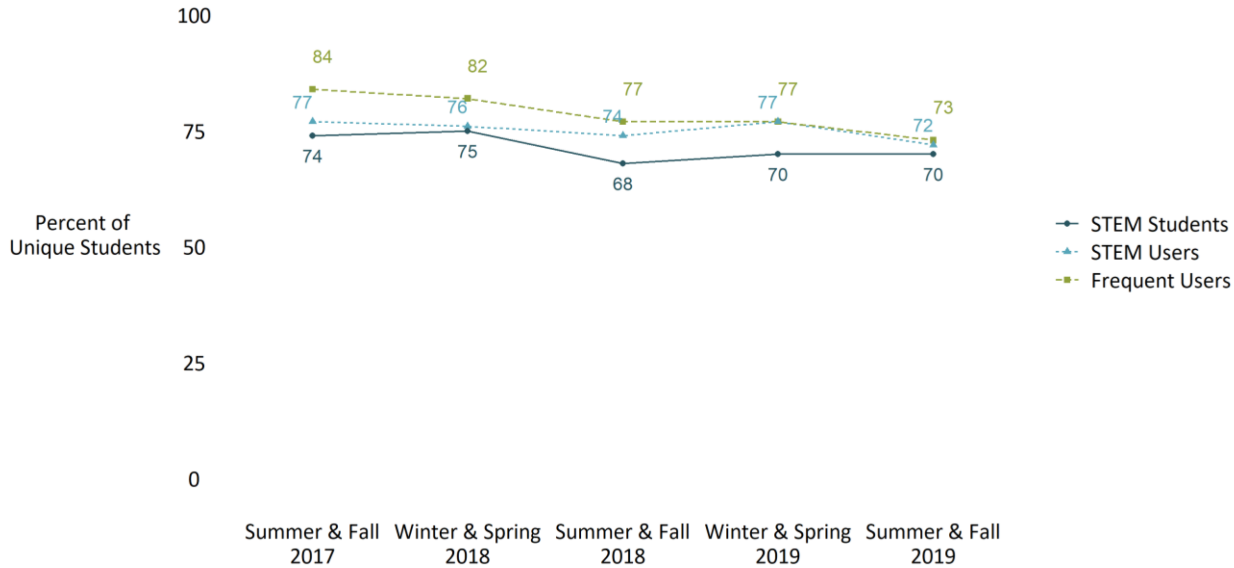
Exhibit 4. Proportionality of Participation for Latinx Students



Proportionality for Low-Income Students

In contrast to Latinx participation, the program met or exceeded proportionality of students who were low-income (defined as Pell Grant or California Promise Grant recipients), although the overrepresentation of low-income students among frequent users diminished over the time study period (Exhibit 5). In summer and fall 2017, 77% of STEM users and 84% of frequent users of SI were low-income relative to 74% of STEM students overall. Though the difference narrowed by summer and fall 2019 to 72% and 73% for STEM users and frequent users of the SI, respectively, compared with 70% of LACC STEM students, the proportion of low-income students remained higher for the SI population.

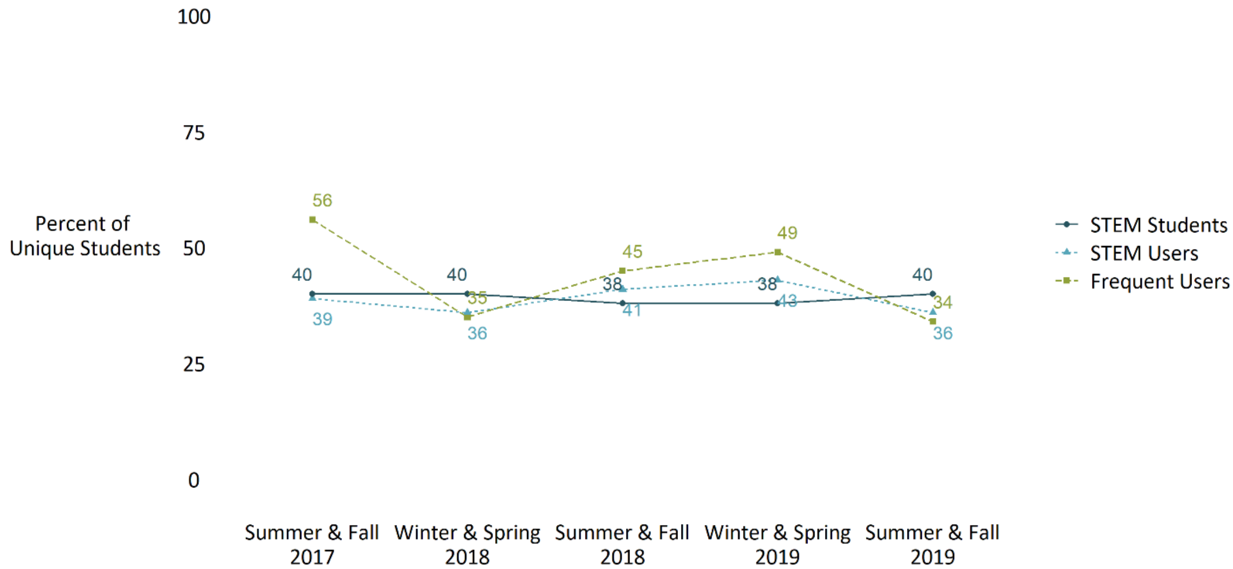
Exhibit 5. Proportionality of Participation for Pell or California Promise Grant Recipients



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 6 shows the proportion of STEM users of the SI who were both Latinx and low-income relative to all STEM students at LACC. The trends for low-income Latinx students were similar to those of Latinx students overall. After initial underrepresentation, the program exceeded proportionality for STEM users in summer and fall 2018 and winter and spring 2019, but dropped below proportionality in summer and fall 2019 with the expansion of SI sections. Proportionality of frequent users who were low-income Latinx fluctuated more due to the small n but followed the same pattern as the overall STEM user group, exceeding proportionality in summer/fall 2018 and winter/spring 2019 before dropping below proportionality in summer/fall 2019 as SI sections were expanded.

Exhibit 6. Proportionality of Participation for Latinx Pell or California Program Grant Recipients



Taken together, these results suggest that the SI program had mixed success meeting its target population of students who are Latinx and/or low-income. While the program consistently reached low-income students, summer and fall 2019 saw a narrowing of differences between low-income SI and STEM student proportionality even as SI usage increased overall. In general, the program had less success with reaching Latinx students during terms when overall SI usage increased than when usage remained constant. As SI continues to expand, the program might attend particularly to engaging Latinx students.

Next, we turn to a discussion of the estimated impacts of the SI on the students served.

Impact Analysis

We estimated the effects of SI participation in each term using propensity score weighted regression.

Methods

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

The analytic sample for this analysis was limited to students enrolled in a focal course in a given term, with focal courses defined as courses that had at least one section offering SI in the term. We defined the treatment group as any STEM student enrolled at the college who attended an SI session at least once within a given fall or spring term from fall 2017 through fall 2019. The comparison group was any STEM student who 1) was enrolled in a SI section of a focal course but did not attend any sessions or 2) was enrolled in a non-SI section of a focal course. To avoid students belonging to the treatment group for one course and the comparison group for another course, we excluded any students enrolled in two or more focal courses who participated in SI for at least one course but not all courses. For students enrolled in two or more focal courses who remained in the sample, we counted them as passing the focal course as long as they passed one focal course. In these cases, we calculated their GPA across the focal courses to determine the focal course grade outcome (see appendix Exhibit A-2 for more information).

The propensity score weighting ensured that the treatment and comparison groups were equivalent on all observed student demographic characteristics, including gender, race and ethnicity, eligibility for a California Promise Grant, and California residency status, as well as prior coursetaking and GPA, both overall and in STEM, and prior program participation (see appendix Exhibit A-3 for a full list of covariates). 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 SI in each term separately, and then combined these estimates using meta-analysis. Please see Appendix A for more detail on the methodology, including definitions for the outcomes and predictor variables used and a description of the models employed.

SI Impact by Term

Exhibit 7 shows the results of the weighted regressions estimating the effect of SI participation on STEM outcomes. For each term and outcome, we show weighted means and standard deviations for treatment and comparison groups, the coefficient (and standard error) on the SI indicator from the weighted regression models, and the effect size.

There were positive and significant effects for SI participation on students' focal course grade and continuation in STEM. These effects were most consistent for focal course grade (significant in three out of five terms), followed by continuation in STEM (significant in one out of five terms). Estimated effect sizes for significant results were small, ranging from 0.20 to 0.31, for focal course grades, and large (0.89) for continuation in STEM.[4] Effect sizes provide useful standardized measures of magnitude that allow for comparisons across different metrics.

[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.

However, for outcomes such as GPA, it is also useful to consider impacts on the scale of their original measurement. On a scale of 0 to 4 of average grade, SI participants had a focal course grade between 0.24 and 0.33 grade points higher across three terms than similar peers who did not use SI. In fall 2017, the predicted probability of continuing in STEM for the typical low-income female Latinx California resident student was 97.6% for SI participants versus 90.4% for non-SI participants.[5]

[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 7. 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
Focal course passing	.72	(0.45)	.87	(0.34)	1.27	(0.70)	.77	.76	(0.43)	.89	(0.31)	0.57	(2.64)	.35	.72	(0.45)	.82	(0.39)	0.86	(0.56)	.52
Focal course grade	2.27	(1.40)	2.56	(1.13)	-0.01	(0.10)	-.01	2.33	(1.34)	2.88	(1.09)	0.33***	(0.10)	.31	2.20	(1.33)	2.52	(1.22)	0.24*	(0.11)	.20
Continuation in STEM	.68	(0.47)	.87	(0.34)	1.47**	(0.56)	.89	.65	(0.48)	.68	(0.47)	0.65	(0.42)	.39	.74	(0.44)	.85	(0.36)	0.79	(0.55)	.48
N	*330*		*69*					*402*		*73*					*334*		*62*				

	Spring 2019							Fall 2019						
	C mean (sd)		T mean (sd)		β (SE)		Effect Size	C mean (sd)		T mean (sd)		β (SE)		Effect Size
Focal course passing	.63	(0.48)	.75	(0.44)	0.46	(0.64)	.28	.73	(0.44)	.81	(0.39)	0.46	(0.43)	.28
Focal course grade	1.97	(1.45)	2.48	(1.41)	0.30***	(0.10)	.21	2.15	(1.27)	2.49	(1.29)	0.17	(0.11)	.14
Continuation in STEM	.69	(0.46)	.81	(0.39)	0.64	(0.56)	.39	NA	NA	NA	NA	NA	NA	NA
N	*426*		*48*					*343*		*90*				

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

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

Combined Estimate of SI Participation

When we combine the results for each outcome across terms, we see positive and significant results for all three outcomes—focal course passing, focal course grade, and continuation in STEM (Exhibit 8). The overall estimate for each outcome is an average of the distribution of the effects of SI participation in the population. On average, the effect of SI on passing at least one focal course was 0.44 standard deviations, the effect on focal course grades 0.17 standard deviations and the effect on continuing in STEM 0.54 standard deviations.

Exhibit 8. Meta-Analysis Impact Estimate Across Terms

Outcome	Effect Size	SE	p
Focal course passing	0.44	0.09	0.01
Focal course grade	0.17	0.06	0.05
Continuation in STEM	0.54	0.12	0.02

Limitations

The goal of this analysis is to estimate the impact of SI participation on student outcomes. Because we are unable to observe outcomes for the same students with and without the SI support and SI 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 SI 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 SI participation. For example, by ensuring the two groups have similar prior STEM GPAs, we minimize the extent to which any observed differences in the course grade earned in the focal terms result from prior achievement rather than SI support. As with any observational study employing propensity score methodologies, a key limitation is effectively accounting for all factors associated with selection into the SI 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 SI participants and nonparticipants vary based on these unobserved characteristics, the impact estimates may be biased, i.e., our findings may overestimate or underestimate program impact.

Additionally, this analysis focuses on outcomes for students enrolled in a finite set of focal courses, potentially reducing bias due to selection based on course enrollment or variation in grading standards by course. However, this also means that inferences are only generalizable to these kinds of focal courses. It is possible that SI would have stronger or weaker effects if offered in other types of STEM courses.

Finally, due to the limited sample size, we are not able to explore possible heterogeneity in effects by course subject. It may be the case the SI is more effective, for example, in math courses than it is in chemistry courses. Larger numbers of treated and comparison students would allow for a more reliable analysis of heterogeneity by course content.

Discussion

The impact analysis results suggest that SI is supporting students' course success as well as their persistence in pursuing STEM coursework. The results were consistently positive across all terms and outcomes examined. Although many of the estimates were not statistically significant in all terms, perhaps due to the small sample size, we see robust positive and statistically significant findings when we combine the estimates across terms using meta-analysis.

References

Austin, P. C., & Stuart, A. S. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Statistics in Medicine*, *34*(28), 3661–3679.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, *2*(4), 358−377. https://doi.org/10.1177/1536867X0200200403

California Community Colleges. (2018). *What is AB705?* https://assessment.cccco.edu/ab-705-implementation

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Dawson, P., van der Meer, J., Skalicky, J., & Cowley, K. (2014). On the effectiveness of supplemental instruction: A systematic review of supplemental instruction and peer-assisted study sessions literature between 2001 and 2010. *Review of Educational Research*, *84*(4), 609–639. https://doi.org/10.3102/0034654314540007

Harder, V. S., Stuart, E. S., & Anthony, J. C. (2010). Propensity score techniques and the assessment of measured covariate balance to test causal associations in psychological research. *Psychological Methods*, *15*(3), 234−49. https://doi.org/10.1037/a0019623

Hirano, K., Imbens, G. W., & Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, *71*(4), 1161–1189.

Hox, J. J., Moerbeek, M., & van de Schoot, R. (2018). *Multilevel analysis: Techniques and applications* (3rd ed.). Routledge.

Los Angeles City College. (2018). *Student profile – fall 2018.* https://www.lacitycollege.edu/About/Why-LACC/Facts-Figures/Demographics

Martin, D. C., & Arendale, D. (Eds.). (1993). Supplemental Instruction: Improving first-year student success in high-risk courses (2nd ed.). Columbia, SC: The University of South Carolina and the National Resource Center for The Freshman Year Experience and Students in Transition. (ERIC Document Reproduction Service No. ED 354 839) Available http://www.umkc.edu/cad/si/sidocs/

Peacock, M. (2008). *A program evaluation of Supplemental Instruction for developmental mathematics at a community college in Virginia.* https://doi.org/10.25777/0HKB-8208

Peterfreund, A. R., Rath, K. A., Xenos, S. P., & Bayliss, F. (2008). The impact of supplemental instruction on students in STEM courses: Results from San Francisco State University. *Journal of College Student Retention: Research, Theory and Practice*, *9*(4), 487–503.

Rath, K. A., Peterfreund, A. R., Xenos, S. P., Bayliss, F., & Carnal, N. (2007). Supplemental instruction in Introductory Biology I: Enhancing the performance and retention of underrepresented minority students. CBE-Life Sciences Education, 6, 203–216. doi:10.1187/cbe.06-10-0198

Riegle-Crumb, C., King, B., & Irizarry, Y. (2019). Does STEM stand out? Examining racial/ethnic gaps in persistence across postsecondary fields. *Educational Researcher*, *48*(3),133–144. https://doi.org/10.3102/0013189X19831006

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association*, *79*(387), 516–524. https://doi.org/10.2307/2288398

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), 33–38. https://doi.org/10.2307/2683903

Santiago, D. A., Taylor, M., & Galdeano, E. C. (2015). *Finding your workforce: Latinos in science, technology, engineering, and math (STEM)*. Excelencia in Education.

Stuart, E. A., Lee, B. K., & Leacy, F. P. (2013). Prognostic score-based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research. *Journal of Clinical Epidemiology*, *66*(8 Suppl), S84–S90.e1. https://doi.org/10.1016/j.jclinepi.2013.01.013

U.S. Department of Education. (n.d.). *Hispanic-serving institutions (HSIs).* https://sites.ed.gov/hispanic-initiative/hispanic-serving-institutions-hsis/

What Works Clearinghouse. (2017). S*tandards handbook* (Version 4.0). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance. https://ies.ed.gov/ncee/wwc/Docs/referenceresources/wwc_standards_handbook_v4.pdf

Yue, H., Rico, R. S., Vang, M. K., & Giuffrida, T. A. (2018). Supplemental Instruction: Helping disadvantaged students reduce performance gap. *Journal of Developmental Education* *41*(2), 18–25*.*

Appendix: Impact Analysis Methodology

Sample and Data Elements

The administrative and SI program participation data LACC provided to SRI enabled us to create the outcome, demographic, enrollment, and coursetaking metrics used in the analysis.

Analytic Sample

The SI analytic sample is comprised of STEM students enrolled in focal courses in each term, with focal courses defined as courses that offered at least one SI section in the term. The sample includes students who participated in SI and their peers enrolled in the same courses in that term who did not participate in SI. Some students who used SI also participated in other STEM Pathways program components in the same term, most notably the SLC (between 30% and 62% were SLC users in each term). While it is possible that effects of SI usage might be conflated with the effects of concurrent usage of these other STEMP program components, we retain these students in the analysis because the targeted nature of SI programming allows us to identify outcomes more likely impacted by SI participation than do the broader supports provided by the SLC and other program components. The sample is limited to the STEM student population, defined as students who enrolled at LACC between fall 2017 and fall 2019, were not dual enrolled, and either 1) declared a STEM major or 2) enrolled in Math 240 or above within LACCD.

We excluded students from the analytic sample if they 1) were enrolled in two or more focal courses in the same term and participated in SI in at least one course but not all, 2) participated in SI but were not in our STEM student population, 3) were enrolled in Math 202 (this is an independent course which did not offer regular instruction), 4) appeared to participate in SI for a course in which they were not enrolled, or 5) participated in SI for CHEM 102 in spring 2019 or three sections of CHEM 101 in fall 2019 because SI was delivered differently in these sections (embedded in whole-class instruction). Exhibit A-1 displays the number of students who were dropped from our analytic sample for each of these reasons, by term, to arrive at the final analytic sample.

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.

Exhibit A-1. Counts of Students Dropped from Analytic Sample

	Fall 2017			Spring 2018			Fall 2018			Spring 2019			Fall 2019		
	T	**C**	**Total**	**T**	**C**	**Total**	**T**	**C**	**Total**	**T**	**C**	**Total**	**T**	**C**	**Total**
All students in SI course	127	341	454	159	424	553	109	346	518	144	437	568	258	363	597
Exclude non-STEM students	38	0	38	50	0	50	25	0	25	32	0	32	47	0	47
Exclude students who participated in SI for a course in which they are not enrolled	8	0	5	18	0	5	9	0	8	15	0	10	15	0	9
Exclude students who participated in SI for CHEM 101 in fall 2019 or three sections of CHEM 102 in spring 2019	0	0	0	0	0	0	0	0	0	38	0	38	87	0	86
Exclude students who participated in SI in one course but did not in another course that also offered SI	12	11	12	17	18	18	15	10	15	8	9	9	17	17	17
Remaining students in sample	69	330	399	74	406	480	60	336	470	51	428	479	92	346	438

Note. Totals represent unduplicated student counts, so treatment and control do not sum to the total. All students enrolled in Math 202 were also excluded for another reason, so the table does not break out these students separately.

Outcome Measures

The goal of the SI program was to provide students with academic support to help them succeed in STEM courses, enabling them to proceed to higher-level STEM coursework in pursuit of a degree or certificate. To capture the impact of SI participation on course success and continuation in STEM, we examined course success in the focal term when a student sought help. We identified a set of focal courses characterized by having at least one section that offered SI in the term. We examined three outcomes: whether a student passed at least one focal course, the student's grade earned in focal courses during the focal term, and a student's continued enrollment in STEM courses in the subsequent two terms (Exhibit A-2).

Exhibit A-2. Outcomes in the Focal Term

Variable [a]	Description
Focal course passing	A student passed at least one focal course (binary indicator).
Focal course grade	Student's grade in the focal course(s), in the focal term only. Focal course grade was calculated as the total grade points earned in STEM courses that offered SI (A = 4, B = 3, C = 2, D = 1, F = 0) divided by the total number of credits attempted in STEM courses that offered SI, excluding withdrawals and courses taken pass/fail. Some students were enrolled in multiple SI courses in a focal term. We dropped any students enrolled in two or more focal courses who participated in SI for at least one but not all courses.
Continuation in STEM	STEM course enrollment in one or more of the two subsequent terms following the focal term (binary indicator).

[a] Focal courses are those courses that have at least one section offering SI in a given term.

Demographic, Enrollment, and Coursetaking Measures

The impact analysis included available student-level measures that would reasonably be associated with both a student's likelihood of using SI and their STEM course success or progress toward degree attainment. These measures encompass demographic indicators of race/ethnicity, gender, socioeconomic status, and California residency as well as academic performance prior to the focal term and coursetaking indicators in the focal term (Exhibit A-3).

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 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, we kept the highest grade (A > B > C > D > F and P > NP) and dropped records where one grade was a "W" (withdrawal) or missing.

For this analysis, we group courses offering SI into three main categories based on subject—math and computer science, advanced math, and biology and chemistry. Some students took multiple courses across groups. In those instances, they were included in a fourth group, general STEM.

Exhibit A-3. 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 California 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.
Multiple coursetaking	
Math and computer science course group	Lower-level math courses (tiers 2–4) and computer science. See description of tiers in ‘Highest math’ description, below (binary indicator).

Variable	Description
Advanced math course group	Upper-level math courses (tiers 5 and 6). See description of tiers in 'Highest math' description, below (binary indicator).
Biology and chemistry course group	Biology and chemistry courses (binary indicator).
Multiple course enrollment	Student enrolled in multiple courses offering SI in a given term within the same course group (binary indicator), e.g., a student is enrolled in two math courses.
Multiple SI course group	Student enrolled in multiple courses offering SI in a given term across the three course groups (binary indicator), e.g., a student is enrolled in a math and chemistry course.
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).
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).

Variable	Description
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 SI 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, SI 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 enrollment, demographic, and coursetaking data elements defined in Exhibit A-3.

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 academic support.

Weighting

This study estimated the average treatment effect on the treated (ATT) of SI 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 when there are few of these students in the sample (Austin & Stuart, 2015). To address this issue, we trimmed the sample to exclude students with propensity scores in the 99th percentile. 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 SI participation on the continuous outcome (focal course grade) and used weighted logistic regression models for the two binary outcomes (focal course passing and continuation in STEM). The regression coefficients from each weighted regression model can be interpreted as the measure of association between SI participation and the STEM outcome, adjusted for the estimated propensity of SI 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.

$$\eta_i = \beta_0 + \beta_1(SI_i) + \mathrm{X}_i B + e_i$$

In the multiple regression model η_i denotes the i-th student's average grade in focal courses. For the logistic regression model with the dichotomous outcome of focal course passing and continuation in STEM, η_i is the logit link function $\eta_i = ln\,(\frac{\pi_i}{1-\pi_i})$, with π_i denoting the probability that the i-th student passing at least one focal course or enrolling in a STEM course in the next two terms. SI_i is the treatment indicator variable, where 1 indicates participation in SI and 0 indicates no SI participation. X_i is the vector of student-level prior achievement, demographic characteristics, coursetaking, and prior program participation defined in Exhibit A-2. The regression coefficient β_1 indicates the difference between SI and non-SI students in the outcome. B represents the vector of regression coefficients for demographic variables, focal course grouping, prior coursetaking, program participation, and 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).

Terms Included

The SI analysis was conducted term by term from fall 2017 to fall 2019. We did not include winter and summer terms in the SI analysis. Due to low participation and the small comparison group, we were unable to achieve balance during propensity score weighting (the number of SI participants in summer and winter terms during the study period ranged from 48 to 58, whereas the number of non-participants during this period ranged from 76 to 140). Because of the increase in course withdrawals in spring 2020 due to the COVID-19 pandemic, we do not report on continuation in STEM for the fall 2019 term. The analysis for the other two outcomes includes students in all five terms.

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 SI participation on STEM learning outcomes across terms (all five terms for STEM course passing and focal course grades; 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.

Descriptive Statistics for Analytic Sample

Exhibit A-4 provides the unweighted descriptive statistics by term for the enrollment, demographic, and coursetaking covariates used in the impact analyses for students who participated in the SI and their peers who did not; Exhibit A-5 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.[6] In Exhibits A-5 and A-6, "C" columns show values for the comparison group—STEM students who were enrolled in a focal course but who did not use SI in the focal term. "T" columns show values for the treatment group—STEM students who used SI at least once during the focal term. In addition to mean values, tables also show the standard deviation ("sd") and standardized mean difference between the treatment and comparison groups ("SMD").

SI participants were more likely to be female than non-users across all terms except for fall 2018 and were more likely to be Latinx or Promise grant recipients in three of five terms. In four of five terms, SI participants were older than non-users and had a higher STEM GPA and overall GPA at the start of the focal term (Exhibit A-4). Consistent with this higher average prior achievement, SI participants had, on average, more positive unadjusted STEM outcomes in the focal term than non-users, passing courses at higher rates, earning higher SI course grades, and exhibiting a greater likelihood of continuing in STEM (Exhibit A-5).

[6] See "Weighting," above. The number of students in the final analytic sample is slightly less than the sample total shown in Exhibit A-1 due to this trimming.

Exhibit A-4. 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	.04	(0.19)	.01	(0.12)	.18	.05	(0.22)	.07	(0.25)	-.07	.03	(0.17)	.02	(0.13)	.11	.03	(0.18)	.04	(0.20)	-.04	.04	(0.19)	.02	(0.15)	.11
Latinx	.41	(0.49)	.49	(0.50)	-.17	.44	(0.50)	.42	(0.50)	.03	.49	(0.50)	.53	(0.50)	-.08	.52	(0.50)	.54	(0.50)	-.05	.50	(0.50)	.41	(0.49)	.18
Asian	.25	(0.43)	.20	(0.41)	.11	.29	(0.45)	.16	(0.37)	.33	.22	(0.42)	.19	(0.40)	.08	.22	(0.42)	.13	(0.33)	.29	.21	(0.41)	.30	(0.46)	-.20
Female	.31	(0.46)	.42	(0.50)	-.22	.40	(0.49)	.44	(0.50)	-.09	.41	(0.49)	.35	(0.48)	.11	.34	(0.47)	.38	(0.49)	-.08	.41	(0.49)	.44	(0.50)	-.06
Age	25.66	(8.08)	25.20	(6.34)	.07	24.50	(6.50)	27.23	(8.33)	-.33	23.85	(6.21)	25.69	(6.08)	-.30	24.49	(6.63)	25.54	(7.39)	-.14	24.31	(6.51)	25.08	(5.36)	-.14
Pell	.40	(0.49)	.55	(0.50)	-.29	.45	(0.50)	.41	(0.50)	.08	.49	(0.50)	.53	(0.50)	-.08	.49	(0.50)	.58	(0.50)	-.20	.48	(0.50)	.42	(0.50)	.11
Promise grant	.71	(0.45)	.80	(0.41)	-.22	.75	(0.43)	.75	(0.43)	.00	.76	(0.43)	.74	(0.44)	.04	.73	(0.44)	.77	(0.42)	-.10	.71	(0.45)	.76	(0.43)	-.10
Non-resident	.20	(0.40)	.14	(0.35)	.15	.18	(0.38)	.12	(0.33)	.17	.16	(0.36)	.11	(0.32)	.13	.15	(0.36)	.13	(0.33)	.09	.21	(0.41)	.17	(0.37)	.12
AB540	.10	(0.30)	.07	(0.26)	.09	.10	(0.30)	.07	(0.25)	.11	.09	(0.29)	.05	(0.22)	.19	.09	(0.29)	.06	(0.24)	.11	.11	(0.31)	.10	(0.30)	.04
Prior coursetaking																									
First term	.09	(0.29)	.09	(0.28)	.01	.05	(0.22)	.11	(0.31)	-.19	.12	(0.32)	.21	(0.41)	-.23	.07	(0.26)	.04	(0.20)	.14	.15	(0.36)	.17	(0.37)	-.05
N terms enrolled	6.58	(4.74)	7.33	(4.75)	-.16	7.82	(5.13)	7.75	(5.83)	.01	6.53	(4.74)	6.71	(5.93)	-.03	7.03	(5.37)	7.96	(5.28)	-.18	6.40	(5.55)	6.18	(5.22)	.04
Credits earned	43.06	(32.62)	52.47	(31.19)	-.30	53.24	(33.69)	52.64	(36.59)	.02	44.34	(32.71)	43.72	(36.82)	.02	44.96	(33.37)	54.59	(30.91)	-.31	42.49	(36.40)	41.44	(34.66)	.03
Any dual enrollment credits	.19	(0.39)	.30	(0.46)	-.25	.26	(0.44)	.16	(0.37)	.26	.31	(0.46)	.21	(0.41)	.24	.25	(0.44)	.17	(0.38)	.23	.25	(0.43)	.19	(0.39)	.15
Prior GPA	2.67	(1.12)	2.97	(0.95)	-.32	2.90	(0.91)	2.85	(1.11)	.04	2.67	(1.12)	2.70	(1.22)	-.03	2.69	(1.03)	2.91	(1.01)	-.22	2.54	(1.24)	2.77	(1.28)	-.18
Focal term coursetaking																									
Credits att.	10.14	(3.93)	11.38	(4.09)	-.31	11.24	(3.80)	9.72	(3.55)	.43	11.26	(3.91)	10.38	(3.51)	.25	10.25	(4.20)	10.04	(3.56)	.06	14.36	(7.48)	15.04	(8.37)	-.08
STEM credits att.	7.81	(3.27)	9.03	(3.75)	-.32	8.38	(3.10)	7.51	(3.05)	.29	8.22	(3.27)	8.11	(2.65)	.04	7.40	(3.54)	7.85	(3.00)	-.15	10.63	(5.99)	10.47	(5.59)	.03
Math and Computer Science course group	.15	(0.35)	.04	(0.21)	.50	.11	(0.31)	.27	(0.45)	-.37	.20	(0.40)	.35	(0.48)	-.31	.32	(0.47)	.31	(0.47)	.01	.15	(0.36)	.34	(0.48)	-.40
Advanced Math course group	.38	(0.49)	.48	(0.50)	-.20	.44	(0.50)	.30	(0.46)	.30	.22	(0.41)	.23	(0.42)	-.02	.36	(0.48)	.38	(0.49)	-.02	.35	(0.48)	.23	(0.43)	.27
Biology and Chemistry course group	.43	(0.50)	.48	(0.50)	-.10	.39	(0.49)	.41	(0.50)	-.05	.53	(0.50)	.40	(0.49)	.26	.25	(0.43)	.29	(0.46)	-.09	.44	(0.50)	.36	(0.48)	.18

	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
Multiple SI course enrollment	.08 (0.28)	.03 (0.17)	.33	.12 (0.32)	.05 (0.23)	.28	.06 (0.24)	.05 (0.22)	.07	.09 (0.29)	.04 (0.20)	.25	.09 (0.28)	.07 (0.25)	.08
Multiple SI course group	.05 (0.22)	.00 (0.00)	DNE[a]	.06 (0.25)	.01 (0.12)	.44	.05 (0.21)	.02 (0.13)	.25	.07 (0.26)	.02 (0.14)	.34	.06 (0.23)	.07 (0.25)	-.04
Prior STEM coursetaking															
Highest math	2.91 (2.21)	3.00 (2.07)	-.05	3.31 (1.96)	2.95 (1.94)	.19	2.62 (2.09)	2.27 (2.07)	.17	2.76 (1.92)	3.15 (1.94)	-.20	2.62 (2.13)	2.63 (1.99)	-.01
No prior math	.16 (0.37)	.12 (0.32)	.15	.09 (0.29)	.16 (0.37)	-.20	.19 (0.39)	.29 (0.46)	-.22	.13 (0.34)	.10 (0.31)	.08	.27 (0.45)	.24 (0.43)	.06
Prior TL STEM credits	15.21 (15.17)	19.58 (16.91)	-.26	19.73 (16.34)	19.33 (17.25)	.02	14.77 (14.88)	15.66 (17.17)	-.05	14.18 (14.34)	20.73 (14.69)	-.45	15.52 (15.69)	15.34 (15.28)	.01
Prior NTL STEM credits	3.89 (4.52)	5.10 (4.76)	-.26	4.17 (4.48)	4.52 (4.87)	-.07	4.16 (4.56)	4.23 (4.75)	-.01	4.61 (4.72)	4.89 (4.81)	-.06	3.28 (4.26)	3.77 (4.81)	-.10
Prior TL STEM GPA	2.33 (1.36)	2.64 (1.22)	-.25	2.51 (1.23)	2.54 (1.34)	-.02	2.20 (1.37)	2.15 (1.47)	.03	2.19 (1.32)	2.63 (1.16)	-.38	2.05 (1.41)	2.50 (1.44)	-.31
Prior NTL STEM GPA	1.47 (1.62)	2.06 (1.69)	-.35	1.66 (1.66)	1.68 (1.72)	-.01	1.59 (1.62)	1.55 (1.63)	.02	1.61 (1.59)	1.92 (1.66)	-.18	1.24 (1.57)	1.42 (1.68)	-.11
No prior NTL STEM credits	.16 (0.36)	.12 (0.32)	.13	.10 (0.30)	.15 (0.36)	-.14	.19 (0.39)	.26 (0.44)	-.16	.15 (0.36)	.10 (0.31)	.15	.24 (0.43)	.18 (0.38)	.17
No prior TL STEM credits	.49 (0.50)	.36 (0.48)	.27	.45 (0.50)	.47 (0.05)	-.03	.45 (0.50)	.47 (0.50)	-.04	.43 (0.50)	.40 (0.49)	.06	.58 (0.49)	.54 (0.50)	.07
Prior program participation															
Prior SI or SLC	.06 (0.24)	.17 (0.38)	-.29	.13 (0.34)	.25 (0.43)	-.27	.12 (0.33)	.31 (0.46)	-.40	.17 (0.37)	.54 (0.50)	-.74	.17 (0.38)	.33 (0.47)	-.34
Prior STEMPP support	.03 (0.17)	.07 (0.26)	-.16	.07 (0.26)	.11 (0.31)	-.12	.09 (0.29)	.18 (0.39)	-.23	.11 (0.31)	.25 (0.44)	-.32	.15 (0.35)	.24 (0.43)	-.23
N	*330*	*69*		*402*	*73*		*334*	*62*		*426*	*48*		*343*	*90*	

[a] Does not exist. No treatment students in fall 2017 were enrolled in multiple SI course groups; therefore, the SMD (calculated as the difference between the control and treatment mean, divided by the treatment SD) cannot be calculated.

Exhibit A-5. 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																										
Focal course passing	.72	(0.45)	.87	(0.34)	-.46	.76	(0.43)	.89	(0.31)	-.40	.72	(0.45)	.82	(0.39)	-.25	.63	(0.48)	.75	(0.44)	-.27	.73	(0.44)	.81	(0.39)	-.19
Focal course grade	2.27	(1.40)	2.56	(1.13)	-.26	2.33	(1.34)	2.88	(1.09)	-.50	2.20	(1.33)	2.52	(1.22)	-.27	1.97	(1.45)	2.48	(1.41)	-.36	2.15	(1.27)	2.49	(1.29)	-.26
Continuation in STEM	.68	(0.47)	.87	(0.34)	-.57	.65	(0.48)	.68	(0.47)	-.07	.74	(0.44)	.85	(0.36)	-.32	.69	(0.46)	.81	(0.39)	-.30	NA	NA	NA	NA	NA
N	*330*		*69*			*402*		*73*			*334*		*62*			*426*		*48*			*343*		*90*		

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. [7] Balance on observable characteristics was greatly improved after applying the propensity score weights. Prior to weighting, standardized differences ranged from -0.57 to -0.07 standard deviations (Exhibit A-5). After propensity score weighting, standardized differences ranged from -0.09 to 0.09 (Exhibit A-6), which is lower than the What Works Clearinghouse 0.25 cutoff for baseline equivalence for quasi-experimental studies (What Works Clearinghouse, 2017). Therefore, SI participants and nonparticipants were very similar on all potentially confounding observed covariates after propensity score weighting.

[7] To calculate SMD between treatment and comparison groups (both before and after weighting), the study team divided differences in each covariate by the treatment group standard deviations (Stuart et al., 2013).

Exhibit A-6. 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	.02	(0.06)	.01	(0.12)	.02	.07	(0.11)	.07	(0.25)	.01	.03	(0.07)	.02	(0.13)	.09	.06	(0.08)	.04	(0.20)	.07	.02	(0.07)	.02	(0.15)	-.03
Latinx	.49	(0.23)	.49	(0.50)	.00	.45	(0.21)	.42	(0.50)	.05	.50	(0.22)	.53	(0.50)	-.06	.52	(0.17)	.54	(0.50)	-.05	.42	(0.25)	.41	(0.49)	.02
Asian	.19	(0.18)	.20	(0.41)	-.02	.17	(0.16)	.16	(0.37)	.02	.22	(0.18)	.19	(0.40)	.06	.12	(0.11)	.13	(0.33)	-.02	.31	(0.23)	.30	(0.46)	.02
Female	.40	(0.22)	.42	(0.50)	-.05	.43	(0.21)	.44	(0.50)	-.02	.39	(0.21)	.35	(0.48)	.07	.41	(0.17)	.38	(0.49)	.07	.45	(0.25)	.44	(0.50)	.01
Age	25.31	(3.66)	25.20	(6.34)	.02	27.11	(3.33)	27.23	(8.33)	-.01	26.27	(3.53)	25.69	(6.08)	.09	25.30	(2.20)	25.54	(7.39)	-.03	24.91	(3.57)	25.08	(5.36)	-.03
Pell	.52	(0.23)	.55	(0.50)	-.06	.41	(0.2)	.41	(0.50)	.00	.53	(0.22)	.53	(0.50)	.00	.59	(0.17)	.58	(0.50)	.02	.43	(0.25)	.42	(0.50)	.02
Promise grant	.78	(0.19)	.80	(0.41)	-.03	.77	(0.17)	.75	(0.43)	.05	.72	(0.19)	.74	(0.44)	-.05	.78	(0.14)	.77	(0.42)	.02	.74	(0.22)	.76	(0.43)	-.04
Non-resident	.15	(0.16)	.14	(0.35)	.02	.14	(0.14)	.12	(0.33)	.04	.13	(0.15)	.11	(0.32)	.07	.12	(0.11)	.13	(0.33)	.00	.18	(0.19)	.17	(0.37)	.04
AB540	.07	(0.12)	.07	(0.26)	.01	.07	(0.11)	.07	(0.25)	.02	.04	(0.08)	.05	(0.22)	-.05	.06	(0.08)	.06	(0.24)	.00	.11	(0.15)	.10	(0.30)	.02
Prior coursetaking																									
First term	.08	(0.13)	.09	(0.28)	-.02	.08	(0.11)	.11	(0.31)	-.09	.19	(0.17)	.21	(0.41)	-.04	.05	(0.07)	.04	(0.20)	.03	.18	(0.19)	.17	(0.37)	.03
N terms enrolled	7.53	(2.25)	7.33	(4.75)	.04	8.09	(2.38)	7.75	(5.83)	.06	6.61	(2.23)	6.71	(5.93)	-.02	7.82	(1.83)	7.96	(5.28)	-.03	6.11	(2.50)	6.18	(5.22)	-.01
Credits earned	53.02	(15.74)	52.47	(31.19)	.02	54.76	(15.52)	52.64	(36.59)	.06	43.86	(14.75)	43.72	(36.82)	.00	53.73	(12.41)	54.59	(30.91)	-.03	41.96	(16.35)	41.44	(34.66)	.02
Any dual enrollment credits	.30	(0.21)	.30	(0.46)	.00	.18	(0.16)	.16	(0.37)	.03	.20	(0.17)	.21	(0.41)	-.03	.16	(0.12)	.17	(0.38)	-.01	.20	(0.20)	.19	(0.39)	.02
Prior GPA	2.98	(0.44)	2.97	(0.95)	.01	2.94	(0.41)	2.85	(1.11)	.08	2.75	(0.52)	2.70	(1.22)	.04	2.91	(0.32)	2.91	(1.01)	.00	2.74	(0.62)	2.77	(1.28)	-.02
Focal term coursetaking																									
Credits att.	11.49	(1.68)	11.38	(4.09)	.03	9.70	(1.53)	9.72	(3.55)	.00	10.52	(1.66)	10.38	(3.51)	.04	10.15	(1.29)	10.04	(3.56)	.03	14.98	(4.26)	15.04	(8.37)	-.01
STEM credits att.	9.13	(1.61)	9.03	(3.75)	.03	7.50	(1.19)	7.51	(3.05)	.00	8.31	(1.41)	8.11	(2.65)	.07	7.90	(1.16)	7.85	(3.00)	.02	10.45	(3.00)	10.47	(5.59)	.00
Math and Computer Science course group	.04	(0.09)	.04	(0.21)	-.02	.27	(0.19)	.27	(0.45)	.00	.37	(0.21)	.35	(0.48)	.02	.32	(0.16)	.31	(0.47)	.01	.30	(0.23)	.34	(0.48)	-.09
Advanced Math course group	.48	(0.23)	.48	(0.50)	.01	.30	(0.19)	.30	(0.46)	-.01	.21	(0.18)	.23	(0.42)	-.04	.38	(0.16)	.38	(0.49)	.01	.25	(0.22)	.23	(0.43)	.04

	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
Biology and Chemistry course group	.48 (0.23)	.48 (0.50)	.00	.42 (0.20)	.41 (0.50)	.01	.42 (0.21)	.40 (0.49)	.02	.28 (0.15)	.29 (0.46)	-.01	.37 (0.24)	.36 (0.48)	.04
Multiple SI course enrollment	.03 (0.08)	.03 (0.17)	.01	.05 (0.09)	.05 (0.23)	-.03	.04 (0.09)	.05 (0.22)	-.02	.04 (0.06)	.04 (0.20)	-.02	.07 (0.13)	.07 (0.25)	.03
Multiple SI course group	.00 (0.00)	.00 (0.00)	DNE	.01 (0.05)	.01 (0.12)	.00	.01 (0.04)	.02 (0.13)	-.04	.02 (0.05)	.02 (0.14)	.01	.07 (0.13)	.07 (0.25)	.03
Prior STEM coursetaking															
Highest math	3.05 (0.98)	3.00 (2.07)	.02	2.98 (0.82)	2.95 (1.94)	.02	2.28 (0.87)	2.27 (2.07)	.00	3.17 (0.65)	3.15 (1.94)	.01	2.65 (0.95)	2.63 (1.99)	.01
No prior math	.12 (0.15)	.12 (0.32)	.00	.13 (0.14)	.16 (0.37)	-.09	.28 (0.19)	.29 (0.46)	-.03	.11 (0.11)	.10 (0.31)	.03	.23 (0.21)	.24 (0.43)	-.03
Prior TL STEM credits	19.88 (8.29)	19.58 (16.91)	.02	19.65 (7.18)	19.33 (17.25)	.02	15.60 (7.03)	15.66 (17.17)	.00	20.25 (5.99)	20.73 (14.69)	-.03	15.19 (6.90)	15.34 (15.28)	-.01
Prior NTL STEM credits	4.86 (2.07)	5.10 (4.76)	-.05	4.75 (2.02)	4.52 (4.87)	.05	4.35 (2.06)	4.23 (4.75)	.03	4.90 (1.65)	4.89 (4.81)	.00	3.70 (2.25)	3.77 (4.81)	-.01
Prior TL STEM GPA	2.66 (0.59)	2.64 (1.22)	.02	2.59 (0.54)	2.54 (1.34)	.04	2.19 (0.65)	2.15 (1.47)	.02	2.65 (0.41)	2.63 (1.16)	.02	2.45 (0.68)	2.50 (1.44)	-.04
Prior NTL STEM GPA	2.00 (0.78)	2.06 (1.69)	-.04	1.79 (0.71)	1.68 (1.72)	.06	1.61 (0.70)	1.55 (1.63)	.04	1.86 (0.58)	1.92 (1.66)	-.04	1.39 (0.82)	1.42 (1.68)	-.02
No prior NTL STEM credits	.12 (0.15)	.12 (0.32)	.01	.13 (0.14)	.15 (0.36)	-.07	.26 (0.19)	.26 (0.44)	.00	.11 (0.10)	.10 (0.31)	.01	.18 (0.19)	.18 (0.38)	.01
No prior TL STEM credits	.38 (0.22)	.36 (0.48)	.03	.43 (0.21)	.47 (0.50)	-.08	.45 (0.22)	.47 (0.50)	-.03	.42 (0.17)	.40 (0.49)	.04	.56 (0.25)	.54 (0.50)	.02
Prior program participation															
Prior SI or SLC	.18 (0.17)	.17 (0.38)	.01	.24 (0.18)	.25 (0.43)	-.01	.31 (0.20)	.31 (0.46)	.00	.55 (0.17)	.54 (0.50)	.01	.33 (0.24)	.33 (0.47)	.00
Prior STEMPP support	.07 (0.12)	.07 (0.26)	.00	.09 (0.12)	.11 (0.31)	-.06	.19 (0.17)	.18 (0.39)	.03	.26 (0.15)	.25 (0.44)	.03	.24 (0.21)	.24 (0.43)	-.01
N	*330*	*69*		*402*	*73*		*334*	*62*		*426*	*48*		*343*	*90*	

[a] Does not exist. No treatment students in fall 2017 were enrolled in multiple SI course groups; therefore, the SMD (calculated as the difference between the control and treatment mean, divided by the treatment SD) cannot be calculated.