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STEM SUMMER PROGRAMS FOR UNDERREPRESENTED YOUTH INCREASE STEM DEGREES

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ABSTRACT

Underrepresentation of Black and Hispanic workers in STEM fields contributes to racial wage gaps and reduces innovation and economic growth. "Pipeline" programs intended to increase diversity are a common intervention to address these problems, but there is little rigorous evidence of their efficacy. We fielded a randomized controlled trial to study a suite of such programs targeted to underrepresented high-school students and hosted at an elite technical institution. Students offered seats in the STEM summer programs were more likely to enroll in, persist through, and graduate from elite colleges and to graduate with a degree in a STEM field. These improvements in college outcomes raised predicted earnings by 3 to 15 percentage points. Increased knowledge of the college application process and a more ambitious college application strategy appear to be a key mechanism.

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1 Introduction

Black and Hispanic workers are underrepresented in the high-wage, college degree–holding science, technology, engineering, and mathematics (STEM) workforce (National Science Board, 2021). The lack of diversity in STEM fields contributes to racial and ethnic wage gaps (Budig et al., 2021), reduces innovation (Parrotta et al., 2014; Hofstra et al., 2020; Yang et al., 2022), and dampens economic growth (Cook et al., 2021; Hsieh et al., 2019).[1] Billions of dollars are spent each year on STEM pipeline programs to correct racial disparities in STEM fields, but we know little about such programs' efficacy.[2]

Increasing STEM college degree attainment among underrepresented minorities is necessary to ultimately diversify the STEM workforce. Approximately 9 percent of STEM bachelor's degrees went to Black students and 16 percent to Hispanic students, despite these groups representing 14 and 21 percent, respectively, of the US college-age population (National Science Board, 2022). The disparity in STEM degree attainment is not due to differences in interest. Upon entering college, underrepresented minority students plan to major in STEM fields at rates similar to those among their white peers, but they are more likely to switch away from a STEM field or leave college (Riegle-Crumb et al., 2019), suggesting that college experiences are important factors in STEM degree attainment. In particular, access to well-resourced colleges and STEM preparation could help students persist in college and in a STEM major.

Given that access to college and preparation for college STEM experiences are shaped prior to college entrance, STEM-focused enrichment programs for high-school students are promising vehicles to reduce disparities in STEM degree attainment and STEM workforce participation. However, the efficacy of such programs in boosting long-term STEM persistence is unknown. The existing evidence primarily relies on short-term survey assessments and on observational studies whose findings may be substantially driven by selection bias (Kitchen et al., 2018a; Kitchen et al., 2018b; Bradford et al., 2021).[3] An exception is Robles's (2018) prior investigation of one of the most intensive of the three programs we examine here. Using long-term administrative data on earlier

[1]The STEM wage premium likely reflects selection into STEM fields by individuals with high earning potential but remains even when student background is accounted for (Arcidiacono, 2004; Altonji et al., 2012; Hastings et al., 2013; Kinsler and Pavan, 2015; Altonji et al., 2016; Kirkeboen et al., 2016; Lovenheim and Smith, 2022).

[2]In 2011, there were over 250 federal programs and $3.4 billion invested in the STEM pipeline (Granovskiy, 2018), including over $1 billion in funding through the National Science Foundation (NSF) with the specific goal of increasing diversity and representation (see NSF budgets for "Broadening Participation" efforts here: `https://www.nsf.gov/od/broadeningparticipation/bp_investments.jsp`.) Approximately three-quarters of this federal investment supports undergraduate and graduate education and training, with K–12 initiatives receiving less support (authors' calculations from Granovskiy, 2018).

[3]Some summer programs to increase representation in STEM-adjacent fields, including the American Economic Association Summer Program (Price, 2005; Becker et al., 2016) and the Robert Wood Johnson Foundation Summer Medical and Dental Education Program (Cosentino et al., 2015), have been rigorously analyzed and found to increase representation in their focus areas. However, although these evaluations offer more rigorous comparisons to nonprogram students than many other studies, they are not randomized trials, and they focus on STEM-adjacent fields (e.g., economics, health professions). These works generally find that program participation leads to greater success in the focus field.

cohorts and a selection-on-observables design, she finds that access to a six-week residential STEM summer program increases matriculation at the host institution, college graduation, and likelihood of graduation with a STEM degree. However, this study does not fully account for selection into the program. Thus, to better understand whether STEM programs for high-school students can serve as tools to successfully diversify STEM fields, we conducted a randomized controlled trial (RCT) of a suite of summer programs targeted at boosting the number of underrepresented students in the STEM degree and career pipeline, following students from their application to the programs through college degree attainment.

This study provides the first randomized evidence on the impact of STEM-focused summer programs on college matriculation, completion, and graduation with a STEM degree. It is also one of the few RCTs among *all* the interventions aimed at diversifying the STEM educational pipeline. Three cohorts of high-achieving, STEM-interested students were randomized to three STEM-focused programs and a control group in the summer between their junior and senior years of high school in 2014, 2015, and 2016, prior to college application. Given program needs, the randomization design partially took into account program application scores. We thus present both estimates for the subpopulation of completely randomized applicants and estimates subject to additional underlying assumptions for the full sample of conditionally randomized applicants.

The programs were held at the Host Institution (HI), an elite technical university in the Northeast. They differed in modality and intensity: the first consisted of six weeks of full-time on-site programming, the second of one week of full-time on-site programming, and the third of six months of periodic online meetings and a short on-site visit. Students were selected into the randomization pool based on their academic preparation and a holistic assessment of need that included whether they had backgrounds that were underrepresented in STEM fields. The six-week program was held on the HI campus and offered a shortened version of the HI's freshman curriculum, along with college counseling, field trips, introductions to role models in STEM fields, and a college-like living experience. The one-week version of the program offered a short, intensive course in a STEM field and an abbreviated version of other aspects of the six-week program, again on the HI campus. Finally, the online version of the program offered a six-month engagement in STEM enrichment activities, with online speakers and interactions and a short "conference" visit to the HI campus over the summer.

Almost all students in the control group (88 percent) attended a four-year college immediately after high-school graduation, and the programs increased this by a small and statistically nonsignificant magnitude (1 to 4 percentage points). However, the programs did induce large, statistically significant shifts toward attending elite schools: For the six-week program, these additional elite-institution enrollments were primarily at the HI. For the one-week and online programs, they were split between the HI and other colleges. The effects of the STEM summer programs on college enrollment became more pronounced as the students progressed through college. By the fourth year of study, those offered a seat in any of the three STEM summer programs were 3 to 12 percentage points more likely to still be enrolled in a four-year college. This effect is largely driven by reductions in the control group's college attendance and by improvements in the treated students' persistence in elite colleges, including the HI.

The programs' effects on college persistence translate to higher rates of on-time college graduation. Despite the control group being academically talented, only 56 percent of control students graduated within four years from any four-year school. The STEM programs increased this by 3 to 7 percentage points, though the differences are not statistically significant. The impacts on graduation become more precise at a longer graduation horizon: All three programs boosted the share of students who attained a BA within 6 years by 2 to 9 percentage points, though the difference is not statistically significant for the six-week program. BA attainment from elite institutions increased by 9 to 15 percentage points, with most of the increase for the six-week program coming via the HI and the gains in elite BA attainment from the other two programs being shared across the HI and other institutions.

The degree gains were primarily in STEM fields, reflecting both an overall increase in the number of degrees earned and a shift to STEM fields among graduates. In the control group, 52 percent of students graduated within six years with a STEM degree—corresponding to 72 percent of the degree recipients in this group. The six-week and one-week programs increased the rate at which students graduated with a STEM degree to 64 percent and the online program to 55 percent (the latter is not significant). We summarize the combined effects of these shifts in quality of the institution of enrollment and in choice of major by means of estimates of program impacts on potential earnings, as measured by the College Scorecard for previous cohorts at each college by major combination. This exercise implies that a student's being offered a spot in one of the summer STEM programs raised his or her potential earnings by 3 to 15 percent via effects on quality of the degree-granting institution and choice of a STEM major.

We find evidence that the programs' effect on degree completion is due to the shifts that they induce in quality of the institutions in which students enrolled. The increases in overall graduation rates are similar to what would be predicted by these shifts alone, as measured by institution-level graduation rates. The programs potentially achieved these shift by enhancing students' information about colleges and the college application process, as shown via administrative application data from the HI and survey data on other college applications. We also use the survey data to explore other mechanisms such as improvements in study and independent living skills and high-school preparation. The programs did boost AP/IB enrollment in high schools and study and life skills, but the magnitudes of these changes are not large. We thus suggest that college quality likely plays the greatest role in explaining the graduation effects that we identify. We find some potential evidence for a role of signaling in college admissions for the six-week program at the HI, but we conclude from the full body of evidence on mechanisms that the college application channel is the most important.

This paper makes three main contributions. First, we add to the evidence on STEM degree attainment and diversity among STEM degree holders. Most research on STEM degree production focuses on what happens during college, concentrating on the gender or race match between students and instructors or peers (see, for example, Bettinger and Long, 2005; Hoffmann and Oreopoulos, 2009; Griffith, 2010; Carrell et al., 2010; Bettinger, 2010; Price, 2010; Fairlie et al., 2014; Fischer, 2017; Griffith and Main, 2019), student beliefs in their own capability and signals from grades (Astorne-Figari and Speer, 2019; Kaganovich et al., 2021; Owen, 2020; Kugler et al., 2021; Owen, 2021) and institutional effects (Griffith, 2010; Arcidiacono et al., 2016). Less attention has been paid to the preparatory experiences that may shape college attendance and major choices and eventually occupational sorting and labor market disparities, despite the potential influence of precollege experiences on STEM degree attainment (Sass, 2015; Green and Sanderson, 2018). The few studies on high-school STEM exposure find differing effects on STEM major choices and degree attainment. For the US, Darolia et al. (2020) find that exposure to more STEM courses in high school does not increase STEM degree attainment in college, while De Philippis (2021) finds that, in the United Kingdom, such exposure increases the likelihood of male students majoring in STEM, and Joensen and Nielsen (2016) find an increase only for female students in Denmark. Although the differences in these findings may be due to differences in context, it is also possible that broad programs with no specific focus on underrepresented students or those that do not affect college applications may have little effect.

Second, we contribute to the understanding of access to college, the match between student preparation and quality of institution of enrollment, and the potential for college education to reduce racial and economic inequality in the US. There are large gaps in college enrollment by family income in the US (Bailey and Dynarski, 2011; Chetty et al., 2020; Dynarski et al., 2021). In addition, there are differences in the type and quality of the institutions where they enroll (Gerber and Cheung, 2008; Baker et al., 2018). College enrollment and selectivity lag behind even for high-achieving underserved students (Hoxby and Avery, 2013; Dillon and Smith, 2017), resulting in "undermatch," whereby students who could succeed at selective institutions do not even apply (and thus cannot enroll). The college a person attends can influence her likelihood of graduating (on time) and of graduating with certain degrees and her future employment and earnings (Hoekstra, 2009; Cohodes and Goodman, 2014; Zimmerman, 2014; Goodman et al., 2017; Chetty et al., 2020; Bleemer, 2021). Interventions prior to college application can influence enrollment and the specific institutions where students enroll (Avery, 2010, 2013; Carrell and Sacerdote, 2017; Castleman and Goodman, 2018; Andrews et al., 2020; Dynarski et al., 2021). Similarly to effective college counseling and informational interventions that modify college application and enrollment behavior, the STEM summer programs we examine happened at a crucial time: when the students were seriously considering college but had not yet applied. However, the STEM summer programs we focus on differ from many college access programs in their intensity and focus on STEM.

Finally, this paper is relevant to a large literature on the impacts (or lack thereof) of affirmative action in college admissions. STEM summer programs do not introduce group-based preferences in college admissions—policies that are typically the focus of the affirmative action literature in economics. They do, however, focus on populations characterized by a broad definition of need that includes belonging to historically underrepresented groups, and they aim to increase access to STEM fields and elite universities for these groups. Much of the literature on affirmative action is concerned with mismatch—the idea that underrepresented minority (URM) students will be unprepared for the academic rigor of campuses with affirmative action preferences and thus might be made worse off by such policies (see Arcidiacono and Lovenheim, 2016) for an overview. Although Arcidiacono et al. (2016) find some evidence of mismatch, Bleemer (2022) finds college and earnings benefits for URM students induced to attend more selective University of California campuses because of affirmative action. Our work adds to the evidence that when URM students are induced to attend high-quality institutions, they successfully reap the benefits of those institutions, in contrast to the predictions of mismatch theory.

The paper proceeds as follows. Section 2 describes the program background and context, including more details on the interventions. Section 3 details the data, and Section 4 explains the study design and estimation methods. Our results are reported in Section 5, with a discussion of potential mechanisms in Section 6. Section 7 concludes.

2 STEM summer programs at the HI

The HI maintains an office devoted to outreach programs to increase representation of URM students in STEM fields; we refer to this unit as the outreach office. Its programming includes outreach to the local community with initiatives designed for elementary and secondary students and national summer programs for high-school juniors. The summer programs are the focus of this study. The aim of the programs is to diversify the STEM workforce and increase access to STEM careers by exposing students to high-achieving peers, STEM mentors, a STEM curriculum, tours of a college campus and research facilities, and college admissions information. Recruitment is national. All programs cover student costs except for transportation to and from the HI. The programs are funded by the HI, with some funding from earmarked charitable gifts. High-achieving students in any geographic region can be recruited as long as they are US citizens or permanent residents. One source of student information used in direct mailings for recruitment is the PSAT, though students do not need to submit test scores to apply to the program.

We describe each summer program below as it existed in the summers of 2014–2016, the period over which the randomization occurred. All of the outreach office's programs offer similar experiences designed to promote persistence in STEM fields, but the intensity and modality of the experiences vary.

1. *Six-week program*: The six-week program is the longest-running summer program of the three studied. It is a residential program that immerses rising high-school seniors in rigorous science and engineering classes. Students take courses in math, physics, life sciences, and humanities, as well as a STEM-related elective course with topics ranging from digital design to genomics. In addition, students take tours of labs and work spaces at the HI, attend workshops with industry leaders, academics, and admissions officers, and interact with teaching assistants who are current college students. Students also visit STEM-focused companies and workplaces. The program encourages social cohesion by bringing students together to live in dorms at the HI and leading team-building exercises. Approximately 80 students are offered a seat in this program each year.

2. *One-week program*: The one-week program encapsulated some aspects of the six-week program in a shorter time frame and was also a residential program. Over the week, students completed a project course in an engineering field, attended admissions and financial aid sessions, toured labs, met with HI faculty, students, and alumni, and participated in social events. The time constraint necessarily reduced the dosage of all aspects of the six-week program, though to what extent outcomes are sensitive to this reduction is an empirical question. Typically, 75 to 120 students participated in this program each year.[4]

3. *Online program*: The online treatment draws on communications technology to serve students. This six-month program provides a platform for multimedia interaction between students and instructors, HI staff, and industry leaders. HI students are hired to mentor small groups of participants and lead discussions. The online summer program provides top-down content in the form of videos, articles, or webinars. Students must also complete project-based engineering assignments. The forum and discussion groups provide user-generated (and instructor-facilitated) content. Students also spend five days on campus presenting their final projects, attending workshops, and meeting their classmates in person. The campus visit occurs five weeks into the online experience, which lasts until the end of the calendar year. Approximately 150 to 175 students participated in the online program. The summer sessions that we study occurred well before the COVID-19 pandemic, but the technology platform used for the online program facilitated a transition to digital learning for all of the summer programs in COVID-affected years.

4. *Control condition*: Students assigned to the control condition also applied to the HI's summer programs but were not randomly assigned to participate in any programs offered by the outreach office. However, these applicants were generally also accomplished students (typically in the top third of applicants to the summer programs as a whole). Being assigned to the control group does not mean that the applicant had no exposure to STEM-focused programming.

[4] This program is no longer operating.

Many students in this group participated in alternative summer programming, both STEM-focused and otherwise, such as programs administered by other universities or organizations such as Girls Who Code or Leadership Enterprise for a Diverse America. However, many also worked or studied over the summer in lieu of enrolling in specialized programming.

3 Data and descriptive statistics

This study measures the effect of STEM summer programs on the college outcomes of high-achieving underrepresented high-school students using data from an experiment that randomized admission to these programs in the summers of 2014, 2015, and 2016. Below, we detail the data sources used, which include records from the outreach office on summer program application and admission, college attendance and graduation records, and survey data, and describe the characteristics of program applicants.

3.1 Data

The data for our main analyses come from two main sources: program application and admissions information from the HI and college attendance and graduation information from the National Student Clearinghouse (NSC). All applicants in the three cohorts from 2014 to 2016 were admitted via conditional random assignment, and the assignment and randomization process was jointly created by the research team, program staff, and the HI institutional research office to meet both research and operational needs (Cohodes et al., 2022). Background information on the randomized sample comes from program applications, which included demographic information, academic qualifications, essays, and a baseline survey. The outreach office provided details on offers of admission and which students ultimately participated in the programs, as well as details on the ratings of applicants' files and about the admissions process.

The outcome data come from records of college enrollment provided by the HI institutional research office and the NSC; the former also provides information on applications and majors at the HI. Almost all of the applicant pool appears in the HI or NSC college enrollment data, and since all students' information was shared with the NSC and HI for matching to enrollment data, there is no differential attrition in the possibility of appearing in the college data (see Online Appendix Table A.3). Our time horizon allows us to observe graduation within 6 years for all three cohorts. The NSC data also include information on students' majors, which we categorize as either a STEM or non-STEM field.[5] We also categorize college institutions as elite if they are

[5] Due to lack of reporting to the NSC, information is missing for 12 to 15 percent of the degree recipients, depending on the time horizon. To address this data missingness issue, we assume that bachelor of science degrees represent STEM majors for those without information on majors. We also explicitly display results by the rate of missingness of degree information and show upper and lower bounds on the results derived when we categorize all missing degrees as either non-STEM or STEM. The HI always reports the degree field. See Table B.9 for details.

ranked "most competitive" by *Barron's Guide.* Online Appendix Figure A.1 shows the timing of the observations through college for each of the three cohorts, assuming on-time progression.

3.2 Surveys

Survey data were also periodically collected from the study sample. Longer surveys were conducted (1) in the fall shortly after the summer program, (2) in May of the students' senior year of high school, and (3) in the spring of the students' sophomore year of college. Shorter, more frequent surveys kept track of college enrollment and students' ultimate or intended college major. Respondents received Amazon gift cards if they participated (not contingent on answering all questions or on treatment assignment), with larger incentives for participating in the longer surveys ($25) and smaller incentives for participating in the shorter surveys ($5).

The survey at the end of the summer program included questions about college plans, knowledge of the application process, intended major, and study and life skills. The survey in May of senior year collected information on college application and admission and fall plans. The final long-format survey at the end of sophomore year in college asked about college experiences, majors, and career intentions. More details on these surveys are in Online Appendix C. When a survey included multiple items on similar topics, we constructed standardized indices of the outcome measures from the surveys by outcome "family" using the method in Anderson (2008) to minimize concerns about multiple hypothesis testing.

Response rates were relatively high but declined over time and were lower for the control group. Online Appendix Table A.3 shows the response rates for each survey. For example, for the first long follow-up survey in the fall after program participation, the treatment groups' response rates ranged from 85 to 90 percent; 65 percent of the control group responded to this survey. These differences in response rates are unsurprising given that treatment students were more likely to have positive associations with the program office or be enrolled in the HI, which was the entity sending out the surveys.

To assess the representativeness of the survey response sample, the analysis compares program impacts on college attendance and graduation between the survey sample and the full sample both with and without inverse propensity-to-respond weights (see Online Appendix Table E.2). Restricting to the survey sample and adding inverse probability weights have an inconsistent impact on the treatment effect estimates. In some cases, these changes to the specification bring the estimates of the impacts on college outcomes for survey responders closer to those for the full sample than to those for the unweighted sample of respondents; in others, they make the estimates for survey respondents look more divergent than those for the full sample. Thus, it is not clear that propensity to respond predicts the program effects in a meaningful way. Following Dutz et al. (2021), we use the unweighted survey responses but caution that the sample is not fully representative. We thus consider our findings based on the surveys to be suggestive.

3.3 Descriptive statistics

Table 1 reports demographic and background academic information for the randomized sample. As described below, the randomization included design strata, so we do not expect the treatment and control groups to be exactly similar on all characteristics. We show in Columns 6 through 8 that after strata adjustment, the treatment group has few differences from the control group.[6] Overall, almost all randomized applicants identified themselves as belonging to a group underrepresented in higher education and STEM fields, with 35 percent of the sample being Black, 43 percent Hispanic, and 4 percent Native American (note that these categories are overlapping, as the students were able to report more than one race or ethnicity). Approximately one-quarter of the group were first-generation college students, which we define as having no parent who ever attended a four-year college. The program applicants had strong academic backgrounds. The average grade point average (GPA) is 3.86 on a four-point scale, and the average standardized math test score is two standard deviations above the national mean.[7] The largest contrast between the treatment and control groups is on gender. The outreach office seeks to host programs equally split between young women and men, but the applicant pool skews male. Thus, the randomization strata included gender.

4 Research design

The STEM summer program applicants were randomized into receiving an offer to participate in one of the three summer programs or being assigned to a control group. To meet programmatic needs, the random assignment was partially conditioned on applicant rating. This section describes the process through which applicants were randomized and how the we estimate the program effects based on that randomization process. Online Appendix A provides further details on the selection and randomization process.

4.1 Selection

Selection into the programs was a multistep process. Each year, after an initial screening, the outreach office sent approximately 600 to 750 highly qualified applicants to a selection committee made up of stakeholders, community members, and affiliates with long-standing ties to the outreach

[6]For more details on covariate balance, see Online Appendix Tables A.4 through A.6, which show that within strata, there are few differences by background characteristics across treatment and control conditions *within* randomization blocks.

[7]Applicants to the STEM summer programs submit standardized test scores from various exams, the most common being the PSAT. We use information on national test score means and standard deviations to convert each test score to a z-score, which allows us to combine across several standardized exams including the PSAT, SAT, ACT, and PLAN. To compare the program applicants' academic backgrounds to those of students typically admitted to the HI, we standardize by the HI's 25th percentile math SAT of the incoming freshman cohort in the same time period as the STEM summer program experiment, which was 740, or 1.91 in standard deviation units. Thus, the average scores of program applicants were in line with the scores of incoming students at the HI.

office. The selection committee ranked applicants in terms of suitability for the six-week program and provided detailed scores on their academic preparation and personal circumstances on the basis of their grades, test scores, letters of recommendation, and application essays. In addition, because the mission of the programs is to promote access to STEM for traditionally underrepresented populations, the selection process included consideration of the following factors on a holistic basis, though no element in isolation guaranteed admission:

1. The applicant would be the first in the family to attend college
2. The applicant's family did not have science and engineering backgrounds
3. The applicant's high school historically sent less than 50 percent of its graduates to four-year colleges
4. The applicant attended a high school that presented challenges for success at an elite, urban university (e.g., a rural high school or a high school with a predominantly URM population)
5. The applicant was a member of a group that is underrepresented in the study and fields of science and engineering (African American or Black, Hispanic or Latino/a, or Native American)

The selection committees were idiosyncratic in how they evaluated applications; for example, some committees emphasized academic preparation, while others were more focused on perceived need for the program.

The outreach office also requested regional priorities to increase representation across the country, and these entered into the rankings in 2015 and 2016. In 2014, the outreach office exempted several applicants from randomization and offered them admission to support national representation; we call these cases "certainty spots" and exclude them from the analytic sample. The HI institutional research office performed the final program assignment by lottery after all students were ranked, creating a ranking variable that was a weighted average of applicant ratings and regional priorities; the rankings were used to allocate students to random assignment blocks as described in Section 4.2 below. Notably, because the randomization occurred in a group designated as top applicants from a pool of more than 2,000 applicants, the program effects estimated here may not apply to all applicants or to others outside the selective applicant pool. The program, if offered to rising high-school seniors in general, might have very different (or no) impacts on those less academically prepared.

4.2 Randomization

The selection process above created a pool of 600 to 750 applicants eligible for randomization each year. Because the outreach office wanted to ensure that top-ranked students had access to one of the summer programs, the study employed a block randomization design. The HI institutional research office placed students into randomization blocks based on the rating variable that took into account application ratings and regional priorities. An overview of the randomization scheme appears in Online Figures 2a through 2c.

In general, the highest-ranked students were placed in Block 1 and randomized between the three summer programs. To maintain gender balance in the program, there were different rating score cutoffs for male and female students. Additionally, to ensure students in Block 1 were prepared to take on the rigorous coursework in the six-week program, a math test score floor was imposed for assignment to Block 1. The remaining students were placed in Block 2 and were randomly assigned between the online program and a control group. The size of the blocks and assignments to programs varied by year based on operational considerations. This randomization scheme formed the research design in cohorts 2 and 3 of the experiment. Cohort 1, in 2014, was subject to a slightly different design, where students were differentiated to a greater extent and randomly assigned within three blocks. Our results are very similar whether we include or exclude the first cohort (see Online Appendix Table C.2). We include the 2014 cohort to increase statistical precision, despite the slightly different underlying randomization structure, which we account for via inclusion of randomization strata.

The crucial component of the conditional randomization design is the overlap of the online program across the blocks, which we use to extrapolate comparisons between Block 1 programs and the control group in Block 2. The key assumption behind this extrapolation is that if we control for randomization strata (based on application year, gender, block, and regional preferences), we fully account for differences across the blocks and can compare the applicants assigned to Block 1 (which has no control group) to those in Block 2 (which has a control group). By design, we can fully account for membership in a block with known variables. To test this assumption, we compare our estimates for the conditionally randomized sample to those for the embedded purely randomized sample and find generally similar results.

4.3 Estimation

We use random assignment to program offers to estimate in two different ways the causal effect of assignment to one of the three STEM summer programs. First, we compare *within* randomization blocks, separately comparing the outcomes for those in the residential programs to those assigned to the online program and the outcomes for students in the online program to those for the control group, as in Cohodes et al. (2024). This comparison relies only on random assignment, with no extrapolation across blocks. However, these comparisons have reduced power given the smaller sample sizes. Second, we follow the structure of the conditional random assignment, comparing the outcomes for students across all of the programs to those of the control group, controlling for blocks. This strategy allows us to use all of the data and increase statistical power but relies on the assumptions that the treatment effects are linear in the rating variable and that we can extrapolate across blocks.

Using random assignment, we make two comparisons. The first is within Block 1. We estimate the causal effect of assignment to a residential STEM summer program relative to the outcomes of students assigned to the online program:

$$Y_i = \beta_{6w} 6week_i + \beta_{1w} 1week_i + \sum_{j=1}^{J} \delta_j S_{ij} + X_i' \gamma + \epsilon_i. \tag{1}$$

Next we make use of the random assignment within Block 2, estimating the causal effect of assignment to the online program relative to the control group's outcomes:

$$Y_i = \beta_o Online_i + \sum_{j=1}^{J} \lambda_j S_{ij} + X_i' \omega + \eta_i. \tag{2}$$

In both equations, we are interested in a college outcome Y_i such as college graduation for applicant i. Random treatment assignment is shown with the indicator variables $6week_i$ and $1week_i$ in Equation 1 and $Online_i$ in Equation 2. Intent-to-treat estimates of the effects of program offers are shown by the β coefficients. β_{6week_i} and β_{1week_i} are the estimates of the difference between applicants offered a seat in one of the residential programs and those offered a slot in the primarily online program. β_{online_i} is the estimate for the difference between applicants offered a spot in the online program and those assigned to a control group. A vector of student-level control variables X_i, including GPA, standardized math scores, race/ethnicity, and free or reduced-price lunch status, increases precision. We include randomization strata, R_{ij}, to account for differences across program years, the preference for gender-balanced enrollment, and the regional preferences. The program offers were randomized within these strata. We use heteroskedasticity-robust standard errors. We refer to the estimates derived with this strategy as the "pure randomization" estimates.

To compare the estimates from Block 1 directly to those for the control group, we use seemingly unrelated regression (SUR) to combine the Block 1 and Block 2 estimates. The interpretation of these estimates as the true program effects relies on the same assumptions that we detail below for our second estimation strategy.

Our second estimation strategy is to jointly estimate the treatment effects in comparison to the control group outcomes but relies on additional assumptions. We estimate the impacts from conditional random assignment as follows:

$$Y_i = \beta_1 6week_i + \beta_2 1week_i + \beta_3 Online_i + \sum_{n=1}^{N} \delta_n R_{in} + X_i' \gamma + \epsilon_i \tag{3}$$

where Y_i is an outcome of interest for applicant i such as enrollment in a top-ranked college and $6week_i$, $1week_i$, and $Online_i$ are the indicators for random assignment to an offer of treatment in each of the three programs. The parameters of interest are the β coefficients, which reflect the intent-to-treat estimate of the effect of assignment to one of the three programs. Most students attended their assigned program if offered a spot, with 87 percent of students accepting a seat in the six-week program, 85 percent in the one-week program, and 77 percent in the online program (Online Appendix Table A.2). Very few students ended up participating in a different program, and the outreach office did not offer any spots to students in the control group. As above, we include a vector of student characteristics X_i to increase precision and use heteroskedasticity-robust standard errors.

Key to our estimation strategy is the inclusion of a set of control variables, or risk sets, R_{in}, which are indicators representing the randomization strata. The randomization strata comprise gender, regional preferences,[8] and randomization block and are formed within randomization year. Offers were randomized within these strata. Students were assigned to randomization blocks based on a rating variable and a standardized test score floor. The rating variable includes ratings by a selection committee, assessment by the HI admissions office, and prioritization for certain regions and states of the country (typically to ensure that the participants were broadly representative of the US as a whole). The conditional randomization estimation method compares students within the same cohort, gender, regional preference, and randomization block.

The fundamental assumption behind our second estimation strategy is that by controlling for randomization block, we control for all differences across blocks and can compare students randomly assigned to a treatment group to those in the control group even when we do not have a direct treatment–control contrast in the same block. Including the online program in both randomization blocks provides the link that makes it possible to draw this comparison. Because block assignment was based completely on known, observable variables, controlling for randomization block should control for all differences between the two groups. We thus refer to our estimates derived with this strategy as the "conditional randomization" estimates. Since the pure randomization estimates align very closely with the conditional randomization estimates, we rely on the latter to draw our main conclusions but report the former, as well.

We consider in detail a potential threat to the validity of our SUR and conditional randomization estimates of the program effects and the conditional randomization scheme: namely, treatment effect heterogeneity. If there are differential returns to the program for different types of applicants—that is, if the treatment effects are heterogeneous—our results may not be fully representative because the control group includes only relatively lower-ranked students. Section 5.5.3 explores this concern and shows limited evidence that differential response by rating drives our estimates of the program effects.

Section 5.5 presents several additional robustness checks. We consider multiple alternative specifications and conduct an exercise in which we omit each cohort in turn. Because the ran-

[8] These are geographic preference indicators for regions of the country that are preferred, neutral, or down-weighted.

domization possibilities are constrained to only those students within the strata discussed above (i.e., complete randomization is not possible), we also present our estimates derived by means of randomization inference to account for the possibility that only a subset of potential outcomes are possible given the constraints of our design (see Athey and Imbens (2017) for a discussion of this approach). Specifically, we rerun our randomization scheme 1,000 times, subject to the same rules and constraints as in the actual randomization. We then compare our point estimate to the distribution of estimates generated by random assignment. As in a Fisher's exact test, if the point estimate exceeds the 97.5th percentile of the distribution of randomized estimates (or 95th percentile with a one-tailed test), we consider that estimate to be different from zero. All of these exercises yield results similar to our main estimates.

5 Results

This section details how the programs affected college enrollment, college graduation, and college quality. All of our outcomes are based on windows from the time of high-school graduation. For example, six-year college graduation reflects college completion within six years of high-school graduation (seven years after the summer program), not six years from the time of college entrance. The tables report the estimates from both the pure randomization (Panels A, B, and C of the relevant tables) and conditional randomization (Panel D) strategies. For conciseness, the figures report only the conditional randomization estimates.

5.1 College enrollment and persistence

We present our key findings on the college trajectory in Table 2, which includes both the pure and conditional randomization estimates for initial college attendance and BA receipt within six years for all four-year colleges, elite colleges, and the HI. Figure 1 reports the attendance and graduation effects of the conditional random assignment, divided among the HI (light shading), other elite institutions (medium shading), and other four-year institutions (dark shading). Complete estimates for all years of college attendance and graduation, at colleges of multiple types, appear in Online Appendix Tables B.1 through B.7.

Almost all students in the study sample attended four-year college immediately after high-school graduation (one academic year after the summer program), with 88 percent of the control group enrolling in the first year (Column 1 of Table 2). The remaining students either enrolled in two-year institutions, joined the military, or worked. Attendance of one of the STEM summer programs has positive, but not statistically significant, impacts on college attendance.

Overall enrollment changed little, but the programs increased enrollment in elite colleges. Unsurprisingly, the programs induced students to attend the HI (Column 2). Approximately 6 percent of the control group enrolled in the HI; an offer of online program admission increased this by approximately four percentage points, according to both the pure (Panel B) and conditional (Panel D) randomization estimates. An offer of admission to the six-week program increased HI enrollment by 11 percentage points above the share in the online comparison group and by 15 to 17 percentage points over the share in the control comparison. This means over 20 percent of students with six-week program offers enrolled in the HI. The one-week program also increased HI enrollment by 4 percentage points over the level in the online comparison group and by 6 to 8 percentage points over the level in the control comparison, though these results are not consistently statistically significant. These results also serve to illustrate that the pure and conditional randomization estimates are very similar.

The shifts to the HI are part of an overall shift toward selective colleges. This can also be seen in Column 3, which reports enrollment at elite institutions (including the HI). We define elite institutions as those that *Barron's Guide* rates "most competitive," its highest rating. An admission offer to the online program increased enrollment in such institutions by 9 percentage points, which means that enrollment increased at elite institutions *beyond* the HI. The six- and one-week programs boosted elite college enrollment by an additional 4 to 7 percentage points over the effect of the online program, resulting in enrollment rates 13 to 16 percentage points higher than those in the control group. As can be seen in Figure 1, for the six-week program, this shift to enrollment in higher-quality institutions is driven by enrollments at the HI. However, the one-week and online programs increased enrollment at both the HI *and* other elite institutions. The effects on attendance in the second and third years of college are generally similar to the effects on initial enrollment (Online Appendix Tables B.2 and B.3).

By their fourth year of college, the STEM summer program participants showed an even greater edge. Students assigned to a summer program maintained enrollment in their fourth year, whereas control students are less likely to have been enrolled, though this difference is statistically significant only for the one-week program (Online Appendix Table B.4). The differences in enrollment reflect a combination of the control students dropping out, taking time off, and delaying. In the first year of college, 88 percent of the control students were enrolled; by the fourth year, control group enrollment had fallen to 78 percent. Persistence in the fourth year is particularly high for those who enrolled at the HI and elite colleges. By sustaining persistence through the first four years of college at elite colleges, the STEM summer programs set the stage for college graduation from prestigious universities.

5.2 College graduation

Only 56 percent of the control students graduated from a four-year college in four years (Figure 1 and Online Appendix Table B.5). This share is higher than the national four-year graduation rate observed at all US institutions of 45.3 percent (U.S. Department of Education, 2020) but could be considered low since the students in this sample have near-perfect GPAs and standardized test scores two standard deviations above the country-wide mean. Additionally, the school-wide four-year graduation rate at the HI for the same cohort is 87 percent. The online program increased the likelihood of graduating with a BA in four years by 3 percentage points, though this difference is not statistically significant. Both the six-week and one-week programs yielded higher graduation rates, but the differences are again not statistically significant. For the six-week and online programs, all of the increases in on-time BA attainment are attributable to graduations from the HI, but the gains from the one-week program are split evenly between the HI and other institutions. Overall, it appears that the gains in on-time degree attainment are small but that those who received program offers were likelier to graduate from an elite institution on time.[9]

The graduation rates at five- and six-year time horizons are higher for all students, with 77 percent of the control students obtaining a BA within six years after high-school graduation (Figure 1). All of the programs increased college graduation in this longer time window, with particularly pronounced gains at elite institutions. As shown in Table 2, the online program boosted BA attainment by 4 percentage points. Both the pure and conditional randomization estimates show slightly smaller graduation impacts of the six-week program (with a statistically nonsignificant effect of 2–2.5 percentage points) and larger ones for the one-week program (an effect of 9 percentage points).

It is notable that the most intensive program delivered the smallest benefit in terms of overall increase in BA attainment within 6 years. Its weaker effect on BA attainment is most pronounced for elite schools other than the HI. The 6-week program increased HI year-one attendance by 17 percentage points and 6-year graduation by 16 percentage points, indicating little drop-off from attendance to graduation. On the other hand, the 6-week program increased attendance at elite universities by 17 percentage points but increased 6-year graduation by only 12 percentage points. Ultimately, though, the boost to overall BA attainment from the 6-week program is not statistically significantly different from that provided by the online group, and thus, these differences may also be due to random variation.

Focusing on institution types beyond the HI, *all* of the programs increased BA attainment in six years from elite colleges. Many control students did graduate from an elite institution in this time frame (43 percent), but we find that, depending on the estimation strategy, the STEM summer programs increased this share by 10 to 15 percentage points. Thus, even in the case of the six-week program with its smaller overall graduation boost, students' college trajectories still changed with respect to the type of institutions that they chose. Attending higher-quality colleges may enhance social networks and improve human capital, and there is evidence that it increases earnings, especially for URM students (Hoekstra, 2009; Dale and Krueger, 2014; Zimmerman, 2014; Goodman et al., 2017; Chetty et al., 2020; Bleemer, 2021).

[9] Note that the college graduation experiences of these students may have been affected by the COVID-19 pandemic; however, this would influence both the treatment and control groups. See Figure A.1 for a timeline of each cohorts' expected college enrollment.

Overall, assignment to any of the three programs increased enrollment in and graduation from college. The gains are concentrated at elite institutions: at the HI for the six-week program and at the HI and other highly ranked colleges for the one-week and online programs. The largest increases in overall graduation come from the one-week program, with the six-week program yielding the smallest gains. The programs succeeded at two of their goals: (1) increasing representation of URM students at the HI and (2) improving the trajectories of students regardless of institution. In the next section, we consider whether the programs induced an increase in attainment of STEM degrees.

5.3 STEM degree attainment and potential earnings

One of the programs' stated goals is to increase the proportion of URM students in STEM careers, and a key segment of the STEM pipeline is completing a degree with a major in a STEM field. We examine STEM degree completion in Column 7 of Table 2. Following the National Center for Education Statistics, our STEM degree category includes any degree within the broad categorizations used by the Integrated Postsecondary Education Data System (IPEDS) to denote STEM fields: computer and information science, engineering, engineering technologies, biological and biomedical sciences, mathematics and statistics, physical sciences, and science technologies.[10] We categorize all other degrees that report a major as non-STEM degrees and also separately report results for degrees with no major code as "missing major" (for details, see Online Appendix Table B.9).

In 2019, 36 percent of bachelor's degrees earned in the US were in STEM fields (National Science Board, 2022). The study population was predisposed to choosing STEM fields in greater proportion than other US students: 67 percent of the degrees earned within six years in the *control group* were in STEM fields. Even so, the STEM summer programs increased the prevalence of STEM degrees. The online program increased STEM degree attainment by approximately 3 percentage points (not significant), with this rise accounting for almost all of the BA boost from this program. The six- and one-week programs increased STEM degree attainment by approximately 12 percentage points over that in the control group (a statistically significant result).

As shown in Online Appendix Table B.9, the six-week program increased overall receipt of four-year degrees by 2 to 2.5 percentage points: This increase reflects shifts away from non-STEM degrees (of -6 to -7 percentage points), a decrease in the number of unreported majors (of -3 percentage points), and an increase in STEM degree attainment (of 8 to 11 percentage points).[11] The shift

[10] If a student is missing information on major but her degree is designated a bachelor of science degree (or some variation thereof, such as BS) rather than a bachelor of arts degree or BA, then we count it as a STEM degree.

[11] Online Appendix Tables B.13 and B.12 report the same results estimated with missing majors counted as non-STEM and STEM majors, respectively. The coding of missing degrees does not affect the overall finding that the programs increased STEM degree attainment, though the various coding schemes do change the magnitudes and statistical significance of some coefficients. However, the pattern of the changes is not systematically smaller or larger.

to STEM induced by the six-week program operated through the HI. For the one-week program, the STEM gains of 8–10 percentage points are attributable mostly to increased graduation, with a small number of switches away from non-STEM majors (accounting for 2–3 percentage points of the change), though the increases are not statistically significant. For the online program, all of the attainment gains are concentrated in STEM fields at the HI.

Online Appendix Tables B.10 and B.11 separate the STEM majors into specific fields at any institution and the HI, respectively. The tables show that engineering dominates the increase in STEM. Almost all of the students at the HI who were exposed to one of these programs went on to major in engineering. In sum, the programs induced not just college graduation but graduation in STEM fields—particularly engineering.

Differences in STEM degree persistence do not seem to be driven by differences in STEM interest. We turn briefly to our survey evidence: The programs did not change reported interest in STEM majors immediately after the program (Figure 3), with 93 percent of both the treatment and control students at the end of the summer of the program reporting plans to major in a STEM degree. Once in college, both treatment and control students maintained very high levels of interest in STEM degrees, with approximately 83 percent planning to declare a STEM major. There are some differences in intentions to pursue a STEM career: Both the six-week and online programs increased students' likelihood of reporting a desire to pursue a STEM career in the fall of their senior year of high school, and the six- and one-week programs induced similar gains in STEM career intentions midcollege (though the increases are not statistically significant). Thus, we conclude that the increase in STEM degree attainment is due to the groups with program offers being more likely to follow through on their STEM intentions—perhaps due to the upgrade in quality of institution of enrollment that we discuss more below—rather than the programs inspiring a greater degree of interest in STEM fields.

To summarize the joint effect of the shifts in choice of college major and college quality, we estimate the programs' impacts on potential earnings. We cannot measure earnings directly, but we use information from the College Scorecard (US Department of Education, 2024) as a proxy for the shift in an individual's potential earnings made possible via shifts in major and institution. The College Scorecard reports earnings by institution and major for students who received federal student aid, who may not be representative of the full student body. We use median earnings information in 2022 dollars for employed, unenrolled individuals 5 years after their exit from college in 2014–15 and 2015–16. If information is unavailable for a particular major by institution (typically because of small sample size), we substitute the institution-level outcome for the same cohort. The information is also available by gender, so we report estimates for four relevant outcomes in Table 3: all who entered college in our sample, where we assign overall median earnings to individuals (Column 1); the same group, but with earnings assigned by gender (Column 2); and the same outcomes, but restricted to those who graduated college by their sixth year after high-school graduation (Columns 3 and 4).

The potential earnings of the control group are relatively high, at approximately \$100,000. As shown in Panel B of Table 3, regardless of how we compute the outcome, random assignment to the online program increased this by approximately \$7,000, an increase of about 7 percent. Assignment to the 6-week program increased earnings to a greater extent, and the 1-week program had a smaller effect than the online one (Panel A). Our summary measures of these effects in Panels C and D show, depending on the specification, that the 6-week program raised potential earnings by \$11,000 to \$15,000 while the one-week program boosted earnings by \$3,000 to \$5,000, though this latter difference is not statistically significant. Of course, the College Scorecard measures for earlier cohorts are not the same as exact earning measures, but they provide a summary measure indicating that the programs induced students to embark on college trajectories with the potential to increase their earnings by 3 to 15 percent.

5.4 Impacts for subgroups

In Online Appendix Tables D.1 through D.8, we present estimates for key outcomes by gender, URM status, self-reported free or reduced-price lunch receipt (a proxy for family income), and first-generation college-going status. These groups correspond to populations of particular interest for increasing representation in STEM fields. However, we note that estimating effects for these subgroups splits our small sample, reducing precision. Both male and female students appear to have benefited equally from the six-week program, but female students saw slightly larger gains from the one-week and online programs, especially with respect to graduating from a highly ranked institution (Online Appendix Table D.1). That female students experienced larger gains is perhaps not surprising because women are less likely to choose STEM majors so there is more room for improvement. Thus, STEM programs that also emphasize serving women (by ensuring gender balance in the program, even while not explicitly focusing on women's representation) can also contribute to closing gender gaps in STEM.

In Online Appendix Table D.3, we show estimates for Black, Hispanic, and Native American individuals separately for students who do not identify themselves as such (white, Asian, multiethnic, and "other race" students are in the non-URM category). Because less than 18 percent of the sample is non-URM, these estimates are noisy, but there is some evidence, at least for STEM degree attainment, that the non-URM impacts are larger for the six- and one-week programs. However, it appears that almost all of the benefits of the online program accrued to URM students. Again, however, the sample of non-URM students is quite small, and there are meaningful benefits for both groups.

We observe the clearest difference between students who reported receiving subsidized lunch at their high school with those who did not (Online Appendix Table D.5). Although exposure to the programs was generally beneficial for both groups, students who did *not* receive subsidized lunch reaped larger gains, especially in regards to graduating from an elite institution and graduating with a STEM degree. Students with more resources may be better poised to upgrade their choice of enrollment institution, perhaps because of fewer concerns about college costs or ease of the social transition. This also implies that increasing representation by race in STEM fields will not necessarily increase representation by family income and vice versa.

The differences by first-generation college-going status (defined as neither parent having ever attending a four-year college) align somewhat with the findings by subsidized lunch status. The gains in graduation from elite institutions induced by the programs (which we showed earlier were split between the HI and other elite institutions) are more consistent for the non-first-generation group.

5.5 Robustness

We consider how robust our estimates are to alternative specifications and whether our conclusions remain similar under randomization inference. We also discuss the role of treatment effect heterogeneity.

5.5.1 Alternative specifications

Online Appendix Table C.1 shows the main estimates without baseline covariates. As expected, precision decreases somewhat, but the magnitude and sign of the estimates remain the same. Online Appendix Tables C.2 through C.4 remove each cohort in turn. We expect there to be idiosyncrasies across cohorts due to sampling variation, but each table reports estimates that are generally in line with the main findings. In some cases, precision declines because of the smaller samples. Online Appendix Tables C.2 is notable in that it removes the 2014 cohort. This cohort was subject to the most modifications to random assignment, featuring more blocks than the two subsequent cohorts. We would expect that if the study design with the greater number of blocks did not remove selection bias as thoroughly as the design with fewer blocks, the conditional randomization estimates in this table should be *smaller* than the main estimates because removing 2014 would remove upwardly biased estimates. Instead, the results limited to the later cohorts with a design that more closely approximates completely random assignment are very similar.

5.5.2 Randomization inference

A different threat to validity is associated with the randomization scheme. By imposing randomization strata and modifying complete random assignment, the study limits the possible range of potential outcomes. For example, if a state is preferred in the assignment for representational reasons, this preference will always limit the range of randomization scenarios possible under the assignment scheme. Standard inference methods do not account for these constraints (Athey and

Imbens, 2017). As an alternative, we present results derived by means of randomization inference. Specifically, we rerandomize applicants into the programs using the same randomization criteria (blocks, location, gender preferences, etc.) 1,000 times and compare the estimate from our main specification with the distribution of estimates from the 1,000 randomizations. Each randomization faces the constraints imposed by our research design, so we effectively limit the possible comparisons to assignments that might actually have occurred rather than those that could have been made in a hypothetical scenario with full randomization. We conduct this exercise for both the pure and conditional randomization estimates, as both of these approaches are subject to at least some constraints.

We display the results from this exercise in Online Appendix Figures C.1 and C.6: first for the coefficients from pure randomization (with the 6- and 1-week programs compared to the online program and the online group compared to the control group) and then for the coefficients from the conditional randomization (all treatments compared to the control). Each panel shows the distribution of treatment estimates from the 1,000 hypothetical randomizations (bars), compared to the relevant estimate (dashed line). If the treatment effect estimate from the tables is at or above the 97.5th percentile (two-tailed test) or 95th percentile (one-tailed test), this implies statistical significance.

For pure randomization, the impact estimates for the online program vs. the control group are often at the 99th percentile, and when they are lower, it is for the outcomes that are also not statistically significant under standard inference methods (attendance of and graduation from any 4-year institution, STEM degree attainment). The impact estimates for the 6- and 1-week programs vs. the online group are never above the 95th percentile, but again, this parallels our results from traditional inference methods, where the Block 1 comparisons tend to have less statistical power. For conditional randomization, the impact estimates for attendance of any 4-year institution fall at the 63rd to the 82nd percentiles, but for elite institutions, the impacts on attendance are at the 98th to 99th percentiles—generally similar to the pattern of findings from the main estimates. The impacts on elite college graduation are from the 96th to the 98th percentiles. Again, this pattern aligns with the trend of our main estimates. The impacts on STEM degree completion follow the pattern in the estimates from traditional inference, with statistically significant effects for the 6- and 1-week programs but not for the online program. We thus consider the randomization inference exercise to offer confirmatory evidence that we can draw inferences from both of our randomization schemes using traditional statistical methods.

5.5.3 Treatment effect heterogeneity

The exercises above and the similarity between the pure and conditional randomization estimates give credence to the idea that our estimates capture the true program effects. However, another threat to validity could be heterogeneity in the treatment effects. If our findings are driven by, for example, the highest-rated students, this might imply that our estimates based on extrapolation using a linear functional form do not actually capture the programs' effectiveness because we do not have similarly rated students in the control group for comparison. This criticism affects the interpretation only of the SUR estimates (Panel C) and conditional randomization estimates (Panel D) since these are the estimates that involve extrapolating across blocks.

In Online Appendix Table C.5, we examine treatment effect heterogeneity for Blocks 1 and 2 individually. Within Block 1, all students are relatively highly rated, and the comparison group is students in the online program. Within Block 2, the students are relatively lower rated, and the comparison group is the control group. *Within* each block, we split the sample into relatively higher- and lower-rated applicants, with separate treatment indicators for the top- and bottom-rated students in each block. The strata are adjusted to include an indicator variable for being a relatively higher-rated student. The program variables can then be interpreted as the treatment effect for students of each type.

The impacts are very similar for relatively higher- and lower-rated students for the 6-week program, with no statistically different program returns. There are some statistically significant differences for the other programs. The 1-week program had larger effects for higher-rated students in terms of attendance and graduation from the HI. For the online program, higher-rated students are more likely to have graduated from an elite institution. Overall, we take this group of findings to mean that while there may be heterogeneous treatment effects for some programs and some outcomes, heterogeneity is not consistently present.

6 Mechanisms

In this section, we explore mechanisms behind the success of the STEM summer programs, focusing on graduation from a four-year college within six years and STEM degree attainment as the main outcomes of interest. For many of these analyses, we use data from the student surveys, which are subject to some differential response by treatment arm. As we noted in Section 3, we use the unweighted survey responses because of the inconsistent influence of reweighting schemes in addressing survey response bias, and we instead consider the findings from the surveys suggestive rather than conclusive.

There are several reasons why the programs might have improved college graduation and STEM degree attainment. We focus on three human capital-related explanations here. First, the program impacts may be driven by an increase in participants' human capital with respect to the college application process, which in turn could enhance the quality of the institution chosen for enrollment and give rise to the differences in outcomes that we observe. We also discuss the extent to which such institutional upgrading is due to greater likelihood of admission because of a signaling effect of the programs. Second, the program may have improved participants' human capital with respect to subject matter knowledge, helping them get ahead in college and be more likely to graduate.

Finally, we consider whether there is an increase in participants' human capital with respect to their soft skills, which could better position them to succeed in college. As we detail below, the evidence that the first channel explains our findings is strongest, though we cannot fully rule out other explanations.

6.1 College application behavior and shifts in quality of college of enrollment

The STEM summer programs have the potential to affect young people's trajectories, but ultimately, even the most intense six-week program covers only a short period in a young person's life. However, by prompting students to apply to better colleges than they would have considered otherwise, the programs may set students on a different path. We have shown that program participation increases enrollment in and graduation from the HI and other highly ranked colleges. Here, we show that the primary path whereby students shifted into these institutions was through a change to their college application strategy. We first show that application and admissions patterns changed for program participants and then discuss how this shift induced students to enroll in higher-quality institutions.

We observe increased applications to the HI (via administrative data from the HI, displayed in Online Appendix Table B.8) and other elite institutions (via survey data, displayed in Table 4). Approximately 32 percent of the control students applied to the HI. This would be a very high rate of application for typical high-school students, but the program applicants are a selected group who were interested in the outreach office's summer programs. Even so, assignment to one of the summer programs more than doubles the rate of application to the HI for all the programs, with almost all students in the six-week group (78 percent) applying to the HI.

Almost 6 percent of the control students were admitted to the HI, again demonstrating that the study sample is a selected group: The HI typically admits fewer than 10 percent of applicants. Given that a little over 30 percent of the control group applied, this is an admission rate of approximately 19 percent. Admission rates are even higher among those with program offers. According to the pure randomization estimates, approximately 37 percent of students assigned to the six-week program were admitted to the HI, with an implied admission rate of 47 percent. For the one-week program, approximately 29 percent were admitted, with an implied admission rate of about 38 percent; for the online program, 15 percent were admitted, with an implied admission rate of approximately 22 percent. Thus, the six-week and one-week programs delivered a bump in likelihood of admission, while admissions rates are similar between the control group and the online group. Greater admission to the HI therefore seems to be due to two factors: the greater likelihood of applying to the HI, and for the six- and one-week programs, the greater likelihood of being admitted to it. We explore the potential of a signaling effect contributing to this in more detail below.

Enrollment and graduation changed beyond the HI, as well, with the programs (especially the one-week and online programs) also shifting students toward elite institutions other than the HI, so admission behavior with respect to these institutions likely changed as well. We turn to the survey responses to examine changes in application behavior more broadly. Survey respondents reported to which colleges they had applied and been admitted in a survey conducted in May of their senior year of high school. As we show in Table 4, those offered a seat at a STEM summer program are more likely to have applied and been admitted to elite institutions, even when the HI is excluded from that category (Column 5). These differences are statistically significant for the six-week and online programs, but not the one-week group. The programs also induced an increase in the overall number of applications and admissions (Column 2), though only the online program's effect on applications is statistically significant. However, the most dramatic change in application behavior was the reduction in applications to a single school (Column 4). Attending the six-week program eliminated the (small) possibility of students applying to only one school, and attendance of the one-week or online program greatly diminished this likelihood. The declines for the six-week and online programs are statistically significant, while that for the one-week program is not.

These improvements in college application behavior likely arose from increased knowledge about the college admissions process. The programs also improved students' college resources by enhancing their knowledge of both the landscape of available colleges and the college application process itself, as we show in Online Appendix Table E.3. The survey responses from the fall of the senior year of high school show that the programs—especially the six-week program, for which we most consistently observe statistically significant differences—increase sources of college application advice (Columns 1 through 4), with students assigned to a treatment group reporting a greater likelihood of obtaining advice from friends and a teacher or counselor. Assignment to a program also increased familiarity with non-HI institutions: Students were more likely to report familiarity with a technical institution (by 7 to 10 percentage points), an elite institution (by 1 percentage point), and a liberal arts college (by 7 to 10 percentage points) and were less likely to report familiarity with a highly ranked public university or a fake institution with a made-up name, though these differences are not significant.

These changes in knowledge of the college application process and application behavior translate into increased enrollment in high-quality institutions, as we show in Section 5. We investigate whether enrollment in these institutions spurs the college graduation and STEM results we observe in Figure 2, which compares the *institution-level* outcome of the university attended immediately after high-school graduation to the individual-level outcome. To generate the institution-level outcomes, we assign the institution-specific graduation rate to those who attended a four-year institution in their first year of college.[12] This outcome then measures the "predicted" graduation rates for each treatment group, assuming that the students in the study group graduated at the four- and six-year graduation rate of of the institution they attendes. We construct a similar outcome for

[12]For students who attended community colleges or did not attend college, we substitute zeroes instead.

STEM degree attainment, namely, the institution-specific share of degrees in STEM fields, based on degrees reported to IPEDS. This outcome does not differentiate by time to graduation, so it is the same for the comparisons of graduation by year 4 and by year 6.

The results from this exercise appear in Figure 2, with more details in Online Appendix Table B.15. Panel A compares the difference in "actual" graduation with the "predicted" graduation rates for graduation within four years and Panel C for graduation within six years. For four-year graduation rates, the change in actual graduation closely parallels the difference in predicted graduation rates (for the six-week and online programs, the change in graduation is slightly smaller than the size of the difference in expected graduation), consistent with many of the program benefits operating through upgrades to students' college of enrollment. For six-year graduation rates, the actual graduation rate almost exactly matches the predicted graduation rate for the online program, and the actual rate exceeds the predicted one for the one-week program. For the six-week program, the actual graduation boost is approximately half of what we would expect given the prediction.

When we conduct a similar analysis for the STEM degree share, we see in Panels B and D that the six-week and online programs increased attendance at institutions with higher proportions of STEM degrees but that the actual gains in STEM degree receipt are even greater than the predicted difference. Thus, students offered STEM summer programs had a higher likelihood of graduating because of the upgrades to their choice of institution of enrollment, but they increased their STEM degree attainment to an even greater extent than predicted, providing evidence that program participation helped students achieve their intention of obtaining STEM degrees in very competitive institutions.

6.2 Signaling

We next consider that participants may have signaled their quality by mentioning their program participation in their college applications as a potential explanation, though it is difficult to disentangle the operation of a signaling mechanism from that of a human capital mechanism. Given that the programs are hosted at the HI, any influence of signaling is probably most powerful there. Since many of the gains from the one-week and online programs were reaped at non-HI elite institutions, the possibility for signaling to play a large role in explaining those effects is limited. Additionally, while signaling may have an impact, we note that it would primarily influence *admission*, not necessarily what happens during college. Thus, it is unlikely to explain the increase in STEM degree attainment, especially given that students in both the treatment and control groups reported an intention to major in STEM fields at very high rates.

We examine how much of the admission effect is due to more ambitious application behavior as opposed to greater odds of admission upon college application in Figure 4 and Online Appendix Table B.14 by using two comparison groups. In this figure, we show application, admission, and admission conditional on applying to the HI (Panels A through C) and to any elite institution excluding the HI (Panels D through F). The results in the latter group of panels are restricted to the survey respondents who reported where they were admitted and where they enrolled. The conditional admission estimates show the increased likelihood of being admitted to an institution for those offered a place in the STEM summer programs, an effect that may be due to signaling or program-induced improvements in students' application packages or human capital. Part of the admissions gains at the HI are attributable simply to the increased likelihood of application, but a share of the gains are from the additional bump in admissions likelihood from attendance of the STEM summer programs (14 percentage points for the six-week program and 5 percentage points for the one-week and online programs, though these differences are not statistically significant). At non-HI elite institutions, the online and one-week programs increased the likelihood of conditional admission by approximately 5 percentage points. Overall, these findings show that there were some increases in conditional admission but that the role of changes in application behavior is large.

A second comparison in this figure compares the students in the HI STEM summer programs to a control group limited to students who reported having *any* STEM summer experience.[13] Students in this control group are more likely to be female and have slightly higher rating scores than the control students without STEM summer experiences, but they are otherwise quite similar to the control group overall (see Online Appendix Table B.17). If we assume that different STEM summer experiences impart similar human capital gains, the comparison of those assigned to the HI STEM summer programs with those in the control group with STEM summer experiences tests whether the HI programs have signaling value above and beyond that of involvement in any STEM summer programming.

Even with this comparison group, there is still a conditional admission gain of 10 percentage points at the HI for attendees of the six-week program, but there is no difference for participants of the one-week and online programs. We interpret this to mean there is likely some role of signaling in explaining the effects of the six-week program at the HI. However, outside the HI, there appears to be little difference in conditional admission between the HI STEM summer groups and control group members with other STEM summer experiences, implying that, outside of the HI, there are no special gains from the summer programs we study here relative to those of any STEM summer programs, except the gains delivered through the application channel. These estimates are consistent with some role for signaling but do not prove its existence. Even when we compare treated students to control students with STEM summer experiences, our assumption of similar human capital gains across programs could be wrong, and the additional boost for students in the six-week program relative to control students with STEM summer experiences might be due to human capital gains from the program. These findings set a ceiling on the effects operating through the signaling mechanism and confirm that the application channel accounts for much of the programs' effects.

[13]These include similar programs at other colleges and universities, nonprofit programs such as Girls Who Code, internships in STEM or medical fields, and STEM summer courses.

6.3 Subject matter knowledge, skills, and confidence

Another way the STEM summer programs may have boosted college graduation and STEM degree attainment is by increasing students' STEM subject matter knowledge, helping them get ahead in college. This could occur in two ways: The programs could have changed which high-school classes the students took prior to college entrance, or they could have directly increased the students' knowledge of STEM, better preparing them for future STEM majors. Additionally, the programs may have improved more general skills such as study skills and soft skills such as confidence and self-esteem.

Table 5 shows impacts on both high-school course plans and on a direct measure of human capital. Most students were already planning to take at least one Advanced Placement (AP) or International Baccalaureate (IB) course in their senior year in high school (control group mean of 92 percent), and program participation had positive impacts on these intentions, as shown in Column 1. The programs also increased the likelihood of taking at least one AP or IB course by 3 to 12 percent, with statistically significant differences for the one-week and online groups. Much of this increase flowed through computer science take-up. Approximately 14 percent of the control group planned to enroll in such a course, and receipt of a program offer increased this share by 7 to 10 percentage points, though the difference is statistically significant only for the six-week program. Perhaps because science and math advanced coursework was already extremely popular (with control means of approximately 75 percent), the STEM programs made little difference for advanced science and math coursework. During the fall of their senior year of high school, applicants offered seats in the programs were slightly better able to answer a calculus question, though the differences are not statistically significant (Column 5). The minor calculus improvement and coursework changes in noncore subjects indicate that, although the programs may have imparted STEM knowledge and inspired subsequent high-school coursework, these changes are likely to have been relatively small.

We also illustrate the program impacts on soft skills in Table 5, which shows student responses to survey questions about life skills, study skills, confidence, interest in learning, and attention span.[14] Life skills include tasks such as setting an alarm to be on time and doing one's laundry. For many program participants, the time on the HI campus might have been their first time away from their family, and we indeed observe an increase in the self-reported life skills that one would gain in such a situation. Unsurprisingly, the gains in life skills are larger for the residential programs than for the online program (even though this program had a short campus visit component). We also see that the programs increased self-reported study skills, such as asking questions and taking notes. However, there is no statistically significant change in confidence, including students' self-assessed math ability. The positive, statistically significant increases in life and study skills are all consistent with the idea that the STEM summer programs better prepared students to succeed in

[14] See Online Appendix E for details on the variables included and how we generated indices from individual variables. Online Appendix E also includes additional survey responses not discussed in the text.

and graduate from college and may have contributed to the increases in STEM degree attainment that we cannot account for solely through the upgrades to students' college of enrollment.

7 Conclusion

We present evidence from the first RCT investigating the impact of STEM summer programs for underrepresented youth, examining a suite of programs that includes a six-week program, a one-week program, and an online program. Receipt of a program offer increased student matriculation at the HI and other elite universities. Students exposed to the STEM summer programs were more likely to persist through college, with the most notable difference in the fourth year of college, when a larger share of the control students were no longer enrolled. The programs increased overall four-year college graduation, with the gains concentrated at the HI and other elite institutions. The programs also induced increases in attainment of STEM degrees. The shift in institutional quality and major may have increased potential earnings by 3 to 15 percent. We show evidence consistent with the idea that a change in college application behavior shifted students into higher-quality institutions, which drives the gains in college graduation. While these programs occur at a particular elite intuition and may not be replicable elsewhere, our findings highlight the important roles of college application and college quality which is applicable in multiple college access contexts.

Much of the gains in STEM degree completion come from increases in bachelor's degree attainment for this highly STEM-motivated group, but some of these gains come from preventing switches out of STEM majors. Almost all of the study sample intended to major in STEM in college, but like students across the nation, such intentions often flounder during college, giving rise to the "leaky pipeline" problem, whereby students leave STEM tracks throughout college. The STEM summer programs made students more resistant to leaks in the pipeline, though there were still STEM-interested students who did not ultimately complete a STEM degree. We cannot definitively say why this occurred, but we note that the programs offered comprehensive coverage of many hypothesized STEM-supportive pathways, including STEM curricula; URM role models in the form of near-peer teaching and residential assistants, staff, instructors, and guest speakers; and a shared group experience.

The contrast between the three programs provides some basis for a back-of-the-envelope cost effectiveness calculation. The six-week and one-week programs generated similar responses, though differing in their intensity. For STEM degree completion, the online program had a smaller effect, but it increased graduation from elite institutions almost as much as the residential programs and actually had a larger overall graduation effect than the six-week program. In 2015, the six-week program cost approximately $15,000 per student, while the one-week and online programs cost approximately $2,000 per student. Perspectives on which program is the most cost-effective will differ by the objective. For the HI, the interest may be greatest in HI graduation, on which the six-week program had a large impact—though this is in part because of to higher admission rates for this group. However, if a policymaker is interested in supporting overall graduation from elite institutions, the six-week program underperformed relative to the one-week program by a small amount, though its impacts were larger than those of the online program. The residential programs did outperform the online program in terms of STEM degree completion (Cohodes et al., 2024). A more detailed cost-effectiveness analysis is left as a future exercise.

This analysis shows that targeted programs to increase representation on college campuses can have wide-ranging benefits for participants. There may be additional spillover benefits for peers at elite institutions, who can benefit from a more diverse and inclusive STEM classroom. As the US Supreme Court continues to erode affirmative action as a component criterion of higher education admissions, more colleges and universities may turn to programs such as the STEM summer programs we study here to provide the benefits of diversity to their campuses through indirect avenues. Indeed, many campuses already have "summer bridge" programs that provide support for matriculating underrepresented students in the summer before their freshman year. Additionally, federal investment in STEM fields is targeted at higher education rather than earlier segments of the pipeline. Our findings show that a focus on higher education *after* students apply to college may neglect a key opportunity to intervene in students' lives *before* they apply to college—a crucial point in time when students choose the institutional affiliations that may ultimately boost their success.

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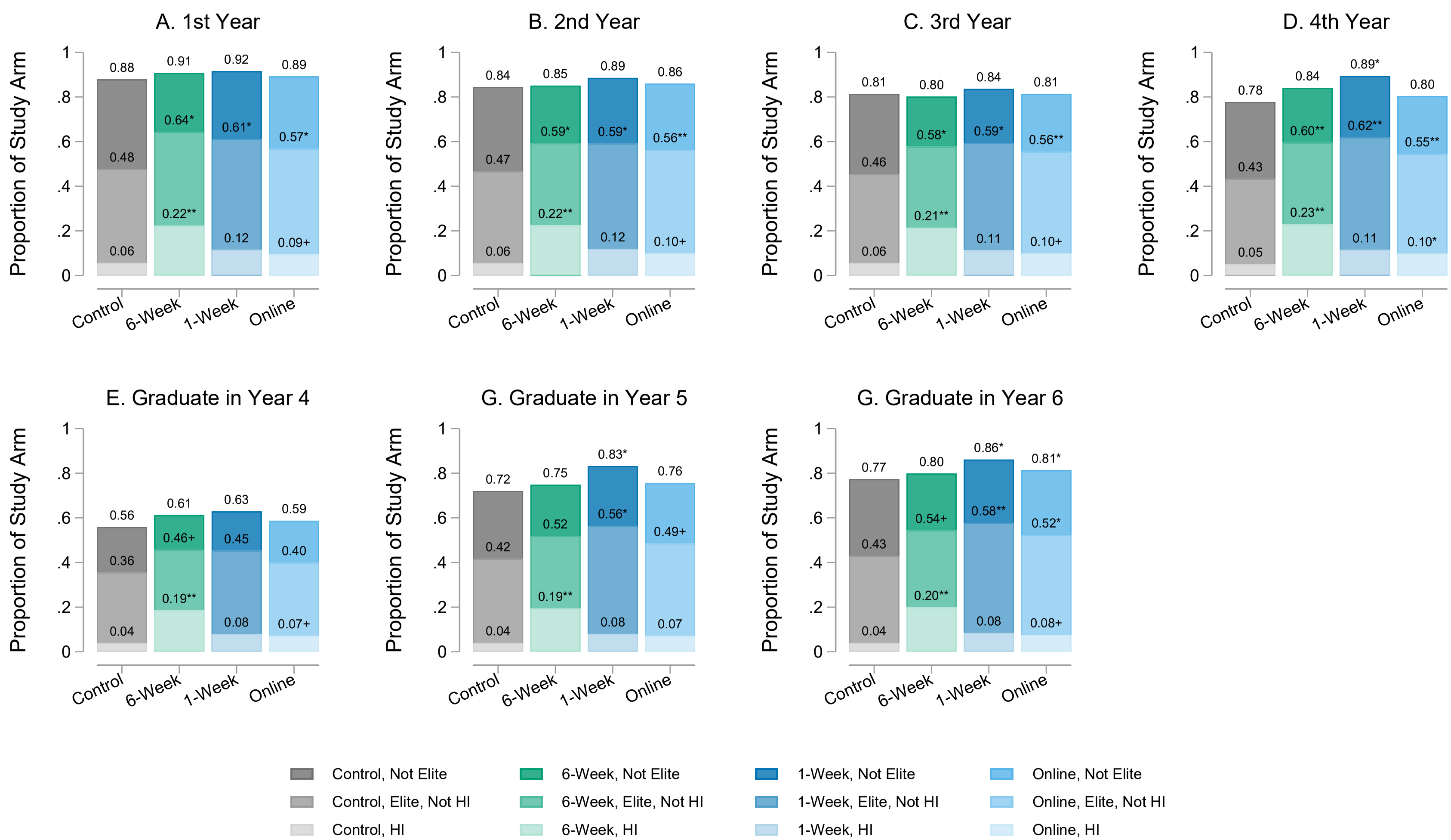
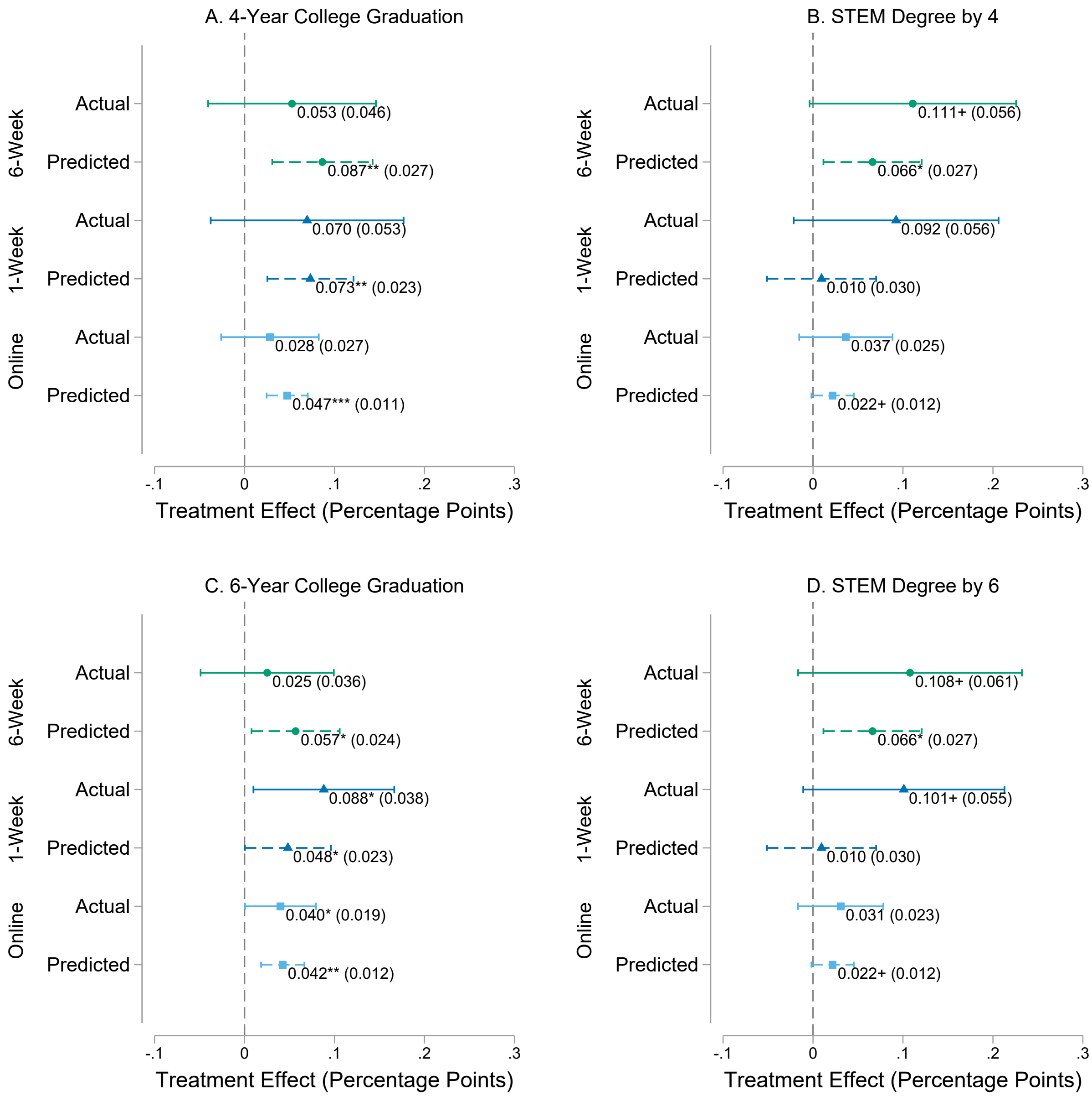
Figure 1: The Impact of STEM Summer Program Assignment on Four-Year College Attendance and Graduation



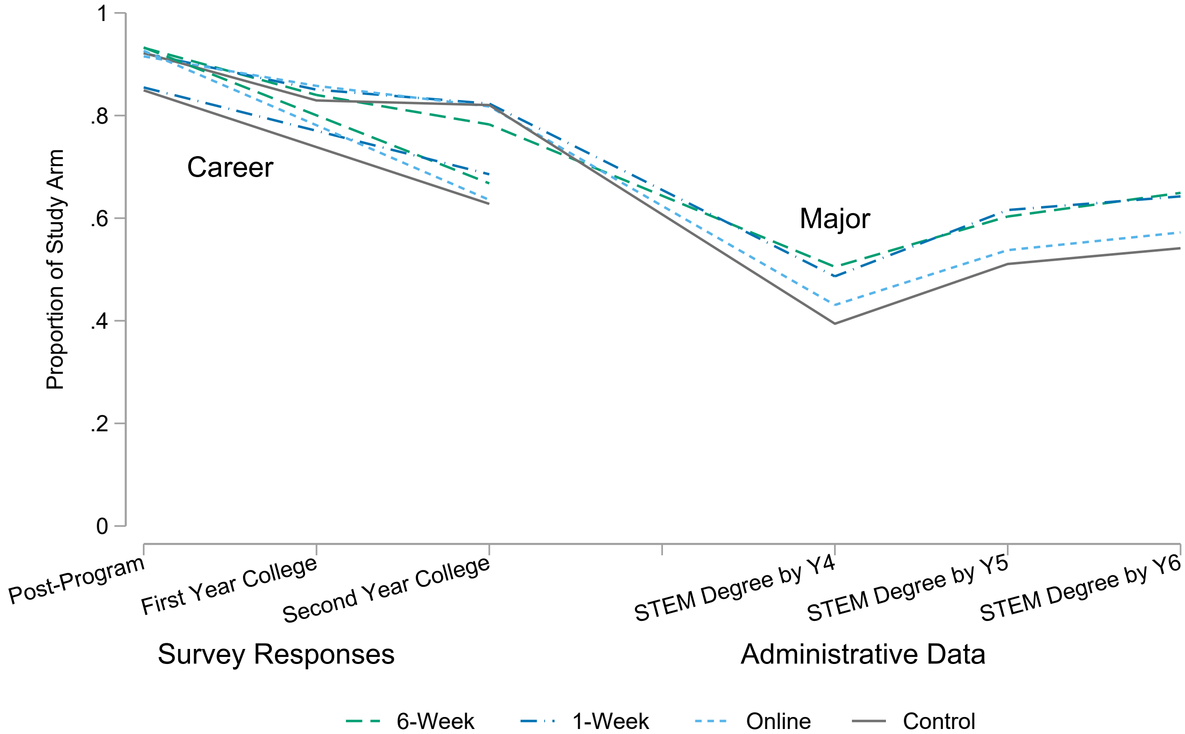
Notes: This figure summarizes conditional randomization impact estimates for attendance of and graduation from four-year institutions, split between the HI, other *Barron's* "most competitive" institutions ("Elite"), and remaining four-year institutions from the conditional randomization model. For details on the point estimates and standard errors, see Appendix B.

Figure 2: Actual vs. Predicted Graduation and STEM Degree Completion Rates



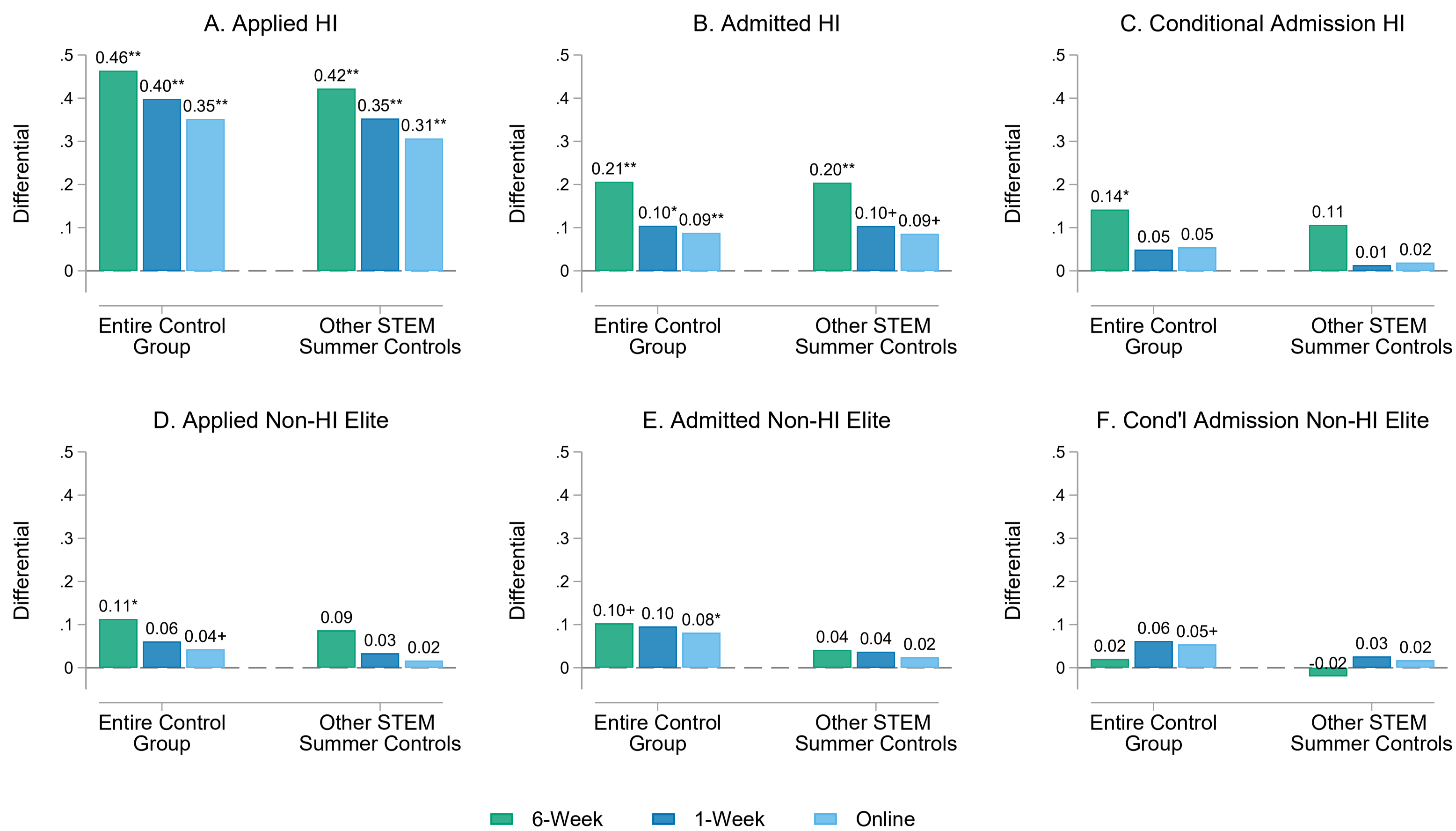
Notes: This figure compares conditional randomization estimates of the program effects on four-year college graduation and STEM degree attainment, marked as "actual," with "predicted" graduation and STEM degree attainment derived on the basis of institution-level characteristics. The institutional-level outcomes are college-level characteristics calculated from IPEDS data in 2013. The "actual" STEM degree values are the share of STEM degrees among all degrees conferred between July 1, 2012, and June 30, 2013, and do not differentiate between four- and six-year graduation. Values for community colleges and non-college-going respondents are set to 0.

Figure 3: The Impact of STEM Summer Programs on Choice of STEM Major and Career Intentions



Notes: This figure shows the proportion of students reporting the intention to major or have a career in a STEM field by program assignment, generated from the conditional random assignment treatment effects. The first set of responses comes from surveys, and the STEM degree information comes from the NSC and HI data. For detailed impact estimates on STEM intentions, see Online Appendix Table B.16.

Figure 4: Admissions Outcomes with Alternative Comparison Group



Notes: This figure shows application, admission, and conditional admission to the HI (Panels A–C) and other elite universities (Panels D–F) comparing treated students to all control group students and only to students who report STEM summer experiences. Data on admissions to the HI come from HI administrative records; data on admissions to other universities come from survey responses. For detailed estimates, see Online Appendix Table B.14.

Table 1: Baseline Characteristics by Program Assignment

	Full Sample	6-Week	1-Week	Online	Control	Strata-Adjusted Differences 6-Week vs. Control	1-Week vs. Control	Online vs. Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.349	0.403	0.351	0.343	0.339	0.069+	-0.033	-0.019
						(0.041)	(0.035)	(0.026)
Hispanic	0.430	0.407	0.412	0.432	0.440	-0.013	0.008	-0.001
						(0.040)	(0.035)	(0.026)
Native American	0.045	0.056	0.052	0.042	0.041	-0.001	0.005	0.001
						(0.020)	(0.016)	(0.012)
Asian	0.136	0.100	0.140	0.140	0.141	-0.036	0.012	0.014
						(0.027)	(0.025)	(0.019)
White	0.039	0.035	0.045	0.040	0.037	-0.020	0.008	0.002
						(0.017)	(0.015)	(0.011)
Multiethnic	0.358	0.377	0.341	0.354	0.361	0.027	0.002	-0.002
						(0.040)	(0.035)	(0.026)
GPA	3.860	3.911	3.896	3.881	3.830	0.004	-0.003	0.019+
						(0.014)	(0.019)	(0.011)
Free/reduced-price lunch	0.391	0.485	0.455	0.373	0.360	-0.003	0.006	-0.023
						(0.042)	(0.037)	(0.026)
Standardized math score	1.929	2.133	2.135	1.939	1.822	-0.021	-0.030	0.001
						(0.073)	(0.067)	(0.059)
Female	0.404	0.502	0.500	0.502	0.312	0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)
First-generation college	0.242	0.303	0.302	0.225	0.219	-0.007	0.046	-0.025
						(0.037)	(0.033)	(0.023)
p-value						0.830	0.971	0.864
N	2084	231	308	472	1073			

Notes: This table summarizes demographic characteristics, test scores, and GPA for program applicants. Column 1 shows averages taken across the entire sample. Columns 2 through 5 display means of these traits at baseline by program assignment. Race/ethnicity categories are not exclusive. First-generation college is defined as no parental college attendance. Students missing parental college information (N=21) are coded as not first-generation. Columns 6 through 8 report coefficients from regressions of the student characteristic on program offer dummies, including controls for randomization strata (+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$). The p-values are from tests of the hypothesis that all coefficients on each program offer variable are zero.

Table 2: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation

	Attended in Year 1			Graduated by Year 6			
	Any (1)	HI (2)	Elite (3)	Any (4)	HI (5)	Elite (6)	In STEM (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.005	0.107*	0.066	-0.019	0.106***	0.036	0.088
	(0.017)	(0.038)	(0.057)	(0.034)	(0.032)	(0.051)	(0.066)
1-week	0.028	0.038	0.043	0.052	0.024	0.046	0.089
	(0.027)	(0.035)	(0.047)	(0.035)	(0.035)	(0.039)	(0.053)
(B) Block 2: Online vs. Control							
Online	0.014	0.040+	0.092*	0.040+	0.038+	0.094*	0.030
	(0.017)	(0.020)	(0.037)	(0.019)	(0.019)	(0.039)	(0.022)
Control Mean	0.879	0.057	0.477	0.774	0.040	0.430	0.520
(C) $\beta_{res} + \beta_{online}$							
6-week	0.018	0.147**	0.159*	0.021	0.144**	0.130+	0.118+
	(0.043)	(0.051)	(0.065)	(0.056)	(0.048)	(0.067)	(0.067)
1-week	0.042	0.078+	0.136*	0.092+	0.062+	0.139*	0.119*
	(0.037)	(0.041)	(0.058)	(0.048)	(0.038)	(0.059)	(0.060)
(D) Conditional Randomization							
6-Week	0.029	0.167***	0.166*	0.025	0.159***	0.115+	0.115+
	(0.025)	(0.041)	(0.065)	(0.036)	(0.036)	(0.061)	(0.063)
1-Week	0.036	0.059	0.134*	0.088*	0.045	0.148***	0.115*
	(0.030)	(0.038)	(0.059)	(0.038)	(0.037)	(0.054)	(0.055)
Online	0.013	0.038+	0.092*	0.040*	0.036+	0.094*	0.028
	(0.016)	(0.020)	(0.035)	(0.019)	(0.019)	(0.037)	(0.022)
Control Mean	0.879	0.057	0.477	0.774	0.040	0.430	0.520

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer programs on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free/reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014–2016 and passed an initial screening, who were then subject to random assignment. Elite colleges are those ranked "most competitive" by *Barron's*. Panel A compares students assigned to one of the residential programs to those assigned to the online program (N = 504). Panel B compares students assigned to the online program to those assigned to the control group (N = 1,327). Panel C combines the estimates from Panels A and B using seemingly unrelated regression. Panel D jointly estimates the program effects for all three programs relative to the outcomes of the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001).

Table 3: The Impact of Random Assignment to STEM Summer Programs on Potential Earnings

	College Attendees		College Graduates	
	All	By Gender	All	By Gender
	(1)	(2)	(3)	(4)
(A) Block 1: 6- and 1-week vs. Online				
6-week	3,915	6,508	4,712	6,623
	(5,832)	(4,684)	(5,952)	(4,531)
1-week	-2,876	-3,005	-2,632	-3,213
	(4,129)	(3,115)	(4,364)	(2,985)
Online Mean	120,503	113,468	122,828	115,324
(B) Block 2: Online vs. Control				
Online	7,388*	6,698***	7,127*	6,823***
	(2,890)	(2,047)	(3,125)	(1,601)
Control Mean	104,213	96,755	109,234	100,241
(C) $\beta_{res} + \beta_{online}$				
6-week	11,303+	13,206*	11,839	13,446+
	(6,666)	(6,018)	(7,567)	(6,914)
1-week	4,512	3,693	4,495	3,610
	(5,539)	(5,047)	(6,141)	(5,648)
(D) Conditional Randomization				
6-Week	12,383+	14,166***	13,201*	14,923***
	(6,078)	(4,712)	(6,285)	(4,270)
1-Week	3,727	3,079	3,519	3,211
	(4,898)	(3,682)	(5,223)	(3,405)
Online	7,493*	6,609***	7,222*	6,758***
	(2,775)	(1,943)	(3,093)	(1,579)
Control Mean	104,213	96,755	109,234	100,241

Notes: The notes for this table are the same as in Table 2, but the sample is further restricted to college attendees (Columns 1 and 2) or college graduates (Columns 3 and 4), resulting in the following sample sizes: Panel A N(attendees) = 594, N(graduates) = 501, Panel B N(attendees) = 1234, N(graduates) = 1027, and Panel D N(attendees) = 1942, N(graduates) = 1627. Potential earnings come from the College Scorecard and reflect the median earnings by college and major of students who graduated in 2014–15 and 2015–16, measured in 2020 and 2021 in 2022 dollars. These measures are linked to study participants via their college and major. If earnings by major are not available because of small sample sizes, earnings by institution are substituted. Columns marked "All" use median earnings, and Columns marked "By Gender" use median earnings for men and women assigned to the matching gender.

Table 4: Impact of Assignment to STEM Summer Programs on Self-Reported College Applications

	Any 4-Year (1)	Number of Apps (2)	Number of Apps Ex. HI (3)	Only One App (4)	Elites Ex HI (5)	Non-Competitive (6)	Technical School (7)	Tech School Ex. HI (8)	State Flagship (9)
(A) Block 1: 6- and 1-week vs. Online									
6-week	0.006	-0.785	-0.859	-0.077*	0.074*	-0.007	0.073	-0.028	0.010
	(0.004)	(1.283)	(1.273)	(0.029)	(0.034)	(0.025)	(0.047)	(0.075)	(0.048)
1-week	0.010	-0.407	-0.371	-0.002	0.012	-0.015	0.010	0.029	-0.010
	(0.008)	(0.634)	(0.612)	(0.024)	(0.046)	(0.016)	(0.029)	(0.048)	(0.049)
Online Mean	0.989	9.328	8.666	0.065	0.874	0.040	0.759	0.494	0.448
(B) Block 2: Online vs. Control									
Online	-0.002	0.863+	0.612	-0.034*	0.044+	-0.021+	0.183***	0.081+	0.024
	(0.007)	(0.413)	(0.404)	(0.014)	(0.023)	(0.011)	(0.031)	(0.040)	(0.039)
Control Mean	0.993	8.422	8.024	0.061	0.849	0.061	0.627	0.503	0.505
(C) $\beta_{res} + \beta_{online}$									
6-week	0.003	0.078	-0.246	-0.111***	0.118**	-0.028	0.256***	0.054	0.034
	(0.010)	(0.894)	(0.892)	(0.033)	(0.045)	(0.032)	(0.068)	(0.079)	(0.079)
1-week	0.008	0.456	0.241	-0.036	0.056	-0.036	0.193**	0.110	0.014
	(0.010)	(0.796)	(0.788)	(0.032)	(0.045)	(0.026)	(0.059)	(0.070)	(0.070)
(D) Conditional Randomization									
6-Week	0.006	0.148	-0.179	-0.094***	0.113*	-0.035	0.247***	0.039	0.026
	(0.009)	(1.184)	(1.164)	(0.030)	(0.041)	(0.024)	(0.054)	(0.082)	(0.060)
1-Week	0.006	0.342	0.141	-0.041	0.062	-0.035+	0.181***	0.101	0.027
	(0.010)	(0.791)	(0.766)	(0.029)	(0.049)	(0.018)	(0.041)	(0.066)	(0.060)
Online	-0.003	0.822+	0.571	-0.032*	0.043+	-0.022*	0.182***	0.080*	0.026
	(0.007)	(0.406)	(0.397)	(0.013)	(0.023)	(0.010)	(0.029)	(0.038)	(0.036)
Control Mean	0.993	8.422	8.024	0.061	0.849	0.061	0.627	0.503	0.505

Notes: The notes for this table are the same as in Table 2, but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A N = 594, Panel B N = 1234, and Panel D N = 1942. Data are from surveys conducted at the end of the senior year of high school. The "Any" application outcomes are created from yes/no questions and available for all survey respondents. The number of applications and admissions outcomes in Columns 2 through 4 are calculated for respondents who provided the full list of colleges to which they applied and were admitted, respectively. The outcomes on applications by type of institution in Columns 5 through 9 are populated for respondents who provided at least a partial list of colleges to which they applied and were admitted, respectively. Robust standard errors are in parentheses (+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001).

Table 5: Impact of Assignment to STEM Summer Programs on Human Capital

	Plans to Take AP or IB Courses					Soft Skills		
	Any Course (1)	Science (2)	Computer Science (3)	Math (4)	Calculus Question (5)	Life Skills (6)	Study Skills (7)	Confidence (8)
(A) Block 1: 6- and 1-week vs. Online								
6-week	0.041	0.022	0.025	-0.072	-0.012	0.279*	0.153	0.049
	(0.039)	(0.056)	(0.021)	(0.059)	(0.056)	(0.105)	(0.121)	(0.128)
1-week	0.091*	0.054	0.005	0.040	0.000	0.142	0.110+	0.165
	(0.039)	(0.054)	(0.035)	(0.055)	(0.040)	(0.110)	(0.061)	(0.109)
Online Mean	0.887	0.750	0.129	0.734	0.242	0.048	0.209	-0.107
(B) Block 2: Online vs. Control								
Online	0.026	0.010	0.069	0.028	0.039	0.117	0.273***	-0.007
	(0.015)	(0.041)	(0.049)	(0.044)	(0.044)	(0.098)	(0.065)	(0.110)
Control Mean	0.916	0.736	0.139	0.750	0.220	-0.000	-0.000	-0.000
(C) $\beta_{res} + \beta_{online}$								
6-week	0.068	0.031	0.094	-0.045	0.027	0.396**	0.426***	0.042
	(0.044)	(0.069)	(0.058)	(0.069)	(0.068)	(0.131)	(0.129)	(0.167)
1-week	0.118**	0.064	0.074	0.068	0.039	0.259*	0.383***	0.159
	(0.039)	(0.067)	(0.057)	(0.067)	(0.068)	(0.118)	(0.114)	(0.164)
(D) Conditional Randomization								
6-Week	0.063	0.026	0.097+	-0.050	0.029	0.378*	0.441***	0.028
	(0.043)	(0.071)	(0.050)	(0.071)	(0.066)	(0.141)	(0.125)	(0.165)
1-Week	0.112*	0.058	0.078	0.060	0.036	0.267+	0.369***	0.134
	(0.041)	(0.067)	(0.057)	(0.067)	(0.051)	(0.143)	(0.088)	(0.143)
Online	0.027+	0.008	0.073	0.025	0.039	0.116	0.268***	-0.017
	(0.015)	(0.042)	(0.047)	(0.042)	(0.038)	(0.100)	(0.058)	(0.105)
Control Mean	0.916	0.736	0.139	0.750	0.220	-0.000	-0.000	-0.000

Notes: The notes for this table are the same as in Table 2, but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A N = 594, Panel B N = 1234, and Panel D N = 1942. Data are from surveys conducted at the end of the summer of the program. Robust standard errors are in parentheses (+ p<0.10, * p<0.05, ** p<0.01, ***p<0.001).

Online Appendix

Diversifying the STEM Pipeline: Evidence from STEM Summer Programs for Underrepresented Youth

Sarah R. Cohodes, Helen Ho, and Silvia C. Robles

Appendix A: Randomization and data details

This appendix describes the application and randomization process in more detail. It also includes more information on the surveys and other outcomes, as well as additional tables and figures.

A.1 Randomization details

Below, we describe the details of the randomization process for each cohort. Randomization processes were slightly different across years, reflecting different operational preferences and leadership over time. Key participants in the selection process are staff in the HI admissions offices. Typically, these employees work to recruit and select the freshman class at the HI; each year they also help winnow the large pool of applications to the summer program from about 2,000 to about 700. Program selection committees also evaluate applications. They consist of program affiliates—alumni, program staff, community members, and professors who participate in the selection process after the admissions office conducts its initial sort. Prior to randomization years, the applicants who scored highest on selection committee ratings were generally admitted to the program, alongside operational criteria (for example, gender balance or the need to admit students from certain locations to maintain regional representation). During randomization, selection committee ratings, alongside admissions office ratings, as well as regional priority criteria and gender, were used to allocate students to blocks for random assignment.

The number of students admitted to each of the programs varies over time. This reflects different operational constraints each year, as well as an increasing willingness on the part of the program staff to offer a few extra seats in the six-week program to account for the small number of students who declined offers each year. Each year a few applicants received "certainty spots" where admission to a program was guaranteed for program operational reasons. These students are excluded from the impact analysis.

A.1.1 Cohort 1 (2014) randomization details

The research team randomized admission to the summer programs with a block randomization design, with applicants assigned to three blocks and then randomized within blocks. The assignment process proceeded in the following steps during winter and spring of 2014:

1. The HI admissions office selected 674 applicants to move on to the program selection committee.

2. The program leadership separated the remaining applicants into regional groupings with about 30 applicants in each group. Each regional group was reviewed by a selection committee of two or three people, and the applicants were rank ordered within their group.

3. The HI admissions office reread the applications and assessed each applicant for their ability to complete the six-week program. Each applicant was tagged with a numeric variable representing a rating of yes, no, or maybe.

4. The research team combined the selection committee ranking and the HI admissions office vote into a weighted rank that program staff approved of because it supported the regional balance they wished to maintain in their programs.

5. Students were randomized to programs within randomization blocks defined by these rankings, for a total of three blocks. Top-ranked students were randomized between the six-week program and the one-week program. The group with the next highest rankings was randomized between the one-week program and the online program, and the final group was randomized between the online program and a control group. Block cutoffs were chosen to ensure appropriate program size.
   - Because there were fewer female applicants than male applicants and the program office wanted gender balance in its programs, we used gender as a stratum within the block randomization. Thus, there were different rankings cutoffs for male and female applicants.
6. Program staff reserved 19 spots in the six-week programs as "certainty" spots, which program staff chose to use to ensure representation from urban areas. The certainty spots were filled by taking the highest-ranked candidates from priority urban areas.

A.1.2 Cohort 2 (2015) randomization details

A staff member of the institutional research office of the HI randomized admission to the summer programs with a block randomization design, with applicants assigned to two blocks and then randomized within blocks. We highlight a few major differences from the 2014 randomization here, which were applied to the 2015 and 2016 randomization processes. The research team did not directly conduct the randomization; instead, a member of the HI institutional research office did. This was at the request of the Institutional Review Board. Additionally, the process with the admissions office and selection committee was streamlined, so that the admissions office scored applications before they were passed to the selection committees rather than the iterative process used in 2014. The admissions office and the selection committees offered more detailed ranking variables than in 2014. There were fewer certainty spots. Most importantly, the number of randomization blocks was reduced from three to two, making comparisons across blocks more plausible. This was to simplify operations and strengthen the research design. While full randomization would have been ideal, the outreach office was concerned that the most qualified candidates might have received no program and that relatively less qualified candidates might have received more intensive interventions.

The assignment process proceeded in the following steps during spring 2015:

1. The HI admissions office selected 701 applicants to move on to the program selection committee. At this time, they gave a yes/no recommendation for admission to the six-week program, and supplied a personal and academic rating score.
2. The program leadership separated the remaining applicants into regional groupings with about 30 applicants in each group. Each regional group was reviewed by a selection committee of two people, and the applications received several scores, including a yes/maybe/no recommendation for the six-week program, an academic score, a personal score, and a "top 5" indicator (for applicants considered one of the top 5 reviewed by each reviewer). Each selection committee also selected a top 5 jointly.
3. The HI institutional research staff member, in consultation with the research team, combined the selection committee rankings and the HI admissions office rankings into a weighted rank.

The weighted rank also included priorities for students from certain states or territories; this was to ensure representation from across the US in the program.

4. Students were randomized to programs within randomization blocks defined by these rankings, for a total of two blocks. Top-ranked students were randomized between the six-week program, the one-week program, and the online program. The next group was randomized between the online program and a control group. Block cutoffs were chosen to ensure appropriate program size.
    - Because there were fewer female applicants than male applicants and the program office wanted gender balance in its programs, we used gender as a stratum within the block randomization. Thus, there were different rankings cutoffs for male and female applicants.
    - Program staff imposed a math standardized test score for eligibility for Block 1. An applicant needed to score above one of the following cutoffs to be eligible for Block 1:
        - SAT: 550
        - PSAT: 55
        - ACT: 24
        - PLAN: 24
        - A small number of applicants were shifted from Block 1 to Block 2 due to not meeting the test score criteria. Applicants who were missing scores were allowed to be placed in Block 1.
5. Four students were offered seats in the six-week program in certainty spots.
6. The HI institutional research staff member ran many randomization scenarios: about 50 scenarios that met the program staff geographical preferences and demonstrated covariate balance were offered to the program staff as potential final randomization scenarios. The research team suggested a scenario that demonstrated covariate balance and the program staff agreed to that scenario.

A.1.3 Cohort 3 (2016) randomization details

A staff member of the institutional research office of the HI randomized admission to the summer programs with a block randomization design, with applicants assigned to two blocks and then randomized within blocks. The changes from the 2014 to the 2015 randomization process remained in place, with minor alterations noted below. The assignment process proceeded in the following steps during spring 2016:

1. The HI admissions office selected 749 applicants to move on to the program selection committee. At this time, they gave a yes/no recommendation for admission to the six-week program and supplied a personal and academic rating score.
2. The program leadership separated the remaining applicants into regional groupings with about 30 applicants in each group. Each regional group was reviewed by a selection committee of two people, and the applications received several scores, including a yes/no recommendation for the six-week program, an academic score, a personal score, and a top 5 indicator (for

applicants considered one of the top 5 reviewed by each reviewer). Each selection committee also selected a top 5 jointly.

3. The HI institutional research staff member, in consultation with the research team, combined the selection committee rankings and the HI admissions office rankings into a weighted rank. The weighted rank also included priorities for students from certain states or territories; this was to ensure representation from across the US in the program.

4. Students were randomized to programs within randomization blocks defined by these rankings, for a total of two blocks. Top ranked students were randomized between the six-week program, the one-week program, and the online program. The next group was randomized between the online program and a control group. Block cutoffs were chosen to ensure appropriate program size.

   - Because there were fewer female applicants than male applicants and the program office wanted gender balance in its programs, we used gender as a stratum within the block randomization. Thus, there were different rankings cutoffs for male and female applicants.
   - Program staff imposed a math standardized test score for eligibility for Block 1. An applicant needed to score above one of the following cutoffs to be eligible for Block 1:
     - SAT: 550
     - Old PSAT: 55
     - New PSAT: 525
     - ACT: 24
     - PLAN: 24
     - ASPIRE: 432
     - All applicants who submitted test scores met the cutoffs. Applicants who were missing scores were allowed to be placed in Block 1.

5. Program staff reserved one spot in Block 1, which program staff chose to use to ensure an applicant who previously participated in programs for middle- and high-school students sponsored by the program office received a spot in one of the programs. This student was randomly assigned to the online program. (Other students also participated in the prior program; however, the rest of them received rating scores high enough that they were all in Block 1 without intervention.) Two other students received a certainty spot in the six-week program and three in the one-week program due to programmatic considerations.

6. The HI institutional research staff member ran many randomization scenarios: about 50 scenarios that met the program staff geographical preferences and demonstrated covariate balance were offered to the program staff as potential final randomization scenarios. The research team suggested a scenario that demonstrated covariate balance and the program staff agreed to that scenario.

A.1.4 Covariate balance

Table A.1 summarizes Tables A.4 through A.6 (shown later in this appendix) and reports the p-values from joint hypothesis tests of equality of coefficients within randomization blocks, for each randomization block by cohort. The generally high p-values show that randomization produced treatment and control groups that were very similar in terms of demographic characteristics. This is not surprising, of course, because the randomization process included criteria for covariate balance. We do not expect student characteristics to be similar across blocks, as by definition blocks are defined by applicant characteristics.

Table A.1: Covariate Balance: Summary of P-Values for Joint Hypothesis Tests of Strata-Adjusted Mean Differences

	6-Week vs. 1-Week (1)	6-Week vs. Online (2)	1-Week vs. Online (3)	Online vs. Control (4)
2014 Cohort	0.980	-	0.943	0.421
2015 Cohort	0.844	0.934	0.987	0.498
2016 Cohort	0.924	0.218	0.563	0.891

Notes: This table shows p-values for test of joint-significance of strata-adjusted within-block mean comparisons for baseline covariates: race/ethnicity, free and reduced-price lunch status, and standardized math score and GPA. See Online Tables A.4 through A.6 for details and sample sizes.

A.1.5 Take-up

Most students assigned to a program ultimately participated in the program. Program staff generally did not permit students to switch programs, but in 4 cases (2 in 2015 and 2 in 2016), students who were assigned to the 6-week program were switched to the online program (2015) or one-week program (2016). These students are included in their original assignment in the intent-to-treat analysis. Across program years, 87 percent of students assigned to the six-week program ultimately participated; 85 percent of students assigned to the one-week program, and 77 percent of student assigned to the online program participated (Online Appendix Table A.2). No students in the control group were permitted to attend the program.

Table A.2: Program Attendance by Program Assignment

	6-Week (1)	1-Week (2)	Online (3)	Control (4)	All (5)
Attended 6-Week	0.87	0.00	0.00	0.00	0.10
Attended 1-Week	0.01	0.85	0.00	0.00	0.13
Attended online	0.01	0.00	0.77	0.00	0.18
Control	0.00	0.00	0.00	1.00	0.51
N	231	308	472	1073	2084

Notes: This table displays program-takeup rates. Columns 1 through 4 show the share of applicants who attended a program, according to the program office, by the program they were assigned to. Column 5 shows takeup across the entire sample.

A.2 Data details

Data for this analysis come from four main sources: the program application, the HI institutional research office, the National Student Clearinghouse (NSC), and surveys fielded by the HI institutional research office. We describe each data source in detail below, as well as attrition rates for outcomes.

A.2.1 Applications and baseline survey

Background information on applicants comes from the program application and a baseline survey. For Cohort 1, the baseline survey was a separate data collection; for subsequent cohorts, baseline survey measures were part of the application itself. Information about applicants from these sources includes demographic and academic information. Family background variables include parental education and demographics, and indicators for immediate family who are summer program or HI alumni. Applicants report income information and an indicator for whether they are eligible for the federal free or reduced price lunch program. High-school performance measures such as GPA, standardized test scores, extracurricular activities, awards, essays, and letters of recommendation are also provided. All measures are self-reported, though students needed to submit to the program high-school transcripts and official records of standardized test scores. Applicants also consented to participate in research surveys at this point; students who declined to participate were not included in follow-up outreach for additional surveys but are included in randomization. The program office also supplied information on who was offered each program and whether applicants accepted that offer.

A.2.2 HI internal records

The HI institutional research office provided information on program applicants' interactions with the HI, including application (early application), admission, enrollment, declared major (if enrolled), and graduation, including degree and graduation date. All applicants were sent to be matched to HI records; if an applicant does not match to HI data systems, we assume a zero value on indicator variables for each of the outcomes described. These data were last updated in June 2021.

A.2.3 NSC

The HI institutional research office sent applicants' personal information from the application (excluding students known to be enrolled in HI) to the NSC for matching. The NSC returns records that include information on enrolled college and dates of enrollment. The NSC also reports graduation and degree fields; we observe four-year and five-year graduation for all cohorts, and six-year graduation for the first two cohorts (2014 and 2015). We match the college information to the federal Integrated Post-secondary Education Data System as well as other sources for information on college characteristics. All applicants were sent to be matched to the NSC or included in the HI records; if an applicant does not match to the HI or any NSC college, we assume a zero value on indicator variables for enrollment. The NSC has almost complete coverage of colleges and universities in the relevant time period, especially the highly ranked institutions that the applicant sample tends to enroll in. These data were last updated in November 2022.

A.2.4 Surveys

The HI surveyed applicants in the fall shortly after program completion (or equivalent for the control group), in May of their senior year in high school, and in the spring of sophomore year in college. Periodic shorter surveys collected information on college enrollment and choice of major. The shorter surveys were not fielded to students attending HI, as HI provided data on attendance and major. Students received $25 Amazon gift cards if they responded to longer-length surveys and $10 gift cards for short surveys, regardless of their treatment status. We discuss the surveys in more detail in Online Appendix C.

A.2.5 Attrition and response rates

Follow-up information on college enrollment exists from either the HI or the NSC for almost all applicants; those without such information we assume did not enroll in college and instead worked or joined the military. Almost all of the high-achieving students in this experiment immediately enrolled in college after on-time college graduation. Table A.3 shows a follow-up rate of 100 percent for college information, because all students' information was sent to the NSC and the HI for matching. However, survey responses were not as universal and declined over time. Unsurprisingly, those offered seats in the programs were more likely to respond to surveys than control group members. We describe the differential attrition in more detail below. Given large levels of differential attrition, we consider results using the survey data suggestive rather than conclusive. However, note that if those who complete surveys tend to be more motivated and have higher follow-through than those who do not complete surveys, if survey measures are biased, they are likely to underestimate program effects.

Table A.3: Survey Response and Data Availability Rates by Program Assignment

	6-Week (1)	1-Week (2)	Online (3)	Control (4)	All (5)
Pre-program survey	0.96	0.95	0.93	0.85	0.89
Senior year HS fall (post-program) survey	0.90	0.88	0.85	0.65	0.76
Senior year HS spring survey	0.81	0.81	0.78	0.57	0.68
First year college survey	0.49	0.55	0.62	0.49	0.53
Second year college spring survey	0.66	0.61	0.67	0.53	0.59
Included in HI/NSC data request	1.00	1.00	1.00	1.00	1.00
N	231	308	472	1073	2084

Notes: This table displays the response rates for follow-up surveys and for whether an applicant was included in the request for National Student Clearinghouse post-secondary data. Columns 1 through 4 show response rates by treatment assignment and column 5 shows response rates across the entire sample.

A.2.6 Experiment timeline and structure

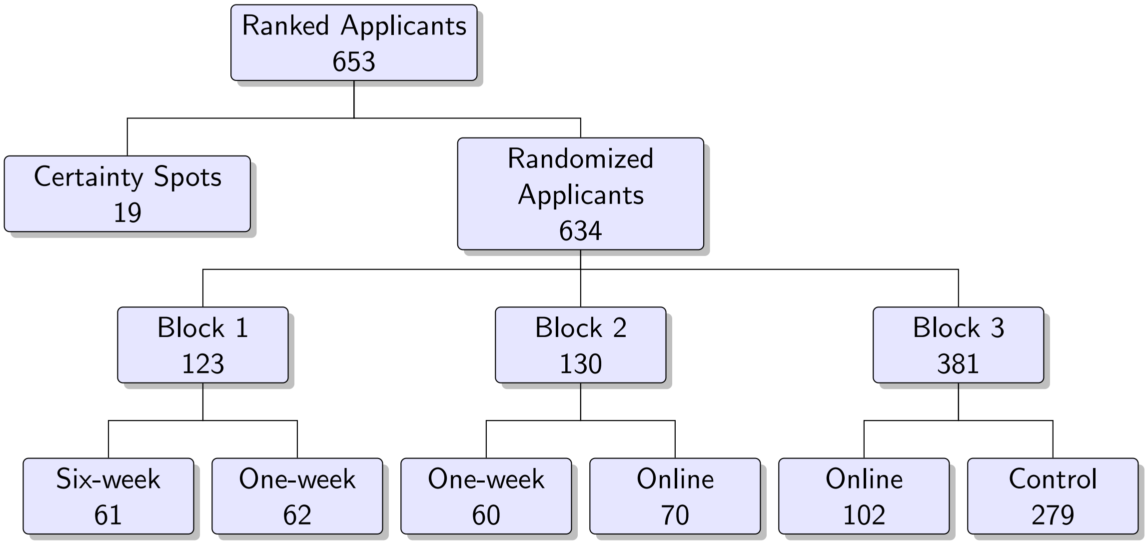
Appendix Figure A.1 shows student progress over time by experimental cohort, assuming students maintain on-time progress through college. Appendix Figures 2a through 2c provide a general overview of the randomization design and the number of applicants allocated to program spots.

Figure A.1: Experiment Timeline and Available Data

Cohort	Program summer	Senior Year of High School	First Year of College	Second Year of College	Third Year of College	Fourth Year of College	Graduate in 4 Years	Graduate in 5 Years	Graduate in 6 Years
2014	2014	2014-15	2015-16	2016-17	2017-18	2018-19	Spring 2019	Spring 2020	Spring 2021
2015	2015	2015-16	2016-17	2017-18	2018-19	2019-20	Spring 2020	Spring 2021	Spring 2022
2016	2016	2016-17	2017-18	2018-19	2019-20	2020-21	Spring 2021	Spring 2022	Spring 2023

Notes: This figure shows student progress over time by experimental cohort, assuming students maintain on-time progress through college.

Figure 2a: Randomization Design: Cohort 1 (2014)

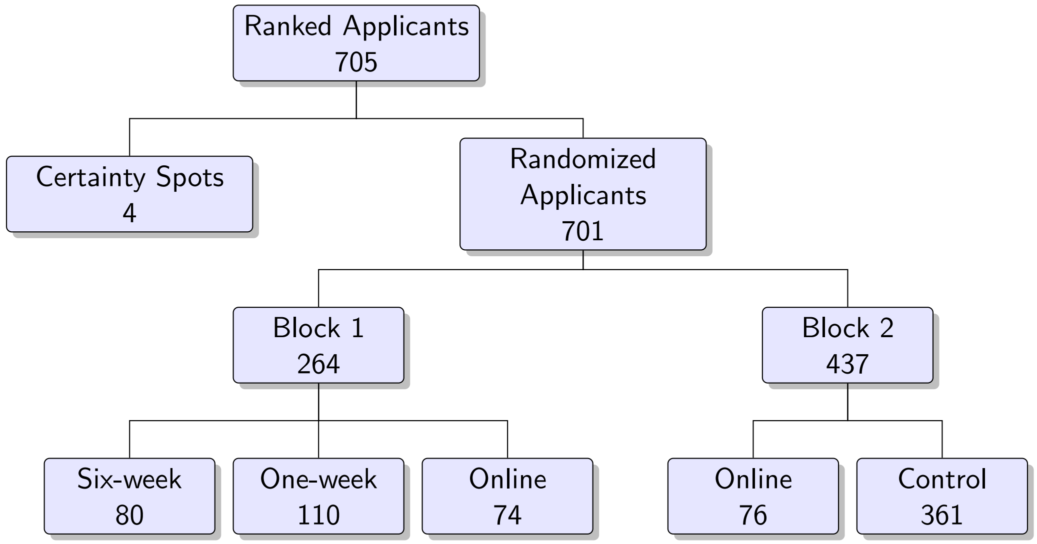


Notes: This figure shows the blocked randomization design in 2014. Certainty spots were applicants offered admission with certainty and excluded from the experimental analysis. All other ranked applicants were subject to random assignment within block. Block assignment reflects applicant ratings, math scores, and regional priorities, with gender as a stratum within block.

A.2.7 Covariate balance by cohort

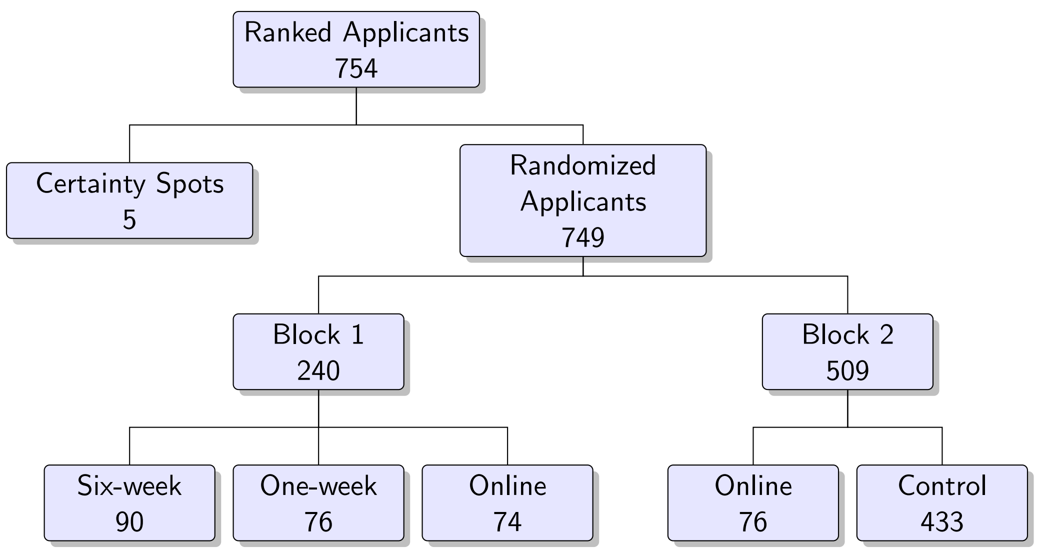
Tables A.4 through A.6 show detailed covariate information and p-values for joint hypothesis tests, separately for each cohort. Because the block structure differs slightly by cohort, not all comparisons are possible in every case. In no cases are there statistically significant differences from joint tests for differences in characteristics within randomization strata.

Figure 2b: Randomization Design: Cohort 2 (2015)



Notes: This figure shows the blocked randomization design in 2015. All other notes are the same as in Figure 2a.

Figure 2c: Randomization Design: Cohort 3 (2016)



Notes: This figure shows the blocked randomization design in 2016. All other notes are the same as in Figure 2a.

Table A.4: Covariate Balance: 2014 Cohort

	Covariate Means						Strata-adjusted Mean Differences		
	6-Week (Block 1) (1)	1-Week (Block 1) (2)	1-Week (Block 2) (3)	Online (Block 2) (4)	Online (Block 3) (5)	Control (Block 3) (6)	6-Week vs. 1-Week (7)	1-Week vs. Online (8)	Online vs. Control (9)
Black	0.377	0.355	0.383	0.329	0.324	0.362	0.026	0.042	-0.065
							(0.088)	(0.087)	(0.058)
Hispanic	0.410	0.419	0.383	0.457	0.510	0.477	-0.004	-0.055	0.050
							(0.091)	(0.087)	(0.062)
Native American	0.066	0.065	0.033	0.014	0.059	0.039	-0.002	0.019	0.024
							(0.044)	(0.028)	(0.031)
Asian	0.131	0.113	0.183	0.157	0.098	0.097	0.015	0.007	0.015
							(0.059)	(0.064)	(0.037)
White	0.016	0.048	0.017	0.043	0.010	0.025	-0.035	-0.013	-0.024
							(0.033)	(0.027)	(0.021)
Multiethnic	0.426	0.371	0.283	0.357	0.480	0.427	0.050	-0.071	0.079
							(0.090)	(0.084)	(0.062)
GPA	3.921	3.915	3.905	3.849	3.880	3.811	0.003	0.053	0.053*
							(0.027)	(0.062)	(0.023)
Free/reduced-price lunch	0.492	0.484	0.367	0.329	0.314	0.301	0.003	0.037	-0.004
							(0.091)	(0.086)	(0.058)
Standardized math score	2.200	2.326	2.044	2.167	1.934	1.870	-0.113	-0.098	0.195*
							(0.157)	(0.137)	(0.096)
Female	0.508	0.484	0.517	0.486	0.520	0.154	0.000	0.000	0.000
							(0.000)	(0.000)	(0.000)
First-generation college	0.213	0.258	0.250	0.200	0.147	0.136	-0.046	0.036	0.023
							(0.077)	(0.076)	(0.045)
						p-value	0.980	0.943	0.421
Observations	61	62	60	70	102	279	123	130	381

Notes: This table shows means for baseline characteristics and outcomes. Columns 1 through 6 shows the proportion of students assigned to each program with a given characteristic. Columns 7 through 9 report coefficients from regressions of the student characteristics on assignment to each program, including controls for randomization strata (+ p<0.10). N=634.

Table A.5: Covariate Balance: 2015 Cohort

	Covariate Means					Strata-adjusted Mean Differences			
	6-Week (Block 1) (1)	1-Week (Block 1) (2)	Online (Block 1) (3)	Online (Block 2) (4)	Control (Block 2) (5)	6-Week vs. 1-Week (6)	6-Week vs. Online (7)	1-Week vs. Online (8)	Online vs. Control (9)
Black	0.425	0.364	0.419	0.408	0.335	0.067	0.053	-0.027	0.076
						(0.073)	(0.081)	(0.070)	(0.058)
Hispanic	0.388	0.391	0.365	0.368	0.418	-0.026	-0.004	-0.006	-0.055
						(0.068)	(0.077)	(0.064)	(0.058)
Native American	0.075	0.055	0.054	0.039	0.042	0.024	0.015	-0.002	-0.008
						(0.038)	(0.046)	(0.033)	(0.023)
Asian	0.087	0.145	0.122	0.132	0.163	-0.046	-0.049	0.024	-0.022
						(0.048)	(0.053)	(0.051)	(0.044)
White	0.025	0.045	0.041	0.053	0.042	-0.018	-0.015	0.010	0.010
						(0.027)	(0.030)	(0.029)	(0.028)
Multiethnic	0.300	0.318	0.284	0.250	0.274	-0.039	-0.009	0.015	-0.039
						(0.069)	(0.077)	(0.067)	(0.052)
GPA	3.896	3.862	3.912	3.851	3.807	0.033	-0.025	-0.050	0.030
						(0.042)	(0.024)	(0.040)	(0.027)
Free/reduced-price lunch	0.487	0.455	0.419	0.303	0.391	0.045	0.069	0.025	-0.076
						(0.077)	(0.084)	(0.074)	(0.058)
Standardized math score	2.215	2.304	2.251	1.799	1.939	-0.123	-0.071	0.055	-0.131
						(0.104)	(0.131)	(0.127)	(0.103)
Female	0.500	0.500	0.500	0.500	0.343	0.000	0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)	(0.000)
First-generation college	0.188	0.209	0.162	0.118	0.205	-0.002	0.035	0.050	-0.078+
						(0.062)	(0.065)	(0.058)	(0.044)
					p-value	0.844	0.934	0.987	0.498
Observations	80	110	74	76	361	190	154	184	437

Notes: This table shows means for baseline characteristics and outcomes. Columns 1 through 5 shows the proportion of students assigned to each program with a given characteristic. Columns 6 through 9 report coefficients from regressions of the student characteristic on assignment to each program, including controls for randomization strata (+ p<0.10). N=701.

Table A.6: Covariate Balance: 2016 Cohort

	Covariate Means					Strata-adjusted Mean Differences			
	6-Week (Block 1) (1)	1-Week (Block 1) (2)	Online (Block 1) (3)	Online (Block 2) (4)	Control (Block 2) (5)	6-Week vs. 1-Week (6)	6-Week vs. Online (7)	1-Week vs. Online (8)	Online vs. Control (9)
Black	0.400	0.303	0.297	0.289	0.328	0.099	0.108	-0.000	-0.042
						(0.073)	(0.073)	(0.074)	(0.056)
Hispanic	0.422	0.461	0.432	0.434	0.434	-0.046	-0.001	0.056	-0.005
						(0.073)	(0.076)	(0.078)	(0.062)
Native American	0.033	0.053	0.041	0.039	0.042	-0.018	-0.013	0.005	0.001
						(0.031)	(0.029)	(0.033)	(0.024)
Asian	0.089	0.118	0.162	0.184	0.150	-0.030	-0.069	-0.044	0.033
						(0.049)	(0.052)	(0.057)	(0.048)
White	0.056	0.066	0.068	0.039	0.042	-0.005	-0.025	-0.017	0.005
						(0.036)	(0.039)	(0.042)	(0.024)
Multiethnic	0.411	0.395	0.297	0.408	0.390	0.010	0.115	0.115	0.011
						(0.077)	(0.074)	(0.078)	(0.062)
GPA	3.918	3.924	3.918	3.876	3.861	-0.005	0.001	0.009	0.013
						(0.019)	(0.020)	(0.021)	(0.018)
Free/reduced-price lunch	0.478	0.500	0.554	0.342	0.372	-0.040	-0.061	-0.039	-0.029
						(0.075)	(0.076)	(0.079)	(0.059)
Standardized math score	2.016	1.808	2.045	1.467	1.694	0.217	-0.024	-0.221	-0.190
						(0.173)	(0.128)	(0.161)	(0.218)
Female	0.500	0.500	0.500	0.500	0.388	0.000	0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)	(0.000)
First-generation college	0.467	0.513	0.419	0.329	0.284	-0.048	0.057	0.103	0.038
						(0.078)	(0.075)	(0.080)	(0.059)
					p-value	0.924	0.218	0.563	0.891
Observations	90	76	74	76	432	166	164	150	508

Notes: This table shows means for baseline characteristics and outcomes. Columns 1 through 5 shows the proportion of students assigned to each program with a given characteristic. Columns 6 through 9 report coefficients from regressions of the student characteristic on assignment to each program, including controls for randomization strata (+ $p<0.10$). N=748.

Appendix B: Detailed College Attendance and Graduation Impacts and Other Results

Table B.1: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance in Year 1

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elites Colleges (4)	Elites Ex. HI (5)
(A) Block 1: 6- and 1-week vs. Online					
6-week	0.107*	0.005	-0.102*	0.066	-0.041
	(0.038)	(0.017)	(0.034)	(0.057)	(0.072)
1-week	0.038	0.028	-0.010	0.043	0.005
	(0.035)	(0.027)	(0.035)	(0.047)	(0.051)
Online Mean	0.156	0.894	0.739	0.633	0.477
(B) Block 2: Online vs. Control					
Online	0.040^{+}	0.014	-0.026	0.092*	0.053
	(0.020)	(0.017)	(0.032)	(0.037)	(0.051)
Control Mean	0.057	0.879	0.822	0.477	0.420
(C) $\beta_{res} + \beta_{online}$					
6-week	0.147**	0.018	-0.129*	0.159*	0.012
	(0.051)	(0.043)	(0.061)	(0.065)	(0.069)
1-week	0.078+	0.042	-0.036	0.136*	0.058
	(0.041)	(0.037)	(0.051)	(0.058)	(0.061)
(D) Conditional Randomization					
6-Week	0.167***	0.029	-0.138***	0.166*	-0.001
	(0.041)	(0.025)	(0.044)	(0.065)	(0.084)
1-Week	0.059	0.036	-0.022	0.134*	0.076
	(0.038)	(0.030)	(0.045)	(0.059)	(0.071)
Online	0.038^{+}	0.013	-0.025	0.092*	0.054
	(0.020)	(0.016)	(0.031)	(0.035)	(0.050)
Control Mean	0.057	0.879	0.822	0.477	0.420

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.2: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance in Year 2

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elites Colleges (4)	Elites Ex. HI (5)
(A) Block 1: 6- and 1-week vs. Online					
6-week	0.104***	-0.017	-0.121*	0.045	-0.061
	(0.032)	(0.034)	(0.047)	(0.059)	(0.068)
1-week	0.039	0.029	-0.010	0.015	-0.016
	(0.034)	(0.030)	(0.037)	(0.035)	(0.042)
Online Mean	0.151	0.876	0.725	0.628	0.482
(B) Block 2: Online vs. Control					
Online	0.045+	0.016	-0.029	0.096***	0.050
	(0.022)	(0.025)	(0.040)	(0.029)	(0.046)
Control Mean	0.056	0.845	0.789	0.463	0.409
(C) $\beta_{res} + \beta_{online}$					
6-week	0.149**	-0.001	-0.150*	0.141*	-0.012
	(0.051)	(0.048)	(0.063)	(0.066)	(0.068)
1-week	0.083*	0.045	-0.039	0.111+	0.034
	(0.040)	(0.040)	(0.053)	(0.058)	(0.060)
(D) Conditional Randomization					
6-Week	0.169***	0.006	-0.162***	0.129*	-0.040
	(0.038)	(0.039)	(0.057)	(0.063)	(0.079)
1-Week	0.064	0.041	-0.023	0.121*	0.061
	(0.038)	(0.037)	(0.052)	(0.047)	(0.063)
Online	0.043+	0.015	-0.028	0.096***	0.051
	(0.022)	(0.025)	(0.040)	(0.028)	(0.045)
Control Mean	0.056	0.845	0.789	0.463	0.409

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.3: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance in Year 3

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elites Colleges (4)	Elites Ex. HI (5)
(A) Block 1: 6- and 1-week vs. Online					
6-week	0.096***	-0.021	-0.116+	0.028	-0.066
	(0.031)	(0.033)	(0.055)	(0.051)	(0.074)
1-week	0.030	0.025	-0.005	0.013	-0.007
	(0.034)	(0.036)	(0.027)	(0.034)	(0.039)
Online Mean	0.156	0.835	0.679	0.596	0.440
(B) Block 2: Online vs. Control					
Online	0.045+	0.001	-0.043	0.098*	0.053
	(0.022)	(0.020)	(0.037)	(0.033)	(0.047)
Control Mean	0.056	0.814	0.758	0.448	0.392
(C) $\beta_{res} + \beta_{online}$					
6-week	0.141**	-0.019	-0.160*	0.126+	-0.013
	(0.051)	(0.053)	(0.065)	(0.067)	(0.068)
1-week	0.075+	0.027	-0.048	0.111+	0.047
	(0.040)	(0.045)	(0.055)	(0.058)	(0.060)
(D) Conditional Randomization					
6-Week	0.159***	-0.012	-0.171***	0.116*	-0.037
	(0.038)	(0.036)	(0.060)	(0.056)	(0.081)
1-Week	0.057	0.023	-0.034	0.119*	0.070
	(0.039)	(0.040)	(0.045)	(0.046)	(0.061)
Online	0.043+	0.001	-0.043	0.097***	0.054
	(0.022)	(0.020)	(0.036)	(0.031)	(0.045)
Control Mean	0.056	0.814	0.758	0.448	0.392

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.4: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance in Year 4

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elites Colleges (4)	Elites Ex. HI (5)
(A) Block 1: 6- and 1-week vs. Online					
6-week	0.114*	0.036	-0.078	0.064	-0.050
	(0.042)	(0.040)	(0.047)	(0.046)	(0.048)
1-week	0.031	0.092+	0.061+	0.068	0.026
	(0.037)	(0.045)	(0.031)	(0.045)	(0.033)
Online Mean	0.147	0.780	0.633	0.546	0.413
(B) Block 2: Online vs. Control					
Online	0.049*	0.027	-0.021	0.094***	0.053
	(0.022)	(0.017)	(0.032)	(0.030)	(0.044)
Control Mean	0.051	0.777	0.726	0.420	0.370
(C) $\beta_{res} + \beta_{online}$					
6-week	0.163**	0.063	-0.099	0.158*	0.003
	(0.051)	(0.056)	(0.066)	(0.067)	(0.067)
1-week	0.080*	0.119*	0.039	0.163**	0.079
	(0.040)	(0.047)	(0.056)	(0.059)	(0.060)
(D) Conditional Randomization					
6-Week	0.178***	0.069	-0.110*	0.147*	-0.026
	(0.044)	(0.042)	(0.053)	(0.055)	(0.065)
1-Week	0.064	0.117*	0.054	0.169***	0.103+
	(0.041)	(0.047)	(0.043)	(0.053)	(0.056)
Online	0.047*	0.027	-0.021	0.092***	0.053
	(0.022)	(0.017)	(0.032)	(0.029)	(0.043)
Control Mean	0.051	0.777	0.726	0.420	0.370

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$).

Table B.5: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Graduation by Year 4

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elite Colleges (4)	Elites Ex. HI (5)	In STEM (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	0.106***	0.029	-0.077	0.071	-0.050	0.103+
	(0.032)	(0.038)	(0.046)	(0.047)	(0.054)	(0.054)
1-week	0.017	0.035	0.017	0.045	0.008	0.060
	(0.034)	(0.048)	(0.028)	(0.051)	(0.039)	(0.051)
Online Mean	0.138	0.610	0.472	0.459	0.339	0.422
(B) Block 2: Online vs. Control						
Online	0.034+	0.028	-0.006	0.045	0.008	0.037
	(0.019)	(0.027)	(0.038)	(0.039)	(0.048)	(0.026)
Control Mean	0.039	0.559	0.520	0.355	0.319	0.377
(C) $\beta_{res} + \beta_{online}$						
6-week	0.141**	0.057	-0.084	0.116+	-0.042	0.140*
	(0.048)	(0.067)	(0.068)	(0.067)	(0.064)	(0.068)
1-week	0.052	0.011	0.090	0.063	0.016	0.096
	(0.037)	(0.059)	(0.061)	(0.059)	(0.057)	(0.059)
(D) Conditional Randomization						
6-Week	0.146***	0.053	-0.094+	0.102+	-0.061	0.124*
	(0.035)	(0.046)	(0.055)	(0.057)	(0.067)	(0.056)
1-Week	0.041	0.070	0.029	0.098	0.036	0.104+
	(0.036)	(0.053)	(0.045)	(0.061)	(0.059)	(0.057)
Online	0.033+	0.028	-0.005	0.044	0.009	0.035
	(0.019)	(0.027)	(0.038)	(0.037)	(0.046)	(0.026)
Control Mean	0.039	0.559	0.520	0.355	0.319	0.377

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.6: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Graduation by Year 5

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elite Colleges (4)	Elites Ex. HI (5)	In STEM (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	0.106***	-0.013	-0.119*	0.047	-0.076	0.086
	(0.032)	(0.024)	(0.040)	(0.053)	(0.067)	(0.063)
1-week	0.024	0.079*	0.055*	0.070	0.031	0.095+
	(0.035)	(0.033)	(0.024)	(0.045)	(0.035)	(0.051)
Online Mean	0.138	0.748	0.610	0.541	0.417	0.505
(B) Block 2: Online vs. Control						
Online	0.033	0.037	0.004	0.070	0.036	0.026
	(0.019)	(0.028)	(0.036)	(0.042)	(0.049)	(0.024)
Control Mean	0.040	0.720	0.680	0.417	0.377	0.490
(C) $\beta_{res} + \beta_{online}$						
6-week	0.139**	0.024	-0.115+	0.117+	-0.040	0.111+
	(0.048)	(0.060)	(0.067)	(0.067)	(0.067)	(0.068)
1-week	0.058	0.059	0.140*	0.117*	0.067	0.121*
	(0.037)	(0.051)	(0.058)	(0.059)	(0.060)	(0.060)
(D) Conditional Randomization						
6-Week	0.155***	0.028	-0.126*	0.102	-0.066	0.104
	(0.036)	(0.037)	(0.048)	(0.065)	(0.077)	(0.062)
1-Week	0.040	0.112*	0.071+	0.148*	0.090	0.119*
	(0.037)	(0.042)	(0.040)	(0.060)	(0.060)	(0.055)
Online	0.032	0.037	0.005	0.069+	0.036	0.023
	(0.019)	(0.028)	(0.035)	(0.040)	(0.048)	(0.024)
Control Mean	0.040	0.720	0.680	0.417	0.377	0.490

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.7: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Graduation by Year 6

	HI (1)	Any 4-Year College (2)	4-Year Ex. HI (3)	Elite Colleges (4)	Elites Ex. HI (5)	In STEM (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	0.106***	-0.019	-0.124*	0.036	-0.086	0.088
	(0.032)	(0.034)	(0.051)	(0.051)	(0.067)	(0.066)
1-week	0.024	0.052	0.028	0.046	0.007	0.089
	(0.035)	(0.035)	(0.033)	(0.039)	(0.038)	(0.053)
Online Mean	0.138	0.798	0.661	0.573	0.450	0.528
(B) Block 2: Online vs. Control						
Online	0.038+	0.040+	0.002	0.094*	0.055	0.030
	(0.019)	(0.019)	(0.028)	(0.039)	(0.047)	(0.022)
Control Mean	0.040	0.774	0.733	0.430	0.390	0.520
(C) $\beta_{res} + \beta_{online}$						
6-week	0.144**	0.021	-0.122+	0.130+	-0.031	0.118+
	(0.048)	(0.056)	(0.066)	(0.067)	(0.068)	(0.067)
1-week	0.062+	0.030	0.139*	0.092+	0.062	0.119*
	(0.038)	(0.048)	(0.055)	(0.059)	(0.060)	(0.060)
(D) Conditional Randomization						
6-Week	0.159***	0.025	-0.134***	0.115+	-0.059	0.115+
	(0.036)	(0.036)	(0.049)	(0.061)	(0.075)	(0.063)
1-Week	0.045	0.088*	0.043	0.148***	0.086	0.115*
	(0.037)	(0.038)	(0.038)	(0.054)	(0.059)	(0.055)
Online	0.036+	0.040*	0.004	0.094*	0.056	0.028
	(0.019)	(0.019)	(0.027)	(0.037)	(0.045)	(0.022)
Control Mean	0.040	0.774	0.733	0.430	0.390	0.520

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.8: The Impact of Assignment to STEM Summer Programs on HI Outcomes

	Applied Early to HI (1)	Applied to HI (2)	Accepted to HI (3)	Attended HI First Year (4)	Attended HI Fourth Year (5)	Graduated HI By 4 (6)	Graduated HI By 6 (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.140*	0.121*	0.106***	0.107*	0.114*	0.106***	0.106***
	(0.052)	(0.047)	(0.029)	(0.038)	(0.042)	(0.032)	(0.032)
1-week	0.047	0.050	0.028	0.038	0.031	0.017	0.024
	(0.045)	(0.053)	(0.036)	(0.035)	(0.037)	(0.034)	(0.035)
Online Mean	0.381	0.661	0.266	0.156	0.147	0.138	0.138
(B) Block 2: Online vs. Control							
Online	0.176***	0.353***	0.091***	0.040+	0.049*	0.034+	0.038+
	(0.034)	(0.024)	(0.028)	(0.020)	(0.022)	(0.019)	(0.019)
Control Mean	0.184	0.317	0.061	0.057	0.051	0.039	0.040
(C) $\beta_{res} + \beta_{online}$							
6-week	0.317***	0.474***	0.197***	0.147**	0.163**	0.141**	0.144**
	(0.066)	(0.062)	(0.057)	(0.051)	(0.051)	(0.048)	(0.048)
1-week	0.223***	0.402***	0.120*	0.078+	0.080*	0.052	0.062+
	(0.057)	(0.056)	(0.047)	(0.041)	(0.040)	(0.037)	(0.038)
(D) Conditional Randomization							
6-Week	0.330***	0.464***	0.207***	0.167***	0.178***	0.146***	0.159***
	(0.058)	(0.050)	(0.041)	(0.041)	(0.044)	(0.035)	(0.036)
1-Week	0.211***	0.398***	0.105*	0.059	0.064	0.041	0.045
	(0.054)	(0.055)	(0.042)	(0.038)	(0.041)	(0.036)	(0.037)
Online	0.176***	0.352***	0.088***	0.038+	0.047*	0.033+	0.036+
	(0.034)	(0.024)	(0.028)	(0.020)	(0.022)	(0.019)	(0.019)
Control Mean	0.184	0.317	0.061	0.057	0.051	0.039	0.040

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).

Table B.9: The Impact of Assignment to STEM Summer Programs on STEM and non-STEM Degrees

	Any Four-Year Institution			Elites			Host Institution	
	STEM (1)	Non-STEM (2)	Missing Major (3)	STEM (4)	Non-STEM (5)	Missing Major (6)	STEM (7)	Non-STEM (8)
(A) Block 1: 6- and 1-week vs. Online								
6-week	0.081	-0.066	-0.034	0.166^{+}	-0.139	-0.027	0.152	-0.152
	(0.063)	(0.045)	(0.022)	(0.093)	(0.083)	(0.028)	(0.102)	(0.102)
1-week	0.071	-0.029	0.010	0.047	-0.064	0.017	0.126	-0.126
	(0.052)	(0.031)	(0.024)	(0.062)	(0.038)	(0.041)	(0.075)	(0.075)
Online Mean	0.550	0.165	0.083	0.696	0.224	0.080	0.800	0.200
(B) Block 2: Online vs. Control								
Online	0.033	0.009	-0.002	0.048	-0.044	-0.004	0.054	-0.054
	(0.023)	(0.019)	(0.026)	(0.036)	(0.034)	(0.038)	(0.114)	(0.114)
Control Mean	0.541	0.142	0.090	0.685	0.202	0.113	0.930	0.070
(C) $\beta_{res} + \beta_{online}$								
6-week	0.114+	-0.057	-0.036	0.215*	-0.183*	-0.032	0.207	-0.207
	(0.067)	(0.048)	(0.033)	(0.084)	(0.074)	(0.051)	(0.161)	(0.161)
1-week	0.104+	-0.020	0.008	0.095	-0.108	0.012	0.181	-0.181
	(0.060)	(0.044)	(0.033)	(0.077)	(0.068)	(0.048)	(0.139)	(0.139)
(D) Conditional Randomization								
6-Week	0.108^{+}	-0.057	-0.026	0.207^{*}	-0.169^{*}	-0.038	0.129	-0.129
	(0.061)	(0.044)	(0.032)	(0.086)	(0.078)	(0.045)	(0.138)	(0.138)
1-Week	0.101^{+}	-0.015	0.002	0.100	-0.113^{*}	0.013	0.181	-0.181
	(0.055)	(0.035)	(0.034)	(0.068)	(0.052)	(0.051)	(0.137)	(0.137)
Online	0.031	0.012	-0.002	0.048	-0.041	-0.007	0.038	-0.038
	(0.023)	(0.019)	(0.026)	(0.035)	(0.034)	(0.037)	(0.123)	(0.123)
Control Mean	0.541	0.142	0.090	0.685	0.202	0.113	0.930	0.070

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).Students are categorized as STEM if any of their degree majors are STEM. Degrees are categorized using CIP and, if CIP is unavailable, whether the degree is a Bachelor of Science. Students are categorized as STEM if at least one major is STEM. Students are categorized as non-STEM if none of their majors is STEM. Students who attained degrees, but have no degree major codes and did not attain Bachelors of Science, are categorized as Missing Major. There are no missing majors at the HI.

Table B.10: The Impact of Assignment to STEM Summer Programs on Detailed STEM Majors (6-Year Graduation)

	Computer Science (1)	Engineering (2)	Engineering Tech (3)	Bio and Biomed Sci (4)	Math and Stats (5)	Phys Sci (6)	Non STEM Major (7)	Missing Major Code (8)
(A) Block 1: 6- and 1-week vs. Online								
6-week	-0.004	0.054	-0.011^{+}	0.025	0.022	0.022	-0.066	-0.041^{+}
	(0.046)	(0.037)	(0.006)	(0.045)	(0.021)	(0.021)	(0.045)	(0.020)
1-week	-0.018	0.052	-0.001	0.051***	0.011	0.013	-0.029	-0.008
	(0.025)	(0.054)	(0.008)	(0.015)	(0.013)	(0.017)	(0.031)	(0.026)
Online Mean	0.138	0.271	0.009	0.046	0.028	0.037	0.165	0.106
(B) Block 2: Online vs. Control								
Online	0.006	0.044^{+}	-0.003	-0.009	-0.003	-0.000	0.009	0.001
	(0.016)	(0.024)	(0.005)	(0.021)	(0.009)	(0.007)	(0.019)	(0.028)
Control Mean	0.130	0.260	0.007	0.057	0.039	0.034	0.142	0.112
(C) $\beta_{res} + \beta_{online}$								
6-week	0.003	0.098	-0.014	0.016	0.019	0.022	-0.057	-0.041
	(0.046)	(0.062)	(0.009)	(0.034)	(0.026)	(0.027)	(0.048)	(0.038)
1-week	-0.012	0.096+	-0.004	0.042	0.008	0.013	-0.020	-0.007
	(0.040)	(0.055)	(0.010)	(0.030)	(0.021)	(0.023)	(0.044)	(0.036)
(D) Conditional Randomization								
6-Week	0.009	0.084^{+}	-0.012	0.026	0.010	0.020	-0.057	-0.033
	(0.047)	(0.045)	(0.008)	(0.043)	(0.023)	(0.020)	(0.044)	(0.033)
1-Week	-0.020	0.098^{+}	-0.004	0.036	0.015	0.016	-0.015	-0.012
	(0.031)	(0.055)	(0.009)	(0.025)	(0.017)	(0.018)	(0.035)	(0.036)
Online	0.005	0.044^{+}	-0.002	-0.010	-0.004	-0.000	0.012	0.000
	(0.016)	(0.023)	(0.005)	(0.021)	(0.009)	(0.008)	(0.019)	(0.028)
Control Mean	0.130	0.260	0.007	0.057	0.039	0.034	0.142	0.112

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).Students who attained degrees, had at least one major code, and had no STEM major codes were categorized as non-STEM. Students who attained degrees, but had no major codes, were categorized as missing major. Coefficients may not add up to the coefficients on degree attainment, since students can have multiple majors.

Table B.11: The Impact of Assignment to STEM Summer Programs on Detailed STEM Majors at the Host Institution (6-Year Graduation)

	Computer Science (1)	Engineering (2)	Bio and Biomed Sci (3)	Math and Stats (4)	Phys Sci (5)	Non STEM Major (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	-0.159	0.219	0.154*	-0.016	0.061	-0.152
	(0.164)	(0.158)	(0.056)	(0.048)	(0.069)	(0.102)
1-week	-0.031	0.163	0.068	0.000	0.057	-0.126
	(0.124)	(0.127)	(0.056)	(0.075)	(0.082)	(0.075)
Online Mean	0.300	0.400	0.033	0.067	0.033	0.200
(B) Block 2: Online vs. Control						
Online	0.007	0.216	-0.123***	-0.024	-0.002	-0.054
	(0.154)	(0.163)	(0.024)	(0.017)	(0.019)	(0.114)
Control Mean	0.256	0.465	0.116	0.023	0.093	0.070
(C) $\beta_{res} + \beta_{online}$						
6-week	-0.152	0.435+	0.031	-0.040	0.059	-0.207
	(0.233)	(0.248)	(0.109)	(0.080)	(0.099)	(0.161)
1-week	-0.024	0.379+	-0.055	-0.023	0.055	-0.181
	(0.226)	(0.230)	(0.095)	(0.087)	(0.087)	(0.139)
(D) Conditional Randomization						
6-Week	-0.172	0.460*	-0.005	-0.051	0.027	-0.129
	(0.201)	(0.189)	(0.062)	(0.045)	(0.074)	(0.138)
1-Week	-0.124	0.543***	-0.077	-0.010	0.014	-0.181
	(0.186)	(0.168)	(0.052)	(0.060)	(0.085)	(0.137)
Online	-0.037	0.313*	-0.151***	-0.028	-0.033	-0.038
	(0.154)	(0.125)	(0.041)	(0.020)	(0.029)	(0.123)
Control Mean	0.256	0.465	0.116	0.023	0.093	0.070

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).Students who attained degrees, had at least one major code, and had no STEM major codes were categorized as non-STEM. There are no students with engineering tech or missing majors at the HI. Coefficients may not add up to the coefficients on degree attainment, since students can have multiple majors.

Table B.12: The Impact of Assignment to STEM Summer Programs on STEM and non-STEM Degrees , Counting Missing as STEM

	Any Four-Year Institution		Elites		Host Institution	
	STEM (1)	Non-STEM (2)	STEM (3)	Non-STEM (4)	STEM (5)	Non-STEM (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	0.047	-0.066	0.139	-0.139	0.152	-0.152
	(0.066)	(0.045)	(0.083)	(0.083)	(0.102)	(0.102)
1-week	0.081^{+}	-0.029	0.064	-0.064	0.126	-0.126
	(0.041)	(0.031)	(0.038)	(0.038)	(0.075)	(0.075)
Online Mean	0.633	0.165	0.776	0.224	0.800	0.200
(B) Block 2: Online vs. Control						
Online	0.031	0.009	0.044	-0.044	0.054	-0.054
	(0.018)	(0.019)	(0.034)	(0.034)	(0.114)	(0.114)
Control Mean	0.632	0.142	0.798	0.202	0.930	0.070
(C) $\beta_{res} + \beta_{online}$						
6-week	0.078	-0.057	0.183*	-0.183*	0.207	-0.207
	(0.065)	(0.048)	(0.074)	(0.074)	(0.161)	(0.161)
1-week	0.112+	-0.020	0.108	-0.108	0.181	-0.181
	(0.058)	(0.044)	(0.068)	(0.068)	(0.139)	(0.139)
(D) Conditional Randomization						
6-Week	0.082	-0.057	0.169*	-0.169*	0.129	-0.129
	(0.058)	(0.044)	(0.078)	(0.078)	(0.138)	(0.138)
1-Week	0.103*	-0.015	0.113*	-0.113*	0.181	-0.181
	(0.043)	(0.035)	(0.052)	(0.052)	(0.137)	(0.137)
Online	0.029	0.012	0.041	-0.041	0.038	-0.038
	(0.019)	(0.019)	(0.034)	(0.034)	(0.123)	(0.123)
Control Mean	0.632	0.142	0.798	0.202	0.930	0.070

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001).Students are categorized as STEM if any of their degree majors are STEM. Degrees are categorized using CIP and, if CIP is unavailable, whether the degree is a Bachelor of Science. Students are categorized as STEM if at least one major is STEM. Students are categorized as non-STEM if none of their majors is STEM. Students who attained degrees, but have no degree major codes and did not attain Bachelors of Science, are categorized as STEM. There are no missing majors at the HI.

Table B.13: The Impact of Assignment to STEM Summer Programs on STEM and non-STEM Degrees , Counting Missing as Non-STEM

	Any Four-Year Institution		Elites		Host Institution	
	STEM (1)	Non-STEM (2)	STEM (3)	Non-STEM (4)	STEM (5)	Non-STEM (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	0.081	-0.099+	0.166+	-0.166+	0.152	-0.152
	(0.063)	(0.047)	(0.093)	(0.093)	(0.102)	(0.102)
1-week	0.071	-0.019	0.047	-0.047	0.126	-0.126
	(0.052)	(0.047)	(0.062)	(0.062)	(0.075)	(0.075)
Online Mean	0.550	0.248	0.696	0.304	0.800	0.200
(B) Block 2: Online vs. Control						
Online	0.033	0.007	0.048	-0.048	0.054	-0.054
	(0.023)	(0.020)	(0.036)	(0.036)	(0.114)	(0.114)
Control Mean	0.541	0.232	0.685	0.315	0.930	0.070
(C) $\beta_{res} + \beta_{online}$						
6-week	0.078	-0.057	0.183*	-0.183*	0.207	-0.207
	(0.065)	(0.048)	(0.074)	(0.074)	(0.161)	(0.161)
1-week	0.112+	-0.020	0.108	-0.108	0.181	-0.181
	(0.058)	(0.044)	(0.068)	(0.068)	(0.139)	(0.139)
(D) Conditional Randomization						
6-Week	0.082	-0.057	0.169*	-0.169*	0.129	-0.129
	(0.058)	(0.044)	(0.078)	(0.078)	(0.138)	(0.138)
1-Week	0.103*	-0.015	0.113*	-0.113*	0.181	-0.181
	(0.043)	(0.035)	(0.052)	(0.052)	(0.137)	(0.137)
Online	0.029	0.012	0.041	-0.041	0.038	-0.038
	(0.019)	(0.019)	(0.034)	(0.034)	(0.123)	(0.123)
Control Mean	0.632	0.142	0.798	0.202	0.930	0.070

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$).Students are categorized as STEM if any of their degree majors are STEM. Degrees are categorized using CIP and, if CIP is unavailable, whether the degree is a Bachelor of Science. Students are categorized as STEM if at least one major is STEM. Students are categorized as non-STEM if none of their majors is STEM. Students who attained degrees, but have no degree major codes and did not attain Bachelors of Science, are categorized as non-STEM. There are no missing majors at the HI.

Table B.14: The Impact of Assignment to STEM Summer Programs on College Applications and Admissions for Summer Experience Attenders

	Full Control Group						Control Group with STEM Summer Experiences					
	HI			Elite, Excluding HI			HI			Elite, Excluding HI		
	App (1)	Uncond Admit (2)	Admit if Applied (3)	App (4)	Uncond Admit (5)	Admit if Applied (6)	App (7)	Uncond. Admit (8)	Admit if Applied (9)	App (10)	Uncond Admit (11)	Admit if Applied (12)
(A) Block 1												
6-week	0.121*	0.106***	0.069+	0.073*	0.027	-0.030	0.121*	0.106***	0.069+	0.073*	0.027	-0.030
	(0.047)	(0.029)	(0.035)	(0.034)	(0.043)	(0.037)	(0.047)	(0.029)	(0.035)	(0.034)	(0.043)	(0.037)
1-week	0.050	0.028	0.005	0.011	0.009	0.010	0.050	0.028	0.005	0.011	0.009	0.010
	(0.053)	(0.036)	(0.056)	(0.045)	(0.055)	(0.031)	(0.053)	(0.036)	(0.056)	(0.045)	(0.055)	(0.031)
Online Mean	0.661	0.266	0.403	0.874	0.770	0.882	0.661	0.266	0.403	0.874	0.770	0.882
(B) Block 2												
Online	0.353***	0.091***	0.055	0.044+	0.083*	0.054+	0.309***	0.083	0.029	0.012	0.028	0.024
	(0.024)	(0.028)	(0.041)	(0.023)	(0.030)	(0.028)	(0.045)	(0.050)	(0.072)	(0.040)	(0.058)	(0.049)
Control Mean	0.317	0.061	0.191	0.848	0.685	0.807	0.373	0.072	0.194	0.864	0.727	0.842
(C) $\beta_{res} + \beta_{online}$												
6-week	0.474***	0.197***	0.124+	0.117**	0.110+	0.024	0.430***	0.189**	0.098	0.086	0.054	-0.007
	(0.062)	(0.057)	(0.074)	(0.045)	(0.066)	(0.060)	(0.081)	(0.064)	(0.095)	(0.059)	(0.084)	(0.075)
1-week	0.402***	0.120*	0.060	0.055	0.092	0.064	0.359***	0.111*	0.034	0.024	0.037	0.033
	(0.056)	(0.047)	(0.065)	(0.045)	(0.058)	(0.050)	(0.076)	(0.056)	(0.088)	(0.059)	(0.078)	(0.068)
(D) Conditional												
6-Week	0.464***	0.207***	0.142*	0.113*	0.103+	0.020	0.422***	0.204***	0.107	0.086	0.041	-0.020
	(0.050)	(0.041)	(0.055)	(0.041)	(0.054)	(0.044)	(0.062)	(0.053)	(0.074)	(0.054)	(0.070)	(0.055)
1-Week	0.398***	0.105*	0.049	0.061	0.096	0.062	0.353***	0.104+	0.013	0.033	0.037	0.026
	(0.055)	(0.042)	(0.064)	(0.049)	(0.060)	(0.040)	(0.064)	(0.054)	(0.082)	(0.059)	(0.074)	(0.053)
Online	0.352***	0.088***	0.055	0.043+	0.081*	0.054+	0.307***	0.086+	0.019	0.017	0.024	0.017
	(0.024)	(0.028)	(0.039)	(0.023)	(0.030)	(0.027)	(0.042)	(0.044)	(0.064)	(0.041)	(0.054)	(0.045)
Control Mean	0.317	0.061	0.191	0.848	0.685	0.807	0.373	0.072	0.194	0.864	0.727	0.842

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001). Data on summer experiences come from the post-program follow-up survey. For Columns 7-12, we excluded control students who did not respond to the follow-up survey or did not attend a STEM summer experience. This limits the sample to N = 1,177 for HI outcomes. Data on non-HI applications and admissions come from the follow-up survey at the end of the senior year of HS. The samples for these outcomes are restricted to those with data on admissions to specific colleges. The sample sizes are N = 1,402 for Columns 4-6 and N = 928 for Columns 9-12. Samples for columns 3, 6, 9, and 12 are conditional on applying to the institution type.

Table B.15: The Impact of Assignment to STEM Summer Programs on Institution-Level Graduation Rates and STEM Degrees

	IPEDS 4-Year BA Grad Rate (1)	4-Year Degree by Y4 (2)	IPEDS 6-Year BA Grad Rate (3)	4-Year Degree by Y6 (4)	IPEDS STEM as Pct of Bachelor's Degrees (5)	STEM Degree by Y4 (6)	STEM Degree by Y6 (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.041	0.029	0.012	-0.019	0.035	0.089	0.081
	(0.028)	(0.038)	(0.023)	(0.034)	(0.025)	(0.056)	(0.063)
1-week	0.023	0.035	0.007	0.052	-0.005	0.048	0.071
	(0.021)	(0.048)	(0.021)	(0.035)	(0.029)	(0.050)	(0.052)
Online Mean	0.659	0.610	0.815	0.798	0.410	0.440	0.550
(B) Block 2: Online vs. Control							
Online	0.047***	0.028	0.043***	0.040^{+}	0.023^{+}	0.038	0.033
	(0.011)	(0.027)	(0.012)	(0.019)	(0.012)	(0.026)	(0.023)
Control Mean	0.604	0.559	0.755	0.774	0.328	0.394	0.541
(C) $\beta_{res} + \beta_{online}$							
6-week	0.088*	0.057	0.055	0.021		0.127+	0.114+
	(0.039)	(0.067)	(0.037)	(0.056)		(0.068)	(0.067)
1-week	0.070*	0.063	0.050	0.092+		0.086	0.104+
	(0.034)	(0.059)	(0.031)	(0.048)		(0.060)	(0.060)
(D) Conditional Randomization							
6-Week	0.087***	0.053	0.057*	0.025	0.066*	0.111^{+}	0.108^{+}
	(0.027)	(0.046)	(0.024)	(0.036)	(0.027)	(0.056)	(0.061)
1-Week	0.073***	0.070	0.048*	0.088*	0.010	0.092	0.101^{+}
	(0.023)	(0.053)	(0.023)	(0.038)	(0.030)	(0.056)	(0.055)
Online	0.047***	0.028	0.042***	0.040*	0.022^{+}	0.037	0.031
	(0.011)	(0.027)	(0.012)	(0.019)	(0.012)	(0.025)	(0.023)
Control Mean	0.604	0.559	0.755	0.774	0.328	0.394	0.541

Notes: Each coefficient labeled by program is the estimate of the impact of assignment to one of three STEM summer program on the outcome indicated in the heading. All regressions control for randomization strata and a vector of characteristics including indicators for GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status. The sample includes STEM summer program applicants who applied in 2014 to 2016 and passed an initial screen, who were then subject to random assignment. Elite colleges are those ranked as *most competitive* by Barron's. Panel A compares students assigned to one of the residential programs to the online program (N = 504). Panel B compares the online program to the control group (N = 1,327). Panel C combines estimates from Panel A and Panel B using seemingly unrelated regression. Panel D jointly estimates program effects for all three programs compared to the control group (N = 2,084). The online and control means are adjusted for randomization strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 *** p<0.001). The institutional-level outcomes in Columns 1, 3, and 5 are college-level characteristics calculated from IPEDS data in 2013. Values for community colleges and non-college-going respondents are set to 0 for both institutional-level bachelor's four-year graduation rates and STEM degrees.

Table B.16: The Impact of Assignment to STEM Summer Programs on STEM Intentions

	STEM Major						STEM Career	
	Post-Program Survey	First Year College Survey	Second Year College Spring Survey	STEM Degree by Y4 NSC	STEM Degree by Y5 NSC	STEM Degree by Y6 NSC	Post-Program Survey	Second Year College Spring Survey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Block 1								
6-week	0.017	-0.027	-0.053	0.089	0.072	0.081	-0.001	0.034
	(0.021)	(0.040)	(0.050)	(0.056)	(0.058)	(0.063)	(0.028)	(0.067)
1-week	0.009	-0.000	0.025	0.048	0.078	0.071	-0.065^{+}	0.065
	(0.022)	(0.039)	(0.033)	(0.050)	(0.050)	(0.052)	(0.032)	(0.050)
Online Mean	0.938	0.870	0.840	0.440	0.528	0.550	0.890	0.645
(B) Block 2								
Online	-0.007	0.032	-0.005	0.038	0.029	0.033	0.078^{+}	0.009
	(0.036)	(0.036)	(0.029)	(0.026)	(0.026)	(0.023)	(0.039)	(0.034)
Control Mean	0.922	0.829	0.820	0.394	0.511	0.541	0.849	0.628
(C) $\beta_{res} + \beta_{online}$								
6-week	0.009	0.005	-0.058	0.127+	0.101	0.114+	0.077	0.043
	(0.038)	(0.060)	(0.068)	(0.068)	(0.067)	(0.067)	(0.048)	(0.086)
1-week	0.002	0.031	0.021	0.086	0.107+	0.104+	0.013	0.073
	(0.034)	(0.053)	(0.058)	(0.060)	(0.060)	(0.060)	(0.046)	(0.076)
(D) Conditional								
6-Week	0.010	0.011	-0.038	0.111^{+}	0.093	0.108^{+}	0.083^{+}	0.040
	(0.042)	(0.055)	(0.058)	(0.056)	(0.059)	(0.061)	(0.047)	(0.079)
1-Week	-0.001	0.021	0.003	0.092	0.105^{+}	0.101^{+}	0.006	0.058
	(0.041)	(0.054)	(0.044)	(0.056)	(0.055)	(0.055)	(0.050)	(0.058)
Online	-0.007	0.028	-0.003	0.037	0.027	0.031	0.077^{*}	0.008
	(0.035)	(0.035)	(0.026)	(0.025)	(0.026)	(0.023)	(0.037)	(0.036)
Control Mean	0.922	0.829	0.820	0.394	0.511	0.541	0.849	0.628

Notes: The notes for this table are the same as in Table 2 but the sample varies by column. The survey variables use declared major, if available, and intended major if the respondent is undeclared. The first-year survey was only fielded to non-HI attenders. The survey was fielded at the end of the spring semester for cohorts 2014 and 2016 and at the end of the fall semester for cohort 2015. Column 2 combines the first-year survey data for non-HI attenders and HI data on declared majors for the fall of sophomore year for HI attenders. Column 4 uses degree data from the NSC and HI. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

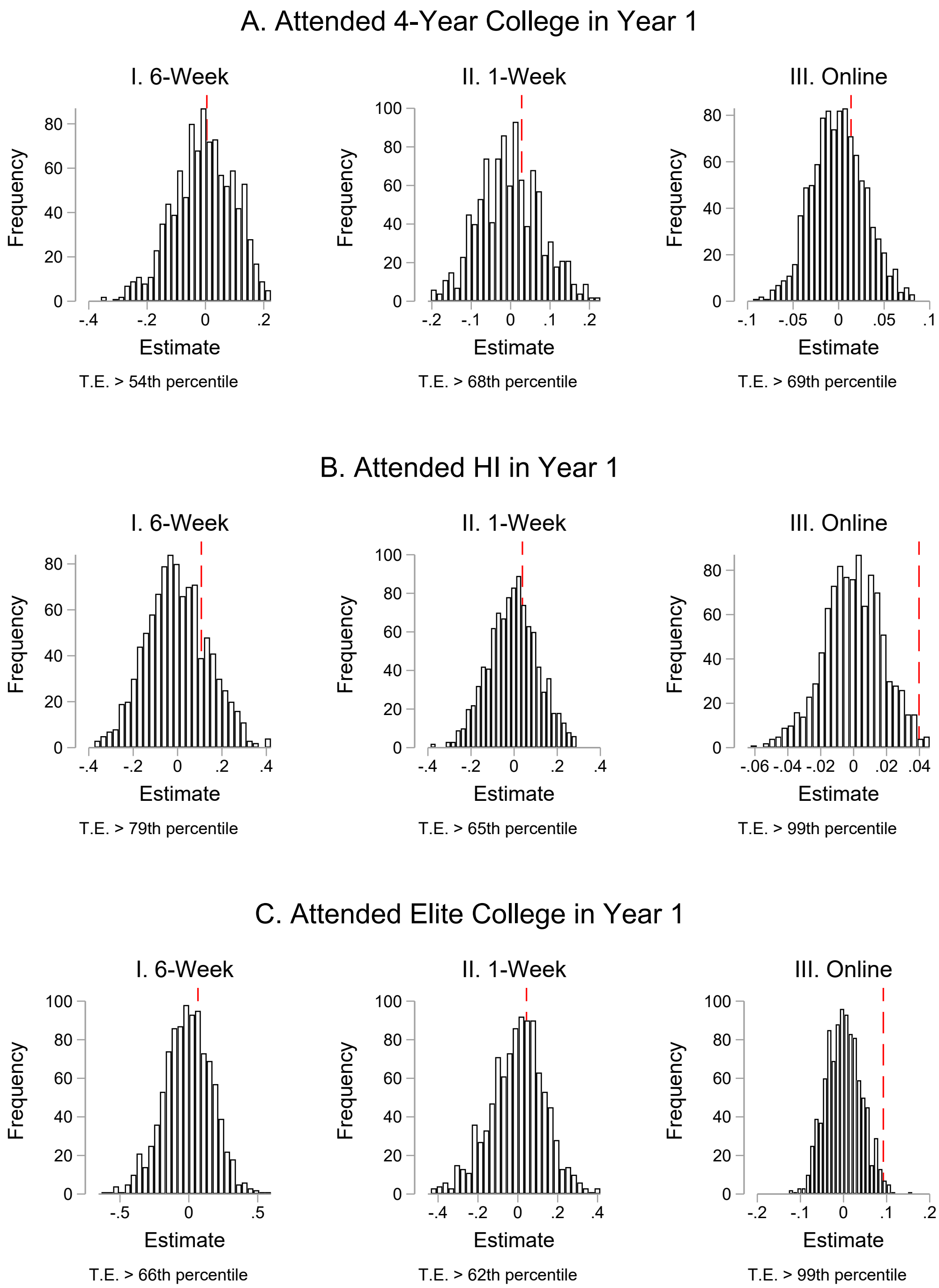
Table B.17: Baseline Characteristics by Program Assignment

	Control Group With STEM Summer (1)	Control Group Without STEM Summer (2)
Black	0.32	0.34
Hispanic	0.45	0.44
Native American	0.04	0.04
Asian	0.16	0.14
White	0.03	0.04
Multiethnic	0.37	0.36
GPA	3.84	3.83
Free/reduced-price lunch	0.40	0.35
Standardized math score	1.83	1.82
Female	0.42	0.29
First-generation college	0.26	0.21
First-generation college	0.26	0.21
Standardized Rating Variable	-0.72	-0.87
N	166	907

Notes: This table summarizes demographic characteristics, test scores, and GPA for program applicants. Column 1 shows averages taken across the entire sample. Columns 2 through 5 display means of these traits at baseline by program assignment. Race/ethnicity categories are not exclusive. First-generation college is defined as no parental college attendance. Students missing parental college information (N=21) were coded as not first-generation.

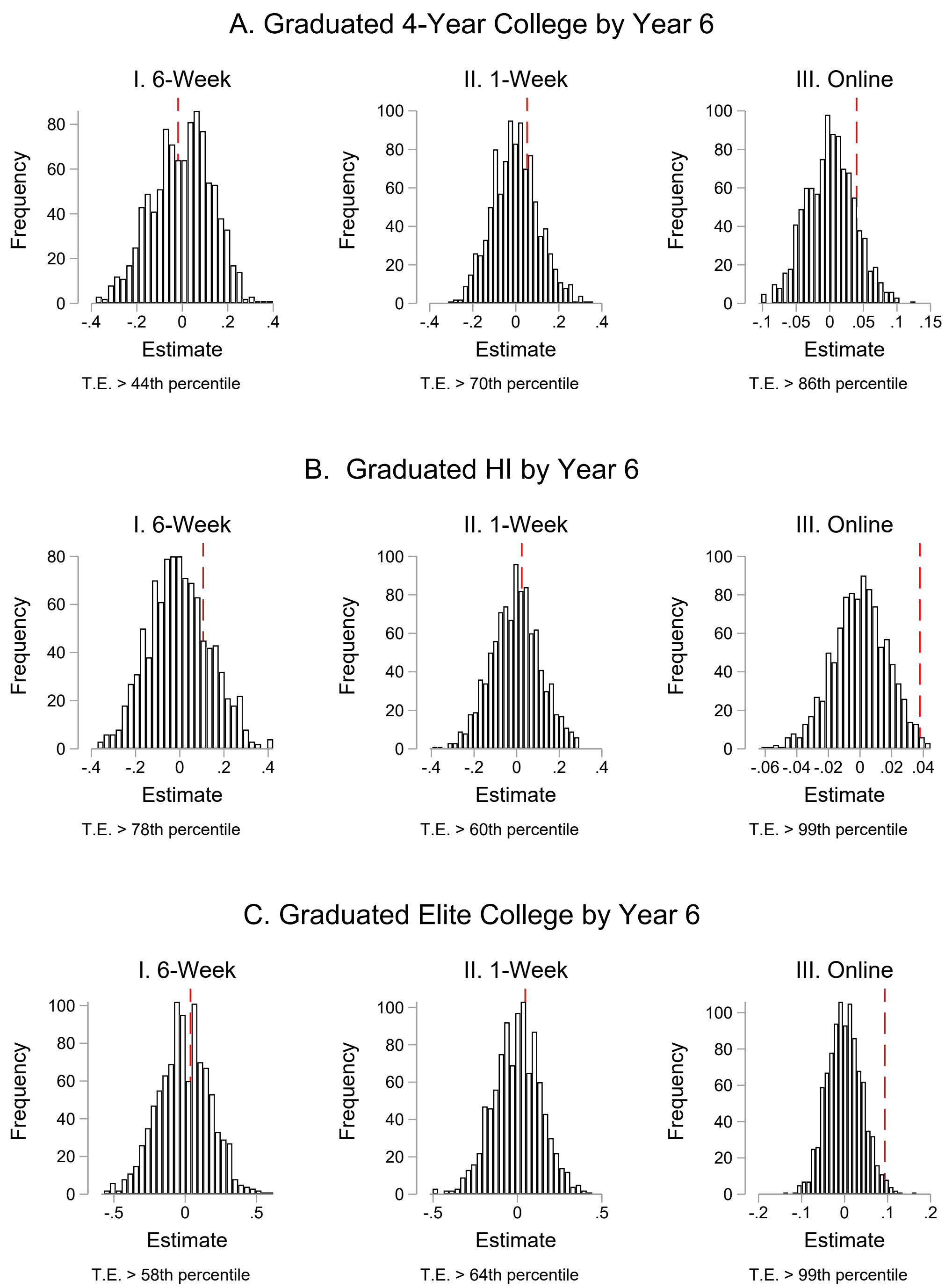
Appendix C: Robustness checks

Figure C.1: Randomization Inference (Pure Randomization): 4-Year Institution Attendance



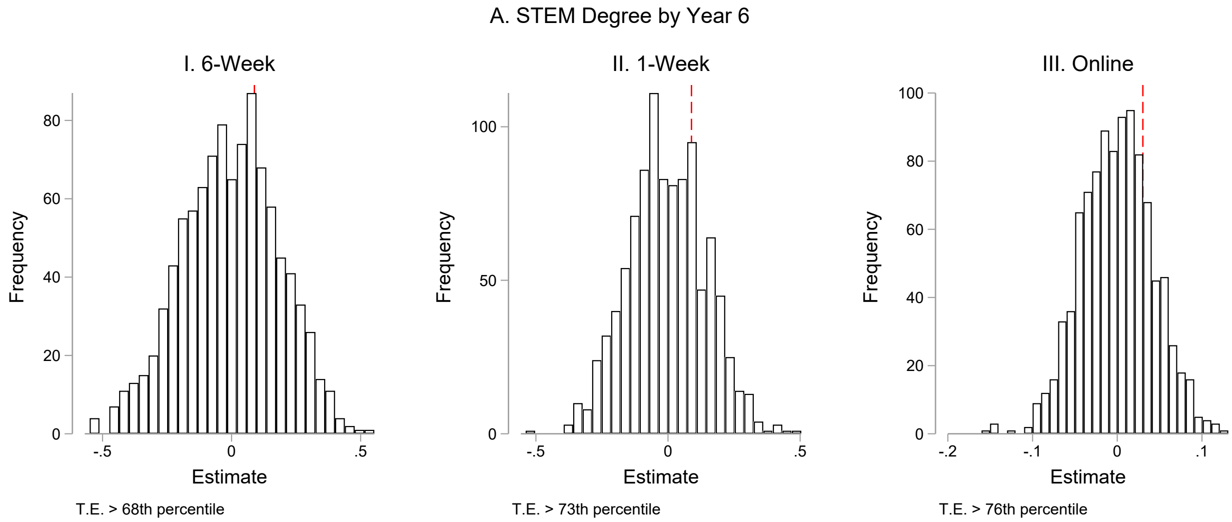
Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the pure randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared. The 6-and 1-week effects are in comparison to the online program. The online program is compared to the control group.

Figure C.2: Randomization Inference (Pure Randomization): Graduation by Year 6



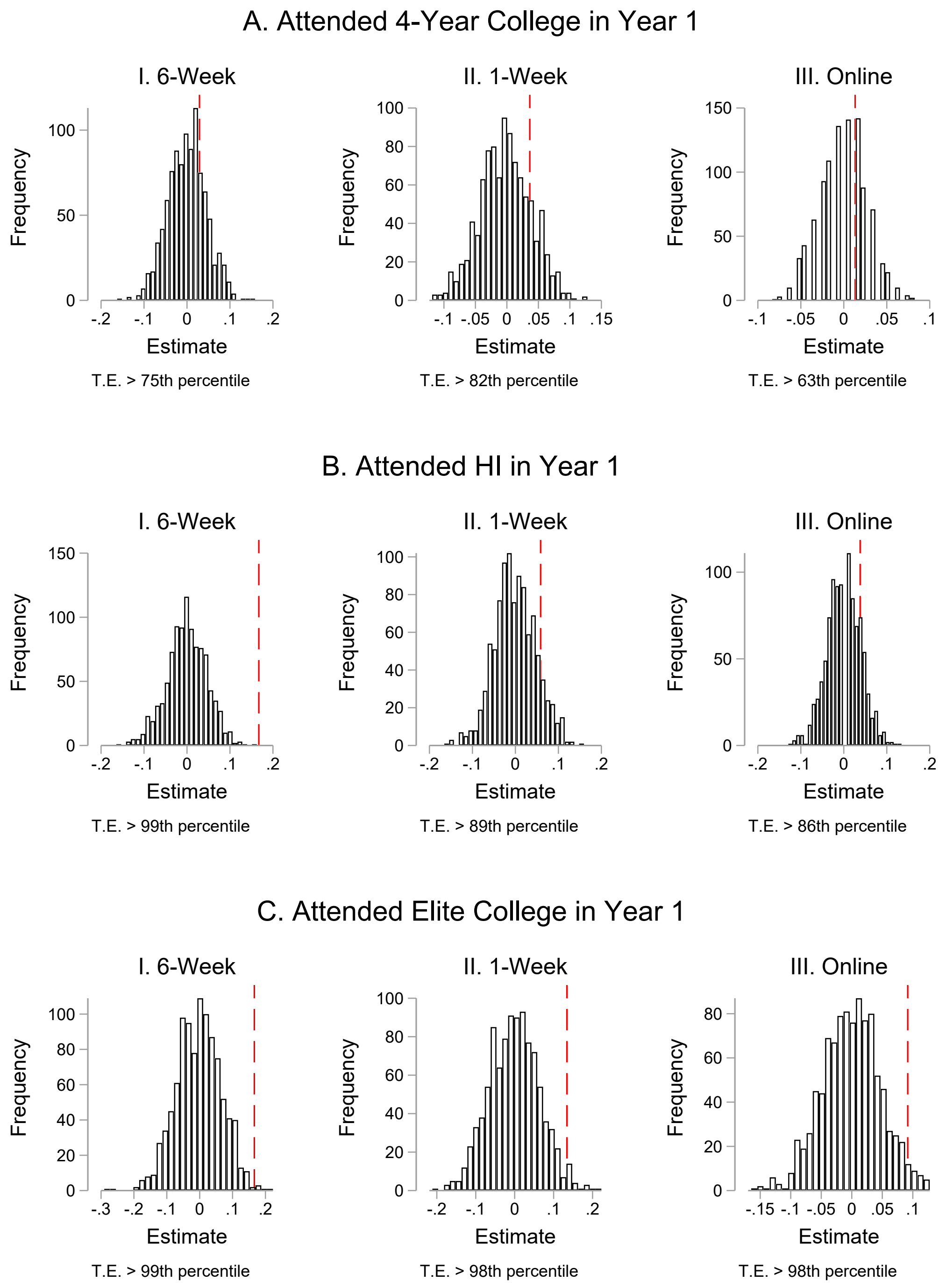
Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the pure randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared. The 6-and 1-week effects are in comparison to the online program. The online program is compared to the control group.

Figure C.3: Randomization Inference (Pure Randomization): STEM Degrees



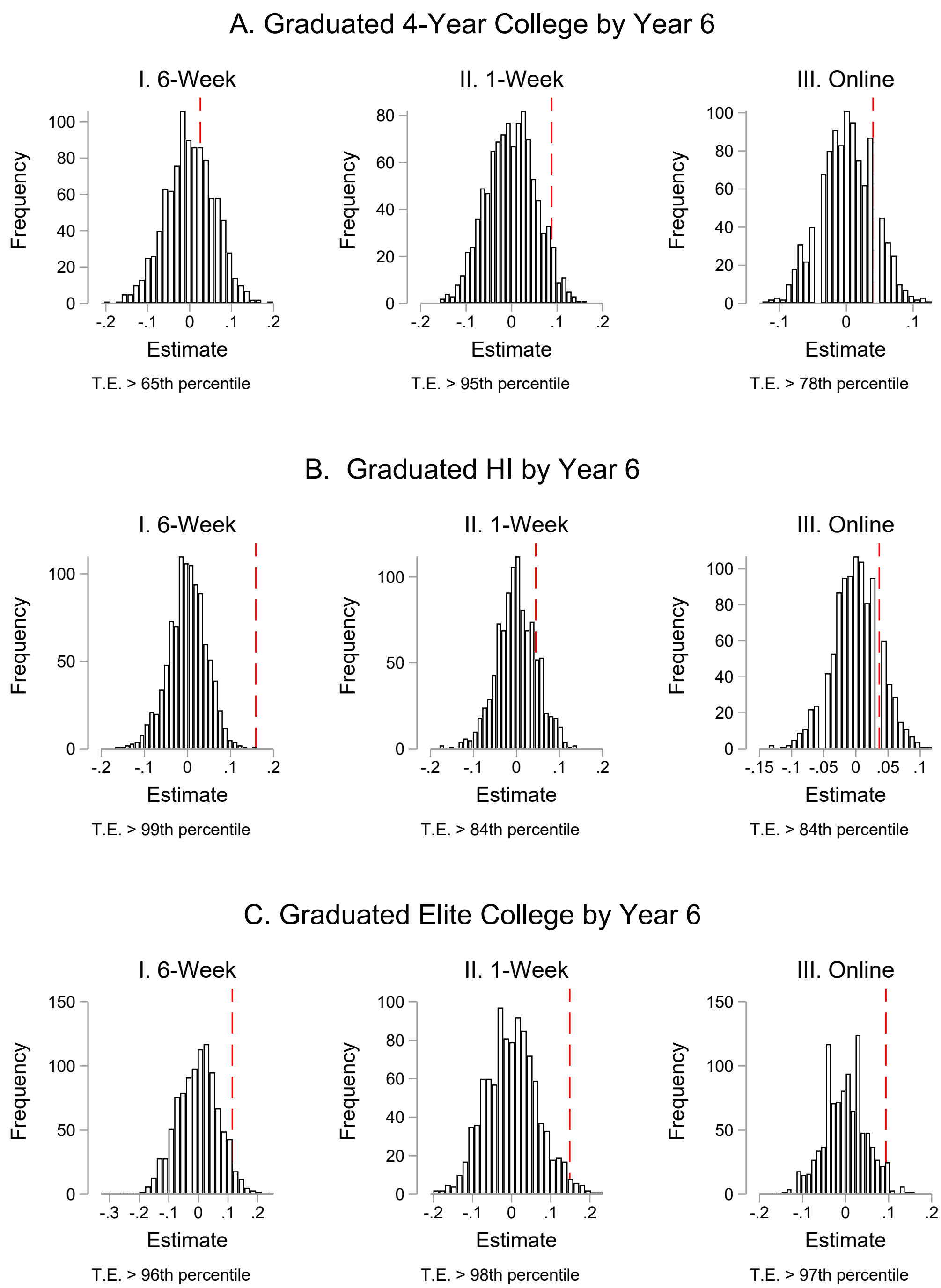
Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the pure randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared. The 6-and 1-week effects are in comparison to the online program. The online program is compared to the control group.

Figure C.4: Randomization Inference (Conditional Randomization): 4-Year Institution Attendance



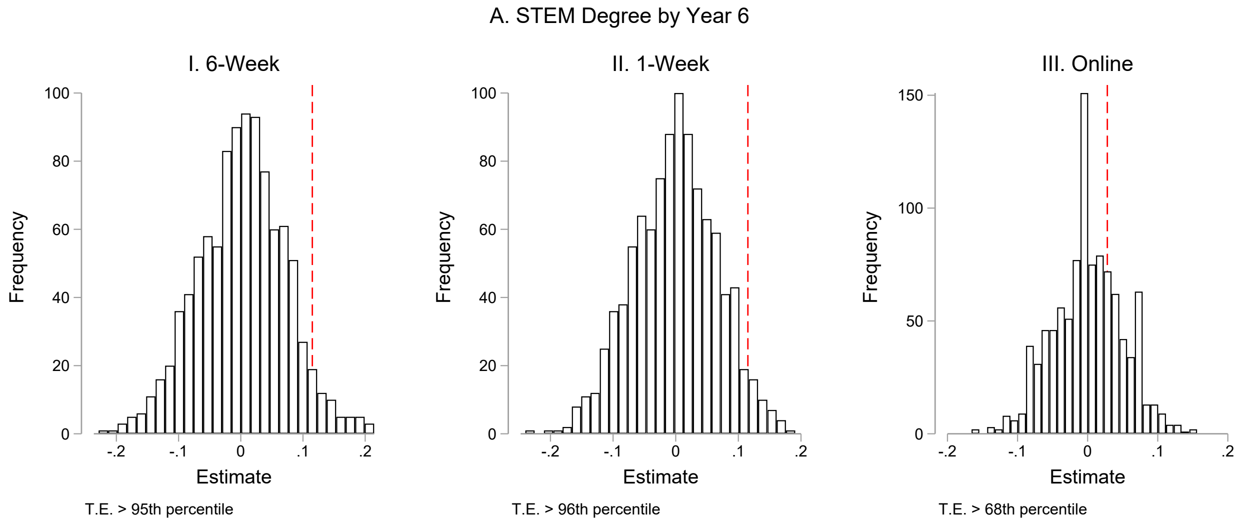
Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the conditional randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared.

Figure C.5: Randomization Inference (Conditional Randomization): Graduation by Year 6



Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the conditional randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared.

Figure C.6: Randomization Inference (Conditional Randomization): STEM Degrees



Notes: Each panel in the above figure shows the distribution of treatment impacts from 1,000 randomizations subject to the same criteria as the conditional randomization design but with a new random number. This generates placebo estimates of impacts on outcomes, to which the actual outcome, indicated by a dashed line, is compared.

Table C.1: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, No Controls

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.005	0.106*	0.074	-0.024	0.102*	0.037	0.076
	(0.017)	(0.044)	(0.067)	(0.038)	(0.037)	(0.062)	(0.071)
1-week	0.027	0.031	0.037	0.047	0.016	0.037	0.082
	(0.028)	(0.036)	(0.050)	(0.040)	(0.035)	(0.044)	(0.055)
Online Mean	0.894	0.156	0.633	0.798	0.138	0.573	0.528
(B) Block 2: Online vs. Control							
Online	0.015	0.039^{+}	0.094*	0.043*	0.037	0.096*	0.034
	(0.016)	(0.021)	(0.038)	(0.020)	(0.021)	(0.040)	(0.024)
Control Mean	0.879	0.057	0.477	0.774	0.040	0.430	0.520
(C) $\beta_{res} + \beta_{online}$							
6-week	0.018	0.147**	0.159*	0.021	0.144**	0.130+	0.118+
	(0.043)	(0.051)	(0.065)	(0.056)	(0.048)	(0.067)	(0.067)
1-week	0.042	0.078+	0.136*	0.092+	0.062+	0.139*	0.119*
	(0.037)	(0.041)	(0.058)	(0.048)	(0.038)	(0.059)	(0.060)
(D) Conditional Randomization							
6-Week	0.029	0.169***	0.170*	0.022	0.159***	0.115	0.111
	(0.025)	(0.045)	(0.075)	(0.041)	(0.039)	(0.070)	(0.068)
1-Week	0.036	0.057	0.131*	0.087*	0.043	0.144*	0.115^{+}
	(0.030)	(0.039)	(0.063)	(0.042)	(0.038)	(0.060)	(0.058)
Online	0.015	0.039^{+}	0.094*	0.043*	0.037^{+}	0.096*	0.034
	(0.016)	(0.021)	(0.037)	(0.019)	(0.021)	(0.039)	(0.024)
Control Mean	0.879	0.057	0.477	0.774	0.040	0.430	0.520

Notes: The notes for this table are the same as Table 2 except that control variables are omitted (N = 2,084). Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table C.2: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Excluding 2014 Cohort

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.019	0.119*	0.080	0.001	0.119***	0.061	0.105
	(0.016)	(0.040)	(0.061)	(0.036)	(0.032)	(0.051)	(0.065)
1-week	0.054+	0.058	0.070	0.084+	0.047	0.088*	0.111+
	(0.028)	(0.042)	(0.049)	(0.045)	(0.040)	(0.036)	(0.050)
Online Mean	0.878	0.155	0.615	0.764	0.128	0.541	0.500
(B) Block 2: Online vs. Control							
Online	0.005	0.052+	0.052	0.023	0.039	0.052	0.007
	(0.022)	(0.028)	(0.038)	(0.026)	(0.029)	(0.042)	(0.022)
Control Mean	0.885	0.053	0.497	0.782	0.034	0.450	0.519
(C) $\beta_{res} + \beta_{online}$							
6-week	0.024	0.171***	0.131+	0.024	0.158***	0.112	0.112
	(0.046)	(0.052)	(0.069)	(0.061)	(0.048)	(0.071)	(0.071)
1-week	0.059	0.110*	0.122+	0.107+	0.086*	0.140*	0.118+
	(0.044)	(0.048)	(0.068)	(0.058)	(0.044)	(0.069)	(0.071)
(D) Conditional Randomization							
6-Week	0.025	0.168***	0.135+	0.022	0.155***	0.114	0.104
	(0.025)	(0.048)	(0.071)	(0.044)	(0.042)	(0.067)	(0.067)
1-Week	0.059+	0.107*	0.123+	0.106+	0.081	0.142*	0.114*
	(0.033)	(0.050)	(0.060)	(0.052)	(0.048)	(0.055)	(0.053)
Online	0.004	0.052+	0.050	0.022	0.040	0.052	0.005
	(0.021)	(0.027)	(0.036)	(0.026)	(0.028)	(0.041)	(0.022)
Control Mean	0.885	0.053	0.497	0.782	0.034	0.450	0.519

Notes: The notes for this table are the same as Table 2 except the sample excludes the 2014 cohort. N (Panel A) = 504, N (Panel B) = 946, and N (Panel D) = 1450. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table C.3: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Excluding 2015 Cohort

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	-0.016	0.151*	0.064	-0.093+	0.127*	-0.020	-0.039
	(0.024)	(0.061)	(0.082)	(0.045)	(0.040)	(0.075)	(0.077)
1-week	-0.003	0.014	-0.014	0.045	-0.002	0.015	0.064
	(0.035)	(0.038)	(0.062)	(0.029)	(0.036)	(0.044)	(0.065)
Online Mean	0.910	0.146	0.646	0.819	0.125	0.590	0.569
(B) Block 2: Online vs. Control							
Online	0.002	0.043*	0.082	0.028	0.039*	0.082	0.035
	(0.021)	(0.016)	(0.052)	(0.020)	(0.011)	(0.052)	(0.025)
Control Mean	0.882	0.063	0.478	0.784	0.041	0.434	0.544
(C) $\beta_{res} + \beta_{online}$							
6-week	-0.013	0.194**	0.146+	-0.065	0.166*	0.062	-0.004
	(0.057)	(0.072)	(0.087)	(0.077)	(0.067)	(0.090)	(0.091)
1-week	-0.001	0.057	0.068	0.072	0.037	0.097	0.099
	(0.047)	(0.051)	(0.073)	(0.058)	(0.046)	(0.074)	(0.075)
(D) Conditional Randomization							
6-Week	0.001	0.215***	0.141	-0.038	0.186***	0.046	0.027
	(0.032)	(0.052)	(0.088)	(0.039)	(0.036)	(0.081)	(0.076)
1-Week	-0.009	0.039	0.073	0.055	0.022	0.107	0.088
	(0.039)	(0.037)	(0.078)	(0.037)	(0.033)	(0.067)	(0.068)
Online	0.003	0.041*	0.083	0.030	0.037***	0.084	0.035
	(0.021)	(0.017)	(0.049)	(0.019)	(0.011)	(0.049)	(0.025)
Control Mean	0.882	0.063	0.478	0.784	0.041	0.434	0.544

Notes: The notes for this table are the same as Table 2 except the sample excludes the 2015 cohort. N (Panel A) = 370, N (Panel B) = 890, and N (Panel D) = 1383. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table C.4: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Excluding 2016 Cohort

	Attended in Year 1			Graduated by Year 6			
	Any (1)	HI (2)	Elite (3)	Any (4)	HI (5)	Elite (6)	In STEM (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.008	0.045	0.061	0.031	0.067	0.064	0.208***
	(0.025)	(0.031)	(0.081)	(0.035)	(0.045)	(0.069)	(0.057)
1-week	0.026	0.034	0.063	0.028	0.018	0.028	0.091
	(0.037)	(0.045)	(0.065)	(0.045)	(0.047)	(0.056)	(0.079)
Online Mean	0.896	0.167	0.639	0.812	0.160	0.590	0.514
(B) Block 2: Online vs. Control							
Online	0.032	0.023	0.138***	0.067*	0.033	0.141***	0.046
	(0.025)	(0.027)	(0.036)	(0.026)	(0.027)	(0.037)	(0.025)
Control Mean	0.867	0.055	0.452	0.752	0.047	0.400	0.495
(C) $\beta_{res} + \beta_{online}$							
6-week	0.041	0.067	0.199*	0.098	0.100	0.205*	0.254**
	(0.059)	(0.071)	(0.088)	(0.076)	(0.069)	(0.092)	(0.092)
1-week	0.059	0.057	0.200**	0.095	0.052	0.169*	0.137+
	(0.045)	(0.050)	(0.071)	(0.058)	(0.048)	(0.073)	(0.074)
(D) Conditional Randomization							
6-Week	0.055	0.123*	0.216*	0.086+	0.139*	0.166*	0.218***
	(0.037)	(0.047)	(0.081)	(0.043)	(0.050)	(0.072)	(0.064)
1-Week	0.052	0.029	0.192*	0.099+	0.029	0.182***	0.143+
	(0.039)	(0.048)	(0.069)	(0.049)	(0.049)	(0.065)	(0.078)
Online	0.031	0.019	0.137***	0.066*	0.031	0.140***	0.042
	(0.022)	(0.026)	(0.032)	(0.025)	(0.026)	(0.034)	(0.026)
Control Mean	0.867	0.055	0.452	0.752	0.047	0.400	0.495

Notes: The notes for this table are the same as Table 2 except the sample excludes the 2016 cohort. N (Panel A) = 394, N (Panel B) = 818, and N (Panel D) = 1335. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table C.5: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Heterogeneous Treatment Effects

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-Week * Higher Rated	0.011	0.113*	0.065	-0.001	0.117***	0.064	0.152
	(0.039)	(0.052)	(0.052)	(0.078)	(0.037)	(0.079)	(0.102)
6-Week * Lower Rated	-0.002	0.111*	0.078	-0.033	0.102*	0.025	0.049
	(0.027)	(0.044)	(0.077)	(0.055)	(0.037)	(0.060)	(0.057)
p (6-Week, Higher = Lower)	0.784	0.977	0.896	0.737	0.791	0.703	0.384
1-Week * Higher Rated	0.036	0.123***	0.022	0.076	0.090*	0.066	0.143*
	(0.049)	(0.042)	(0.069)	(0.057)	(0.042)	(0.065)	(0.054)
1-Week * Lower Rated	0.027	-0.042	0.075	0.034	-0.043	0.043	0.047
	(0.023)	(0.042)	(0.067)	(0.045)	(0.040)	(0.063)	(0.072)
p (1-Week, Higher = Lower)	0.868	0.009	0.600	0.564	0.028	0.807	0.292
Online Mean, Higher Rated	0.867	0.154	0.698	0.774	0.144	0.602	0.488
Online Mean, Lower Rated	0.912	0.155	0.559	0.791	0.126	0.521	0.525
(B) Block 2: Online vs. Control							
Online * Higher Rated	0.024	0.057^{+}	0.136*	0.040	0.060^{+}	0.161***	0.013
	(0.028)	(0.033)	(0.053)	(0.027)	(0.031)	(0.034)	(0.032)
Online * Lower Rated	-0.001	0.017	0.040	0.035	0.013	0.019	0.046
	(0.017)	(0.015)	(0.080)	(0.033)	(0.015)	(0.069)	(0.062)
p (Online, Higher = Lower)	0.462	0.273	0.312	0.912	0.183	0.067	0.647
Online Mean, Higher Rated	0.868	0.081	0.522	0.775	0.053	0.472	0.528
Online Mean, Lower Rated	0.887	0.029	0.427	0.772	0.024	0.383	0.507

Notes: The notes for this table are the same as Table 2 except only the pure randomization estimates are reported with the program assignment split between higher-rated and lower-rated individuals. The strata are modified to fully interact rating status with the previous strata. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Appendix D: Impacts by Subgroups

Table D.1: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Girls

	Attended in Year 1			Graduated by Year 6			
	Any (1)	HI (2)	Elite (3)	Any (4)	HI (5)	Elite (6)	In STEM (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.005	0.083^{+}	0.041	-0.059	0.091^{*}	-0.033	0.083
	(0.020)	(0.042)	(0.075)	(0.050)	(0.034)	(0.053)	(0.103)
1-week	0.057	0.076	0.076	0.071	0.080	0.053	0.192^{***}
	(0.033)	(0.047)	(0.059)	(0.060)	(0.048)	(0.049)	(0.050)
Online Mean	0.880	0.130	0.639	0.824	0.111	0.620	0.472
(B) Block 2: Online vs. Control							
Online	0.015	0.013	0.122^{+}	0.053	0.009	0.142^{+}	0.020
	(0.035)	(0.021)	(0.058)	(0.040)	(0.008)	(0.058)	(0.025)
Control Mean	0.875	0.045	0.490	0.782	0.024	0.448	0.457
(C) $\beta_{res} + \beta_{online}$							
6-week	0.019	0.096	0.163+	-0.006	0.100	0.109	0.103
	(0.067)	(0.068)	(0.096)	(0.081)	(0.062)	(0.098)	(0.100)
1-week	0.071	0.090+	0.197*	0.124+	0.089+	0.196*	0.212*
	(0.054)	(0.054)	(0.085)	(0.067)	(0.050)	(0.087)	(0.089)
(D) Conditional Randomization							
6-Week	0.025	0.137^{*}	0.144	0.001	0.139^{***}	0.077	0.110
	(0.037)	(0.050)	(0.082)	(0.054)	(0.040)	(0.070)	(0.092)
1-Week	0.065	0.070	0.192^{*}	0.122^{+}	0.073	0.198^{*}	0.212^{***}
	(0.044)	(0.045)	(0.073)	(0.066)	(0.043)	(0.068)	(0.054)
Online	0.013	0.022	0.116^{*}	0.054	0.019^{*}	0.141^{*}	0.020
	(0.032)	(0.021)	(0.054)	(0.036)	(0.009)	(0.050)	(0.022)
Control Mean	0.875	0.045	0.490	0.782	0.024	0.448	0.457

Notes: The notes for this table are the same as Table 2 except the sample is limited to girls. N (Panel A) = 317, N (Panel B) = 464, and N (Panel D) = 842. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.2: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Boys

	Attended in Year 1			Graduated by Year 6			
	Any (1)	HI (2)	Elite (3)	Any (4)	HI (5)	Elite (6)	In STEM (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	-0.002	0.114	0.089	0.011	0.102^{+}	0.106	0.070
	(0.029)	(0.062)	(0.088)	(0.048)	(0.051)	(0.077)	(0.083)
1-week	-0.004	-0.016	0.003	0.040	-0.042	0.043	-0.021
	(0.039)	(0.044)	(0.078)	(0.044)	(0.033)	(0.067)	(0.068)
Online Mean	0.909	0.182	0.627	0.773	0.164	0.527	0.582
(B) Block 2: Online vs. Control							
Online	0.010	0.051	0.059	0.023	0.051	0.046	0.034
	(0.016)	(0.033)	(0.043)	(0.024)	(0.033)	(0.046)	(0.034)
Control Mean	0.881	0.062	0.472	0.770	0.047	0.421	0.549
(C) $\beta_{res} + \beta_{online}$							
6-week	0.008	0.164*	0.148+	0.034	0.153*	0.152+	0.104
	(0.056)	(0.077)	(0.088)	(0.078)	(0.074)	(0.092)	(0.091)
1-week	0.006	0.034	0.062	0.063	0.009	0.089	0.013
	(0.050)	(0.060)	(0.078)	(0.068)	(0.056)	(0.080)	(0.081)
(D) Conditional Randomization							
6-Week	0.015	0.187*	0.167^{+}	0.032	0.173***	0.137	0.103
	(0.034)	(0.065)	(0.095)	(0.047)	(0.056)	(0.083)	(0.071)
1-Week	-0.005	0.032	0.055	0.055	0.007	0.097	0.011
	(0.039)	(0.058)	(0.088)	(0.046)	(0.049)	(0.080)	(0.071)
Online	0.009	0.047	0.056	0.021	0.048	0.043	0.029
	(0.015)	(0.032)	(0.042)	(0.023)	(0.032)	(0.045)	(0.034)
Control Mean	0.881	0.062	0.472	0.770	0.047	0.421	0.549

Notes: The notes for this table are the same as Table 2 except the sample is limited to boys. N (Panel A) = 317, N (Panel B) = 863, and N (Panel D) = 1242. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.3: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Underrepresented Minority Students

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.000	0.093*	0.031	-0.040	0.102*	0.005	0.009
	(0.023)	(0.041)	(0.059)	(0.043)	(0.034)	(0.057)	(0.069)
1-week	0.043	0.012	0.032	0.060	-0.008	0.039	0.021
	(0.034)	(0.043)	(0.052)	(0.038)	(0.040)	(0.049)	(0.053)
Online Mean	0.880	0.171	0.657	0.794	0.154	0.594	0.571
(B) Block 2: Online vs. Control							
Online	0.024	0.042+	0.119*	0.030	0.039+	0.099*	0.025
	(0.020)	(0.021)	(0.040)	(0.032)	(0.022)	(0.044)	(0.027)
Control Mean	0.875	0.064	0.477	0.769	0.043	0.428	0.505
(C) $\beta_{res} + \beta_{online}$							
6-week	0.024	0.135*	0.150*	-0.010	0.141**	0.104	0.034
	(0.049)	(0.057)	(0.072)	(0.064)	(0.054)	(0.074)	(0.075)
1-week	0.067	0.053	0.150*	0.090+	0.031	0.138*	0.046
	(0.042)	(0.046)	(0.064)	(0.054)	(0.042)	(0.066)	(0.067)
(D) Conditional Randomization							
6-Week	0.040	0.152***	0.154*	0.006	0.150***	0.089	0.039
	(0.031)	(0.044)	(0.067)	(0.052)	(0.038)	(0.068)	(0.069)
1-Week	0.058	0.032	0.146*	0.081	0.014	0.142*	0.038
	(0.037)	(0.045)	(0.063)	(0.048)	(0.040)	(0.064)	(0.057)
Online	0.023	0.037+	0.117***	0.030	0.035	0.097*	0.022
	(0.019)	(0.021)	(0.039)	(0.032)	(0.021)	(0.042)	(0.027)
Control Mean	0.875	0.064	0.477	0.769	0.043	0.428	0.505

Notes: The notes for this table are the same as Table 2 except the sample is limited to underrepresented minority students. N (Panel A) = 522, N (Panel B) = 1091, and N (Panel D) = 1717. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.4: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Not Underrepresented Minority Students

	Attended in Year 1			Graduated by Year 6			
	Any (1)	HI (2)	Elite (3)	Any (4)	HI (5)	Elite (6)	In STEM (7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.070	0.229*	0.347***	0.135	0.157	0.287+	0.515***
	(0.073)	(0.100)	(0.110)	(0.080)	(0.094)	(0.150)	(0.091)
1-week	-0.026	0.207+	0.149	0.064	0.225+	0.143	0.371*
	(0.052)	(0.105)	(0.123)	(0.094)	(0.108)	(0.124)	(0.132)
Online Mean	0.953	0.093	0.535	0.814	0.070	0.488	0.349
(B) Block 2: Online vs. Control							
Online	-0.032	0.011	-0.036	0.020	0.011	0.035	-0.018
	(0.058)	(0.036)	(0.072)	(0.079)	(0.036)	(0.082)	(0.058)
Control Mean	0.896	0.026	0.477	0.793	0.026	0.435	0.591
(C) $\beta_{res} + \beta_{online}$							
6-week	0.038	0.239+	0.311+	0.154	0.168	0.322+	0.497**
	(0.091)	(0.123)	(0.168)	(0.125)	(0.110)	(0.175)	(0.153)
1-week	-0.058	0.218*	0.113	0.084	0.236**	0.177	0.353*
	(0.082)	(0.092)	(0.142)	(0.111)	(0.091)	(0.142)	(0.141)
(D) Conditional Randomization							
6-Week	-0.008	0.229*	0.303*	0.068	0.176*	0.257	0.421***
	(0.085)	(0.089)	(0.140)	(0.118)	(0.086)	(0.166)	(0.108)
1-Week	-0.040	0.176+	0.111	0.118	0.192+	0.205	0.403***
	(0.075)	(0.094)	(0.135)	(0.113)	(0.095)	(0.143)	(0.130)
Online	-0.026	0.018	-0.024	0.027	0.017	0.040	-0.012
	(0.058)	(0.036)	(0.070)	(0.075)	(0.035)	(0.080)	(0.054)
Control Mean	0.896	0.026	0.477	0.793	0.026	0.435	0.591

Notes: The notes for this table are the same as Table 2 except the sample is limited to not underrepresented students. N (Panel A) = 112, N (Panel B) = 236, and N (Panel D) = 367. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.5: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Free/Reduced Lunch Receipt

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	-0.046	0.119^{+}	-0.041	-0.093	0.126^{+}	-0.092	-0.045
	(0.040)	(0.062)	(0.074)	(0.075)	(0.069)	(0.084)	(0.093)
1-week	-0.033	0.086	-0.046	0.016	0.106*	-0.021	0.021
	(0.038)	(0.051)	(0.073)	(0.049)	(0.045)	(0.054)	(0.101)
Online Mean	0.926	0.116	0.663	0.811	0.074	0.600	0.537
(B) Block 2: Online vs. Control							
Online	-0.003	0.032	0.101^{+}	0.021	0.011	0.081	0.014
	(0.046)	(0.028)	(0.055)	(0.043)	(0.026)	(0.055)	(0.039)
Control Mean	0.876	0.054	0.464	0.751	0.041	0.409	0.500
(C) $\beta_{res} + \beta_{online}$							
6-week	-0.048	0.152*	0.060	-0.072	0.138*	-0.010	-0.031
	(0.064)	(0.073)	(0.100)	(0.087)	(0.064)	(0.103)	(0.106)
1-week	-0.036	0.119+	0.055	0.037	0.117*	0.060	0.035
	(0.060)	(0.062)	(0.093)	(0.078)	(0.054)	(0.096)	(0.099)
(D) Conditional Randomization							
6-Week	-0.037	0.144*	0.064	-0.065	0.139*	-0.036	-0.025
	(0.057)	(0.062)	(0.091)	(0.081)	(0.064)	(0.097)	(0.092)
1-Week	-0.040	0.101^{+}	0.036	0.035	0.094^{+}	0.056	0.040
	(0.055)	(0.056)	(0.089)	(0.066)	(0.049)	(0.078)	(0.099)
Online	-0.003	0.029	0.096^{+}	0.026	0.008	0.079	0.018
	(0.044)	(0.030)	(0.054)	(0.044)	(0.027)	(0.055)	(0.039)
Control Mean	0.876	0.054	0.464	0.751	0.041	0.409	0.500

Notes: The notes for this table are the same as Table 2 except the sample is limited to students who report receiving free or reduced price lunch in school. N (Panel A) = 287, N (Panel B) = 467, and N (Panel D) = 814. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.6: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, No Free/Reduced Lunch Receipt

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.045	0.097*	0.151+	0.055	0.087+	0.145*	0.193*
	(0.041)	(0.038)	(0.078)	(0.072)	(0.043)	(0.052)	(0.083)
1-week	0.085*	0.005	0.128*	0.093	-0.030	0.119+	0.144*
	(0.032)	(0.050)	(0.055)	(0.068)	(0.047)	(0.057)	(0.050)
Online Mean	0.870	0.187	0.610	0.789	0.187	0.553	0.520
(B) Block 2: Online vs. Control							
Online	0.022	0.039	0.092*	0.042	0.046	0.101*	0.026
	(0.026)	(0.027)	(0.041)	(0.030)	(0.030)	(0.043)	(0.029)
Control Mean	0.881	0.058	0.485	0.786	0.039	0.441	0.531
(C) $\beta_{res} + \beta_{online}$							
6-week	0.067	0.136+	0.243**	0.097	0.133+	0.247**	0.219*
	(0.060)	(0.076)	(0.088)	(0.077)	(0.073)	(0.093)	(0.092)
1-week	0.106*	0.044	0.220**	0.135*	0.016	0.220**	0.171*
	(0.048)	(0.055)	(0.074)	(0.060)	(0.053)	(0.076)	(0.077)
(D) Conditional Randomization							
6-Week	0.079+	0.189***	0.244***	0.089	0.169***	0.231***	0.214***
	(0.046)	(0.053)	(0.079)	(0.076)	(0.052)	(0.064)	(0.076)
1-Week	0.100*	0.021	0.220***	0.132+	-0.001	0.227***	0.167***
	(0.041)	(0.052)	(0.069)	(0.072)	(0.050)	(0.070)	(0.053)
Online	0.024	0.038	0.093*	0.042	0.045	0.101*	0.025
	(0.026)	(0.026)	(0.040)	(0.029)	(0.029)	(0.042)	(0.028)
Control Mean	0.881	0.058	0.485	0.786	0.039	0.441	0.531

Notes: The notes for this table are the same as Table 2 except the sample is limited to who do not report receiving free or reduced price lunch. N (Panel A) = 347, N (Panel B) = 860, and N (Panel D) = 1270. Robust standard errors are in parentheses (+ $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$).

Table D.7: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, First-Generation Students

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	-0.075^{+}	0.162	0.022	-0.013	0.172	0.039	0.055
	(0.042)	(0.099)	(0.103)	(0.062)	(0.108)	(0.092)	(0.082)
1-week	-0.102*	0.027	-0.069	0.052	0.058	0.008	0.088
	(0.046)	(0.091)	(0.089)	(0.054)	(0.076)	(0.077)	(0.091)
Online Mean	0.930	0.105	0.649	0.737	0.070	0.544	0.456
(B) Block 2: Online vs. Control							
Online	-0.001	-0.011	-0.023	-0.009	-0.023	-0.071	0.038
	(0.034)	(0.018)	(0.044)	(0.056)	(0.021)	(0.058)	(0.064)
Control Mean	0.868	0.043	0.472	0.787	0.034	0.447	0.523
(C) $\beta_{res} + \beta_{online}$							
6-week	-0.075	0.151+	-0.001	-0.022	0.150+	-0.032	0.093
	(0.081)	(0.088)	(0.128)	(0.111)	(0.078)	(0.129)	(0.132)
1-week	-0.103	0.017	-0.092	0.043	0.035	-0.063	0.126
	(0.083)	(0.071)	(0.122)	(0.104)	(0.064)	(0.123)	(0.127)
(D) Conditional Randomization							
6-Week	-0.048	0.182*	0.039	-0.008	0.173^{+}	-0.035	0.122
	(0.051)	(0.082)	(0.107)	(0.080)	(0.090)	(0.097)	(0.099)
1-Week	-0.099^{+}	0.017	-0.087	0.069	0.017	-0.052	0.155
	(0.053)	(0.078)	(0.101)	(0.078)	(0.068)	(0.093)	(0.098)
Online	0.004	-0.010	-0.016	-0.002	-0.025	-0.069	0.049
	(0.035)	(0.018)	(0.046)	(0.056)	(0.022)	(0.056)	(0.060)
Control Mean	0.868	0.043	0.472	0.787	0.034	0.447	0.523

Notes: The notes for this table are the same as Table 2 except the sample is limited to first-generation college students. N (Panel A) = 191, N (Panel B) = 284, and N (Panel D) = 504. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table D.8: The Impact of Random Assignment to STEM Summer Programs on 4-Year College Attendance and Graduation, Not First Generation Students

	Attended in Year 1			Graduated by Year 6			
	Any	HI	Elite	Any	HI	Elite	In STEM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Block 1: 6- and 1-week vs. Online							
6-week	0.037	0.091^{***}	0.088	-0.015	0.091^{*}	0.044	0.109
	(0.022)	(0.021)	(0.061)	(0.037)	(0.034)	(0.053)	(0.066)
1-week	0.060^{*}	0.041	0.090^{+}	0.042	0.021	0.076^{+}	0.094^{+}
	(0.021)	(0.040)	(0.043)	(0.043)	(0.043)	(0.041)	(0.053)
Online Mean	0.882	0.174	0.627	0.820	0.161	0.584	0.553
(B) Block 2: Online vs. Control							
Online	0.017	0.052^{+}	0.123^{***}	0.051	0.053^{+}	0.137^{***}	0.018
	(0.023)	(0.029)	(0.038)	(0.030)	(0.028)	(0.036)	(0.036)
Control Mean	0.882	0.061	0.479	0.770	0.042	0.425	0.519
(C) $\beta_{res} + \beta_{online}$							
6-week	0.054	0.142*	0.211**	0.035	0.143*	0.182*	0.127
	(0.052)	(0.064)	(0.077)	(0.067)	(0.060)	(0.080)	(0.080)
1-week	0.077+	0.092+	0.214**	0.092+	0.074	0.213**	0.112
	(0.042)	(0.050)	(0.066)	(0.054)	(0.047)	(0.069)	(0.070)
(D) Conditional Randomization							
6-Week	0.052^{+}	0.159^{***}	0.210^{***}	0.035	0.153^{***}	0.162^{*}	0.112
	(0.029)	(0.036)	(0.068)	(0.048)	(0.039)	(0.062)	(0.069)
1-Week	0.075^{*}	0.073	0.212^{***}	0.093^{+}	0.059	0.222^{***}	0.116^{+}
	(0.029)	(0.044)	(0.057)	(0.050)	(0.044)	(0.055)	(0.061)
Online	0.016	0.051^{+}	0.123^{***}	0.052^{+}	0.052^{+}	0.138^{***}	0.016
	(0.022)	(0.028)	(0.036)	(0.030)	(0.027)	(0.034)	(0.037)
Control Mean	0.882	0.061	0.479	0.770	0.042	0.425	0.519

Notes: The notes for this table are the same as Table 2 except the sample is limited to not first generation students. N (Panel A) = 443, N (Panel B) = 1043, and N (Panel D) = 1580. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Appendix E: Additional survey results

We detail the contents of the three longer-form surveys below. This appendix also shows different survey weighting schemes and additional survey results.

E.1 Survey Details

E.1.1 Post-program survey

The first long-form outcome survey was offered to the randomized applicants in the fall after the programs. It asked students about:

- Summer programs attended (in addition to HI programs for treatment groups, any for control group)
- College application plans
- Preferences for various college offerings (location, academics, extracurriculars, etc.)
- College major plans
- Familiarity with various colleges
- Career plans
- Sources of advice on college and careers
- AP, IB, and mathematics high-school course taking plans
- Study skills
- Life skills
- Self-confidence
- Math problems and a brain teaser

E.1.2 End-of-high-school survey

The second long-form outcome survey was offered to the randomized applicants at the end of their senior year in high school (about eight months after the first long-form survey). It asked students about:

- College enrollment plans
- College application and admissions offers
- SAT and/or ACT scores
- High-school GPA

E.1.3 Second-year college spring survey

The third long-form outcome survey was offered to the randomized applicants in the spring of their sophomore year of college (about 2.5 years after the first long-form survey). It asked students about:

- College enrollment
- College major

- College math courses
- College study skills
- Educational experiences outside of class
- Social life
- Summer plans
- Graduate school plans
- Career plans

E.2 Creating indices from survey responses

To avoid emphasizing spurious results due to multiple hypothesis testing, outcomes are grouped into related "families." Following Anderson (2008), each family is converted into an index according to the following procedure:

- For each individual outcome in the family, we define each variable such that higher values are "better."
- We then normalize each outcome into a z-score relative to the control group for that cohort. That is, subtract the cohort-specific control group mean and divide by the standard deviation.
- Construct the weighted average of all the outcomes in the family by cohort. The weight on each outcome is the inverse of the covariance matrix of the outcomes.
- Normalize the index again by subtracting the cohort's control group mean and dividing by the standard deviation.
- If a respondent is missing the answer to some, but not all, items in a family, construct the index based on non-missing items.

We report our findings using survey data with such indices.

The indices used in Table 5 use the following outcomes:

- Life skills
  - I set my alarm each night before I go to bed when I need to wake up early.
  - I return phone calls and emails in a timely manner.
  - I can do my own laundry.
  - I can plan meals for myself.
  - I can balance my checking account. (2014 only)
- Study skills
  - I ask myself questions to make sure I know the material I have been studying.
  - Before I begin studying, I think about the things I will need to do to learn.
  - When I'm reading, I stop once in a while and go over what I have read. (2015 and 2016 only)

- When I get stuck on a problem, I ask a classmate or friend for help. (2015 only)
- I always persist to the end of a project, even when the work is hard. (2014 only)
- I work hard to get a good grade even when I don't like a class. (2014 only)
- When I get stuck on a problem, I ask a teacher for help. (2015 and 2016 only)

- Confidence
  - I am confident that I will succeed in my courses this semester. (2015 only)
  - I am good at math. (2015 and 2016 only)
- Likes intellectual activities
  - I like to tinker (take things apart, fix things, etc.). (2015 and 2016 only)
  - I like brain teasers and puzzles. (2015 and 2016 only)
- Attention
  - I often find that I have been reading for class but don't know what it is all about. (2015 and 2016 only)
  - I find that when the teacher is talking, I think of other things and don't really listen to what is being said.

The indices used in Appendix Table E.6 use the following outcomes:

- Community and belonging
  - I feel a sense of belonging to my college community
  - I feel that I am a member of my college's community
  - I see myself as part of my college's community
  - My friends are taking the same classes as me
- Use of school academic supports
  - I have attended professors' office hours (hours per semester)
  - I have attended teaching assistants' office hours (hours per semester)
  - I have used my university's tutoring resources
- Use of peer academic supports
  - I have a study group for at least one of my classes
  - My friends help me with coursework (e.g., study groups, doing problem sets together).
- Professional development
  - I have worked with a professor as a research assistant
  - I have had an internship while enrolled at my university
  - I know a professor who would be willing to write me a recommendation letter

Table E.1: Predictors of Survey Response

	Post-Program (1)	End of High School (2)	Sophomore Year (3)
main			
6-Week	0.745***	0.546***	0.176
	(0.206)	(0.181)	(0.167)
1-Week	0.668***	0.518***	0.046
	(0.192)	(0.167)	(0.154)
Online	0.680***	0.526***	0.245***
	(0.109)	(0.100)	(0.094)
Rating Variable	0.201***	0.179***	0.035
	(0.063)	(0.056)	(0.054)
Free/Reduced Lunch	0.092	0.054	0.151*
	(0.070)	(0.065)	(0.062)
GPA	0.097	0.092	0.272+
	(0.127)	(0.124)	(0.143)
Standardized Math Score	0.039	0.086***	0.010
	(0.034)	(0.031)	(0.033)
Black	0.165	-0.052	0.217
	(0.168)	(0.165)	(0.152)
Hispanic	0.240	-0.029	0.394*
	(0.171)	(0.168)	(0.155)
Native American	-0.089	-0.104	-0.001
	(0.226)	(0.213)	(0.201)
Asian	0.296	0.141	0.562***
	(0.181)	(0.178)	(0.164)
Multiethnic	-0.010	-0.066	-0.025
	(0.078)	(0.073)	(0.069)

Notes: Each column displays probit regression coefficients for the predictors of survey response. Regression coefficents for randomization strata are not displayed. N = 2,084. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table E.2: Conditional Randomization Estimates Restricted to Survey Responders and Inverse Propensity Weights, with Assignment Variables

		Post-Program		End of High School		Sophomore Year	
	Full Sample	Responders Unweighted	Responders IPW	Responders Unweighted	Responders IPW	Responders Unweighted	Responders IPW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(A) Attended Any Four-Year College in Year 1							
6-Week	0.029	0.018	0.008	0.003	-0.001	-0.010	0.026
	(0.040)	(0.043)	(0.056)	(0.044)	(0.051)	(0.048)	(0.054)
1-Week	0.036	0.036	0.038	-0.003	0.005	0.013	0.032
	(0.036)	(0.040)	(0.050)	(0.041)	(0.044)	(0.044)	(0.048)
Online	0.013	-0.012	-0.008	-0.006	-0.000	0.020	0.027
	(0.024)	(0.027)	(0.035)	(0.027)	(0.029)	(0.029)	(0.032)
(B) Attended Elite College in Year 1							
6-Week	0.166***	0.118+	0.148+	0.113+	0.165*	0.097	0.199*
	(0.059)	(0.063)	(0.082)	(0.066)	(0.076)	(0.071)	(0.078)
1-Week	0.134*	0.092	0.124	0.080	0.144*	0.110	0.184*
	(0.055)	(0.061)	(0.078)	(0.063)	(0.071)	(0.067)	(0.074)
Online	0.092***	0.035	0.065	0.058	0.077+	0.068	0.088+
	(0.035)	(0.040)	(0.052)	(0.041)	(0.045)	(0.044)	(0.048)
(C) Degree from Any Four-Year College by Year 6							
6-Week	0.025	0.043	0.080	0.001	0.042	0.009	0.064
	(0.052)	(0.056)	(0.071)	(0.059)	(0.070)	(0.063)	(0.072)
1-Week	0.088+	0.111*	0.139*	0.069	0.101+	0.076	0.097
	(0.046)	(0.051)	(0.063)	(0.052)	(0.060)	(0.057)	(0.064)
Online	0.040	0.029	0.072+	0.034	0.058	0.050	0.060
	(0.029)	(0.033)	(0.044)	(0.034)	(0.037)	(0.037)	(0.041)
(D) Degree from Elite College by Year 6							
6-Week	0.115+	0.083	0.089	0.043	0.102	0.036	0.124
	(0.060)	(0.065)	(0.083)	(0.068)	(0.078)	(0.074)	(0.082)
1-Week	0.148***	0.118+	0.135+	0.108+	0.163*	0.136*	0.189*
	(0.056)	(0.062)	(0.079)	(0.064)	(0.073)	(0.069)	(0.076)
Online	0.094***	0.041	0.073	0.073+	0.090*	0.067	0.073
	(0.035)	(0.040)	(0.051)	(0.042)	(0.045)	(0.045)	(0.049)
(E) STEM Degree by Year 6							
6-Week	0.115+	0.117+	0.169*	0.065	0.097	0.088	0.143+
	(0.061)	(0.066)	(0.085)	(0.070)	(0.078)	(0.076)	(0.084)
1-Week	0.115*	0.136*	0.185*	0.097	0.122+	0.126+	0.125
	(0.057)	(0.062)	(0.079)	(0.065)	(0.072)	(0.071)	(0.078)
Online	0.028	0.025	0.076	0.012	0.031	0.044	0.047
	(0.035)	(0.040)	(0.052)	(0.042)	(0.045)	(0.045)	(0.050)

Notes: Each panel uses a different attendance or graduation outcome. Column 1 is the main specification. Columns 2, 4, and 6 restrict the sample to survey responders. Columns 3, 5, and 7 use inverse propensity weighting with survey responders. The response prediction regression includes assignment to programs, randomization strata, rating variable, GPA, standardized math score, race/ethnicity, and free and reduced-price lunch status.

Table E.3: The Impact of Assignment to STEM Summer Programs on College Application Knowledge

	Sources of Application Advice				Have Heard of Specific Colleges				
	Teacher or Counselor (1)	Family Members (2)	Friends (3)	Internet or Other Written (4)	Non-HI Technical Institute (5)	Ivy League (6)	Liberal Arts College (7)	Top Public (8)	Fake College (9)
(A) Block 1: 6- and 1-week vs. Online									
6-week	0.088+	0.015	0.073	-0.002	-0.038	0.007	0.032	-0.013	-0.047
	(0.042)	(0.038)	(0.073)	(0.054)	(0.033)	(0.006)	(0.038)	(0.064)	(0.033)
1-week	0.001	0.004	-0.068	0.042	-0.027	0.006	0.037	-0.060	-0.026
	(0.037)	(0.036)	(0.061)	(0.050)	(0.041)	(0.006)	(0.058)	(0.044)	(0.027)
Online Mean	0.774	0.610	0.565	0.746	0.815	0.994	0.706	0.631	0.107
(B) Block 2: Online vs. Control									
Online	0.023	0.025	0.074*	-0.027	0.101***	0.007	0.069***	-0.036	-0.008
	(0.034)	(0.039)	(0.031)	(0.063)	(0.023)	(0.004)	(0.016)	(0.054)	(0.016)
Control Mean	0.802	0.668	0.493	0.730	0.687	0.993	0.583	0.610	0.099
(C) $\beta_{res} + \beta_{online}$									
6-week	0.111+	0.039	0.147+	-0.029	0.063	0.014+	0.102	-0.049	-0.055
	(0.058)	(0.069)	(0.076)	(0.068)	(0.064)	(0.007)	(0.072)	(0.075)	(0.041)
1-week	0.023	0.028	0.006	0.016	0.074	0.013+	0.106+	-0.096	-0.035
	(0.056)	(0.062)	(0.069)	(0.061)	(0.056)	(0.007)	(0.064)	(0.067)	(0.040)
(D) Conditional Randomization									
6-Week	0.102+	0.065	0.133+	-0.018	0.071+	0.014+	0.108*	-0.080	-0.052
	(0.052)	(0.052)	(0.074)	(0.078)	(0.037)	(0.007)	(0.044)	(0.082)	(0.034)
1-Week	0.035	0.019	0.016	0.000	0.068	0.013+	0.102+	-0.076	-0.039
	(0.050)	(0.050)	(0.066)	(0.075)	(0.044)	(0.007)	(0.056)	(0.070)	(0.030)
Online	0.023	0.023	0.069*	-0.030	0.101***	0.007+	0.069***	-0.036	-0.007
	(0.034)	(0.039)	(0.030)	(0.060)	(0.022)	(0.004)	(0.016)	(0.051)	(0.015)
Control Mean	0.802	0.668	0.493	0.730	0.687	0.993	0.583	0.610	0.099

Notes: The notes for this table are the same as in Table 2 but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A (N = 594), Panel B (N = 1234), and Panel D (N = 1942). Data are from surveys conducted at the end of the program summer. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table E.4: The Impact of Assignment to STEM Summer Programs on Perceptions of College Costs and Financial Aid

	Estimated Minus IPEDS		Minus IPEDS Windsorized		Estimate with IPEDS Controls	
	Cost of Attendance (1)	Financial Aid Coverage (2)	Cost of Attendance (3)	Financial Aid Coverage (4)	Cost of Attendance (5)	Financial Aid Coverage (6)
(A) Block 1: 6- and 1-week vs. Online						
6-week	-143.814	0.002	288.869	0.003	610.141	0.021
	(2230.671)	(0.017)	(2252.006)	(0.016)	(2580.294)	(0.014)
1-week	-474.140	-0.009	172.355	-0.011	-444.248	-0.017
	(1384.550)	(0.009)	(1419.608)	(0.008)	(1278.461)	(0.010)
Online Mean	9819.246	-0.048	9121.856	-0.048	52262.597	0.675
(B) Block 2: Online vs. Control						
Online	-410.270	0.018	-741.866	0.020	-280.427	0.031
	(2059.775)	(0.024)	(2005.770)	(0.024)	(2061.820)	(0.021)
Control Mean	8938.691	-0.058	8863.356	-0.060	49620.811	0.607
(C) $\beta_{res} + \beta_{online}$						
6-week	-554.084	0.021	-452.997	0.022	339.697	0.051
	(2968.540)	(0.044)	(2606.975)	(0.043)	(3074.693)	(0.042)
1-week	-884.410	0.009	-569.511	0.009	-336.336	0.006
	(2690.692)	(0.040)	(2369.395)	(0.040)		(0.039)
(D) Conditional Randomization						
6-Week	-1536.093	0.012	-626.145	0.013	-788.329	0.040
	(2925.196)	(0.028)	(2782.066)	(0.028)	(3137.525)	(0.024)
1-Week	-472.928	0.013	-671.962	0.013	-322.789	0.021
	(2414.361)	(0.025)	(2343.805)	(0.025)	(2385.733)	(0.023)
Online	-462.730	0.016	-757.968	0.017	-344.489	0.029
	(1961.822)	(0.022)	(1907.674)	(0.022)	(1972.852)	(0.019)
Control Mean	8938.691	-0.058	8863.356	-0.060	49620.811	0.607

Notes: The notes for this table are the same as in Table 2 but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A (N = 594), Panel B (N = 1234), and Panel D (N = 1942). Data are from surveys conducted at the end of the summer of the programs. Columns 1 and 2 take the average of respondents' estimates of their first three college choices and subtract the averaged IPEDS figures for those colleges. Robust standard errors are in parentheses (+ $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$).

Table E.5: The Impact of Assignment to STEM Summer Programs on College-Level Courses By Fall of Sophomore Year

	Single Variable Calculus		Multivariable Calculus		Linear Algebra		Probability and Statistics	
	Completed in HS (1)	Completed by Year 2 (2)	Completed in HS (3)	Completed by Year 2 (4)	Completed in HS (5)	Completed by Year 2 (6)	Completed in HS (7)	Completed by Year 2 (8)
(A) Block 1: 6- and 1-week vs. Online								
6-week	0.046	0.039	0.036	0.067	0.010	-0.138***	0.082	-0.065
	(0.050)	(0.030)	(0.029)	(0.073)	(0.025)	(0.044)	(0.064)	(0.081)
1-week	-0.027	0.025	0.029	0.071	0.012	0.010	0.037	0.009
	(0.038)	(0.022)	(0.035)	(0.068)	(0.053)	(0.077)	(0.056)	(0.082)
Online Mean	0.848	0.940	0.185	0.768	0.093	0.603	0.199	0.517
(B) Block 2: Online vs. Control								
Online	0.002	-0.007	-0.014	0.096*	0.019	0.020	-0.078	-0.077+
	(0.031)	(0.033)	(0.034)	(0.039)	(0.038)	(0.036)	(0.049)	(0.036)
Control Mean	0.830	0.944	0.180	0.718	0.159	0.616	0.217	0.508
(C) $\beta_{res} + \beta_{online}$								
6-week	0.047	0.032	0.022	0.163*	0.029	-0.117	0.004	-0.142+
	(0.061)	(0.038)	(0.066)	(0.069)	(0.056)	(0.084)	(0.069)	(0.084)
1-week	-0.026	0.019	0.014	0.167**	0.031	0.030	-0.041	-0.067
	(0.056)	(0.034)	(0.058)	(0.062)	(0.050)	(0.074)	(0.060)	(0.076)
(D) Conditional Randomization								
6-Week	0.052	0.028	0.020	0.164*	0.020	-0.116*	-0.016	-0.162+
	(0.059)	(0.043)	(0.046)	(0.076)	(0.047)	(0.054)	(0.079)	(0.087)
1-Week	-0.029	0.020	0.015	0.167*	0.040	0.037	-0.021	-0.056
	(0.050)	(0.039)	(0.046)	(0.073)	(0.063)	(0.079)	(0.070)	(0.087)
Online	0.002	-0.006	-0.016	0.099*	0.017	0.022	-0.073	-0.074*
	(0.032)	(0.032)	(0.032)	(0.037)	(0.037)	(0.035)	(0.047)	(0.035)
Control Mean	0.830	0.944	0.180	0.718	0.159	0.616	0.217	0.508

Notes: The notes for this table are the same as in Table 2 but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A (N = 594), Panel B (N = 1234), and Panel D (N = 1942). Data are from follow-up surveys administered during the projected second year of college in the fall. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table E.6: The Impact of Assignment to STEM Summer Programs on College Experiences

	Any College				HI in Year 2				Not HI in Year 2			
	Belonging (1)	Used School Help (2)	Used Peer Help (3)	Prof Dev (4)	Belonging (5)	Used School Help (6)	Used Peer Help (7)	Prof Dev (8)	Belonging (9)	Used School Help (10)	Used Peer Help (11)	Prof Dev (12)
(A) Block 1												
6-week	0.296***	-0.122	0.084	0.049	0.151	-0.165	0.387	1.058***	0.327***	-0.048	-0.036	-0.014
	(0.088)	(0.125)	(0.106)	(0.110)	(0.199)	(0.380)	(0.340)	(0.299)	(0.106)	(0.134)	(0.119)	(0.111)
1-week	0.136	-0.029	0.037	0.142	-0.255	-0.508	0.184	0.909***	0.191+	0.031	-0.034	0.032
	(0.117)	(0.085)	(0.120)	(0.123)	(0.198)	(0.319)	(0.391)	(0.297)	(0.107)	(0.080)	(0.126)	(0.140)
Online Mean	-0.199	0.180	0.120	-0.076	0.238	0.288	-0.082	-0.450	-0.261	0.165	0.149	-0.023
(B) Block 2												
Online	0.044	-0.038	0.084	-0.099	-0.596+	-0.545+	-0.175	-0.220	0.102	-0.039	0.095	-0.108
	(0.077)	(0.101)	(0.077)	(0.062)	(0.287)	(0.295)	(0.518)	(0.308)	(0.082)	(0.108)	(0.071)	(0.091)
Control Mean	-0.000	0.000	0.000	0.000	0.234	0.202	0.213	0.163	-0.015	-0.012	-0.013	-0.010
(C) $\beta_{res} + \beta_{online}$												
6-week	0.340*	-0.160	0.168	-0.050	-0.446	-0.710	0.211	0.838	0.430*	-0.087	0.059	-0.122
	(0.162)	(0.169)	(0.154)	(0.175)	(0.432)	(0.580)	(0.566)	(0.682)	(0.182)	(0.185)	(0.177)	(0.194)
1-week	0.180	-0.067	0.122	0.042	-0.851*	-1.053+	0.008	0.689	0.293+	-0.008	0.061	-0.076
	(0.148)	(0.151)	(0.140)	(0.151)	(0.392)	(0.548)	(0.525)	(0.627)	(0.163)	(0.162)	(0.151)	(0.161)
(D) Conditional												
6-Week	0.248+	-0.156	0.124	0.006	-0.519+	-0.862+	0.332	0.638	0.378*	-0.096	0.059	-0.054
	(0.128)	(0.153)	(0.124)	(0.130)	(0.292)	(0.462)	(0.553)	(0.444)	(0.145)	(0.163)	(0.130)	(0.153)
1-Week	0.225	-0.081	0.147	-0.001	-0.808***	-1.044*	0.141	0.681	0.332*	-0.014	0.073	-0.110
	(0.134)	(0.134)	(0.135)	(0.132)	(0.265)	(0.431)	(0.573)	(0.416)	(0.130)	(0.137)	(0.136)	(0.161)
Online	0.033	-0.039	0.080	-0.099	-0.571*	-0.479+	-0.061	-0.168	0.093	-0.034	0.091	-0.107
	(0.074)	(0.101)	(0.076)	(0.064)	(0.207)	(0.264)	(0.447)	(0.304)	(0.079)	(0.109)	(0.071)	(0.093)
Control Mean	-0.000	0.000	0.000	0.000	0.234	0.202	0.213	0.163	-0.015	-0.012	-0.013	-0.010

Notes: The notes for this table are the same as in Table 2 but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A (N =), Panel B (N =), and Panel D (N =). Data are from surveys conducted in the projected second year of college. The outcomes are indices constructed from multiple survey questionsas described in Section E.2. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).

Table E.7: The Impact of Assignment to STEM Summer Programs on College Clubs and Societies

	Any Club or Society (1)	Race/Ethnicity Affinity (2)	Gender Affinity (3)	Major-Related Club/Society (4)
(A) Block 1: 6- and 1-week vs. Online				
6-week	0.043	0.048	-0.027	0.020
	(0.055)	(0.061)	(0.052)	(0.064)
1-week	0.018	-0.086	-0.006	0.005
	(0.034)	(0.055)	(0.033)	(0.049)
Online Mean	0.815	0.384	0.265	0.344
(B) Block 2: Online vs. Control				
Online	0.004	-0.008	0.009	0.032
	(0.049)	(0.034)	(0.046)	(0.035)
Control Mean	0.774	0.287	0.193	0.366
(C) $\beta_{res} + \beta_{online}$				
6-week	0.047	0.040	-0.018	0.052
	(0.067)	(0.080)	(0.073)	(0.081)
1-week	0.022	-0.094	0.003	0.037
	(0.061)	(0.069)	(0.065)	(0.073)
(D) Conditional Randomization				
6-Week	0.032	0.007	-0.003	0.014
	(0.067)	(0.073)	(0.069)	(0.069)
1-Week	0.032	-0.075	-0.018	0.062
	(0.058)	(0.063)	(0.056)	(0.058)
Online	0.005	-0.008	0.010	0.032
	(0.047)	(0.032)	(0.046)	(0.034)
Control Mean	0.774	0.287	0.193	0.366

Notes: The notes for this table are the same as in Table 2 but the sample is further restricted to survey respondents, resulting in the following sample sizes: Panel A (N = 594), Panel B (N = 1234), and Panel D (N = 1942). Data are from surveys conducted in the projected second year of college. The outcomes are indices constructed from multiple survey questionsas described in Section E.2. Robust standard errors are in parentheses (+ p<0.10 * p<0.05 ** p<0.01 ***p<0.001).