Research Report

Combining Entrepreneurship and Web Development for High School Students

A Pilot Evaluation of the Startup Tech Program and High School Students' College and Career Aspirations

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Preface

Educational systems today face the challenge of preparing students with the skills to compete in a rapidly evolving and increasingly global labor market. Educators must prepare students to be able to work in current high-demand fields and may also need to help students develop "soft" skills, such as creativity, problem-solving, and social skills that can enable students to adapt to new opportunities as they arise. In this context, educational programs may be needed that go beyond teaching rote skills and core academic subjects and that encourage student interest in emergent careers fields where students are more likely to be successful. This evaluation examines one innovative program that is characterized by these goals. We evaluate the extent to which students in the program experience changes in their career and college aspirations or mind-sets.

Startup Tech Intermediate (Startup Tech) is a program designed by the Network for Teaching Entrepreneurship. The focus of the program is to introduce high school students to entrepreneurship while teaching skills related to the technical aspects of web design. During the course, students engage with material in several areas of entrepreneurship or business start-up, including opportunity recognition, market research, marketing, and business financials. Students are also taught foundational skills related to web design coding, including HTML and CSS. Startup Tech is designed as a yearlong course to give students the personal business skills to develop and confidently pitch their ideas to peers and authority figures, as well as technical skills that may serve as a foundation for future work or study in technical fields.

This report serves as an independent pilot evaluation of the impact of the Startup Tech program on students' reported self-efficacy and college and career aspirations in one New York City high school. We examine the relationship between participation in the program and survey-reported outcomes, including students' college and career plans and their academic self-efficacy in general and in specific subject areas. The findings from this report can serve to guide future investigation of the possible impacts of the program on students' mind-sets, among other outcomes.

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Summary

In a rapidly evolving global economy, improving the alignment between how students are prepared in education systems and the demands they will face in the labor market may be increasingly important. Challenges include not only effectively introducing students to emerging, high-demand fields but also training students in practical skills, such as creativity and problem-solving and social skills, such as presentation and persuasion. In this context, educational programs may be needed that go beyond teaching rote skills and core academic subjects and that encourage student interest in career fields where they will be more likely to be successful.

In this report, we examine an innovative new program for high school students, Startup Tech Intermediate (Startup Tech).[1] This full-year program follows a curriculum that blends entrepreneurship and introductory computer science. It gives students the hands-on experience of developing and marketing a web-based business idea and trains them in the basics of web design; the program also exposes them to coding languages that can be used in more-advanced web applications. The intention is to give students the personal and business skills to pitch their own projects and confidently share their ideas, along with an introduction to technical skills that may pique their interest in coding and computer science. The program employs a train-the-trainer model in which regular classroom teachers are trained to implement the Startup Tech curriculum; therefore, the program is intended to be scalable to a wide range of high school contexts. If successful, the Startup Tech program might be expected to bolster students' interest in and aptitude for work or further education in high-demand fields in the near term, with corresponding benefits to their longer-term career trajectories as adults.

Study Approach

We evaluated the relationship between participation in the Startup Tech program and short-term outcomes that we hypothesized could be immediately affected by the program, including students' reported self-efficacy and their college and career aspirations. In this pilot evaluation, we limited our focus to a single example of the Startup Tech program across two classrooms, taught by a single teacher in one New York City high school. We collected survey data at two points, as well as a variety of student administrative and course data for Startup Tech students and potential comparison students. Our survey data include measures of students' college and career interests and plans, as well as students' reported self-efficacy in general and in specific subject areas, including computer science, math, science, and engineering.

[1] Although this evaluation is focused on Startup Tech Intermediate, other variations of the Startup Tech program series have also been implemented in middle school and summer school settings.

We include in our evaluation a descriptive overview of students' survey responses and statistical analysis aimed at evaluating the impact of the program on students. Our statistical analyses consist of a doubly robust, propensity-weighted, cross-sectional comparison of students in the Startup Tech program to students at the same school who did not participate in the program, as well as a second, more-rigorous, difference-in-differences analysis that also accounts for changes in individual students' responses to the survey over our two survey administrations.

Startup Tech and Students' Plans and Self-Efficacy

We found that participation in the entrepreneurship-focused Startup Tech program corresponded to a significant increase in students who reported a recent interest in business as a primary career focus. This finding reflects a substantial differential increase in the number of Startup Tech students who reported that they recently changed their primary career interests and planned to pursue careers in the field of business, across our two survey administrations and relative to their peers. These results are plausible evidence of impact given the program's primary focus on hands-on instruction in entrepreneurship and business development skills. We did not, however, observe an increase in interest in computer science or other technical careers despite the program's complementary focus on coding and web design. However, because we only asked students about their primary career interests, we could not assess whether students had developed a secondary interest in computer science.[2] We also do not find evidence of any Startup Tech impacts on students' self-efficacy, either in general or in specific subject areas.

Limitations and Next Steps

This is a small-scale pilot evaluation, and our analyses are limited in several important ways. Students were not randomly assigned to participate in Startup Tech, and we cannot be sure that our methods fully account for potential unobserved differences between our treatment and comparison groups. The study is also limited to implementation of the Startup Tech program by just one newly trained teacher in a single New York City high school and might not generalize to other settings or to the program more broadly. Finally, the study focused on a limited set of short-term survey-reported outcomes and did not investigate the specific academic or business skills that are central to the Startup Tech curriculum. Future research is needed to evaluate the program across more-diverse contexts and with respect to the fuller range of potential impacts, including on students' skills, academic performance, and long-term career trajectories.

[2] The survey instrument required respondents to choose a single area that "most closely represents the career or occupation" that they planned to pursue. Given that Startup Tech is designed to affect interest in both computer science and entrepreneurship, it is possible that increased interest in computer science was masked by the increase in business interest. Still, there was no detectable increase in computer science self-efficacy, which one might also expect to see if there was increased interest in computer science careers attributable to the Startup Tech curriculum.

Acknowledgments

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Abbreviations

IEP	individualized education plan
NFTE	Network for Teaching Entrepreneurship
NYC	New York City
STEM	science, technology, engineering, and mathematics

1. Introduction

Preparing High School Students for 21st-Century Careers

Educators and policymakers are increasingly concerned with the alignment between the skills and career interests that educational systems encourage for students and the labor market those students will face in an increasingly global economy (National Governors Association, 2015). Preparing students for in-demand careers in science, technology, engineering, and mathematics (STEM) fields is a growing area of focus, particularly at the federal level (Johnson, 2012; Atkinson and Mayo, 2010). According to the U.S. Bureau of Labor Statistics, "computer and mathematical occupations is the fourth fastest growing major occupational group," and the bureau projects an increase in employment in this area by about 13 percent, or roughly 500,000 new jobs over the next decade (Bureau of Labor Statistics, undated).

In addition to the growing importance of preparing students for particular high-demand career paths, educators and policymakers are calling for reforms to education that place increased emphasis on 21st-century skills, such as creative problem-solving, collaboration, and communication, that will allow students to compete in a highly competitive global labor market (Wagner, 2008; Levy and Murnane, 2005; Friedman and Mandelbaum, 2011). In this formulation, such "soft" skills are viewed as a key competitive advantage in fields increasingly saturated with technically proficient specialists in the global labor force. There is evidence that social skills, including presentation and persuasion skills, are increasingly being rewarded in the labor market, particularly via jobs that are simultaneously cognitively demanding (Deming, 2015).

In response to the need for preparation in these areas, the Network for Teaching Entrepreneurship (NFTE) has developed a specialized high school program called Startup Tech Intermediate (Startup Tech) that is aimed at developing students' abilities and interest in the area of tech-entrepreneurship while also providing an introduction to web design and coding. Startup Tech is designed as a yearlong course for students in any grade from nine through 12. It aims to give students business and entrepreneurial skills in the context of web-based business start-ups, as well as an introduction to the technical skills of web design and coding.

Student Self-Efficacy and Career Aspirations

In this pilot evaluation of Startup Tech, we assessed the potential impact of the program on short-term measures that might have plausibly been affected by participation in the program and that have been shown to be predictive of students' longer-term success. These include measures of students' college and career aspirations, as well as measures of students' self-efficacy. When

assessing both career aspirations and self-efficacy, we considered both general and field-specific measures.

Previous research has shown that high school students' career aspirations are predictive of their future life outcomes, including educational outcomes, career trajectories, social status, and earnings (Ashby and Schoon, 2010; Homel and Ryan, 2014; Schoon and Polek, 2011). Career aspirations and self-efficacy (both general and subject-specific) have also been shown to be malleable in the short term as a consequence of student participation in specialized educational programs (Carpi et al., 2016; Berk et al., 2014). As such, we anticipated that participation in the Startup Tech program could plausibly affect students' career aspirations over the span of a school year, particularly for high school students on the verge of a transition to college or career.

Self-efficacy is another potentially important mediator of student success that has been frequently shown to predict future performance (Bandura and Locke, 2003; Multon, Brown, and Lent, 1991), although the evidence with respect to a causal link between self-efficacy and future outcomes is mixed (Sitzmann and Yeo, 2013; Park and John, 2014). Changes in general and subject-specific self-efficacy can occur in response to students' positive and negative experiences in academics (Zusho, Pintrich, and Coppola, 2003). Positive academic experiences are associated with increases in confidence and therefore may be motivational for students, encouraging greater effort, reducing apprehension, and increasing self-regulation (Zimmerman and Kitsantas, 2005; Komarraju and Nadler, 2013; Bruning and Kauffman, 2015). If the Startup Tech program provides a positive learning experience for students, we expected that students' general or subject-specific self-efficacy would improve as a result of their participation in the program. Such an effect could be an indicator of a positive educational experience and might also be a factor in students' longer-term success.

Research Questions: Evaluation of Startup Tech

In light of the aforementioned research, we focused our pilot evaluation of the program on several survey-reported outcomes that might have been immediately affected by participation in the yearlong Startup Tech program. In particular, we examined whether students who participated in the Startup Tech program experienced either improved self-efficacy or changes in their college and career plans during the year in which they were in the program. Our evaluation addressed the following research questions:

1. To what extent does the Startup Tech program affect students' college and career aspirations in the area of business or in such technical fields as computer science, math, science, and engineering?
2. To what extent does the Startup Tech program affect students' belief in their abilities to accomplish difficult tasks in general; in the area of problem-solving; or in the specific subject areas of science, math, computer science, and engineering?

Our pilot evaluation did not directly address the wide range of student skills or web development areas that are covered in the Startup Tech curriculum and that may be affected by participation in the course. Additional research would be needed to gauge these other potential impacts of the program.

In the rest of the report, we begin by providing additional details about the Startup Tech program and about the school in which we conducted our study. We then describe our data, including administrative and course data from school district records and our own survey instrument and data. This is followed by a detailed discussion of our method for evaluating the impact of Startup Tech and of the outcomes that we investigated. After presenting the results, we conclude with a discussion of the implications of our findings and our study limitations.

2. Describing the Startup Tech Program and Our Study Context

Description of Startup Tech

Startup Tech is a full-year high school course recently developed by the NFTE that blends entrepreneurship with web design and coding. The program model is classroom-based and includes an entrepreneurship curriculum aimed at teaching career skills in the context of building a business plan. Over the course of the program, students first identify a web-related business opportunity and design a marketing plan and pitch related to that opportunity. The web design component is meant to provide students with the coding skills needed to develop working websites for their business ideas.

NFTE's project-based lessons are designed to provide students with the opportunity to develop an entrepreneurial mind-set that supports their abilities to solve complex problems, recognize opportunity, and understand the value of assessing and taking calculated risks. The technical skills covered in the course include introductory coding in HTML and CSS, which students learn primarily through online courses provided by the platform Treehouse. Additional Treehouse content related to website design, including Javascript, jQuery, and other applied coding languages, are also offered to students during the year, time permitting.

The Startup Tech program is designed to be implemented in regular high school settings via a train-the-trainer model. Prior to teaching the course, teachers receive five days of intensive training about the curriculum from experienced NFTE facilitators. The training is focused on orienting teachers to the curriculum and modeling key components of the course. Teachers also receive periodic visits (typically monthly) from NFTE facilitators, who observe classroom instruction and provide structured feedback; occasional guest speakers are invited to give talks in the Startup Tech classrooms. NFTE facilitators are also available to provide additional ad hoc support at teachers' requests. As of the 2015–2016 school year, the Startup Tech program and curriculum were in active use in a total of six high schools in New York City (NYC), one of which is the focus of this study. NFTE is planning further expansion of this and similar programs, both in NYC and elsewhere.

In Figure 2.1, we provide an overview of the intended scope and sequence of the Startup Tech curriculum. The first eight weeks of the course focus primarily on foundations of entrepreneurship, while the rest of the course includes a mix of entrepreneurship skills and applied web design and coding topics. Over the full-year course, each student is expected to identify, research, and develop a web page corresponding to a specific business idea, as well as to present and "pitch" the product to peers and the instructor. Students whose business plans are particularly promising (including one student from our study school) are encouraged to participate in a regional competition with other program participants.

Figure 2.1. Scope and Sequence of the Startup Tech Curriculum

Week 1: Introduction to Startup Tech

Weeks 2–3: Introduction to Entrepreneurship
Exploration of entrepreneurship
Characteristics of an entrepreneur
Technology entrepreneurship

Weeks 4–8: Opportunity Recognition and Market Research
Learn start-up methodology
Opportunity recognition
Market research

Weeks 9–16[a]: Product Development
How to make a website (introduction to HTML and CSS)
HTML coding (tutorials)
CSS style sheets (tutorials)

Weeks 17–19: Product Development
Applied coding

Weeks 20–21: Business Financials
Financials
Customer Acquisition

Weeks 23–25: Marketing and Sales
Inbound versus outbound marketing
Promotion and advertising
Marketing and sales

Weeks 26–30[b]: Coding
Javascript
jQuery
Applied coding

SOURCE: Startup Tech curriculum sequence provided by NFTE.

[a] Our first survey administration occurred during this block of the curriculum, around week 12.

[b] Our second survey administration occurred during this block of the curriculum, around week 26.

Although the course was initially intended to cover computer coding to a similar degree as a regular high school computer science course, in this first year of its implementation, most teachers implementing Startup Tech were not computer science teachers but were instead trained in business, web design, or other skills. In our study school in particular, the program was taught by a web design teacher rather than a computer science teacher. In addition, in our study school, the course was delayed by a few weeks at the start of the school year because of an approval process at the school. Perhaps as a consequence of these factors, even though all students completed their business plans, not all of the coding content of the course was covered. In particular, many of the more-advanced Treehouse coding modules in Javascript, jQuery, and other applied coding topics were not completed by students in our study school.

Context of the Pilot Evaluation

The goal of our pilot evaluation of Startup Tech was to assess plausible short-term outcomes of students' participation in the program. Our study focused on outcomes in the year in which students first took the course—specifically, student survey responses measuring constructs that we hypothesized could be immediately influenced by the program. Additional research would be necessary to assess other potential impacts of the program on such outcomes as students' skill development, future academic success, and college and career trajectories.

As of school year 2015–2016, the Startup Tech program was being implemented in six high schools in NYC. However, because of the limited resources available for this pilot evaluation, we restricted our study to a convenience sample of students in just a single participating school in NYC, and we did not interview staff or collect detailed data on the program's implementation or course assessments. We chose this school as our pilot evaluation research site based in part on the interest of school administrators in supporting our survey administration. Our analysis is exploratory in nature, and we recognize that any effects we identify might not be representative of how the Startup Tech program may be implemented across a wider range of school contexts in NYC or elsewhere.

In addition to this caveat, the school that we focused on is unique in some respects. Most important, it is a vocational technology school that offers specialized programs related to students' career interests, in addition to a traditional core academic curriculum. Students must apply to be admitted into the school, and they submit applications in the following seven admissions tracks: visual arts, information technologies, electrical installation, automotive technologies, robotics/STEM, mechanical technology, and medical careers. Once admitted, students then select from one of 12 specific subtracks offered by the school, each of which includes some specialized courses that supplement the core academic curriculum.

In Table 2.1, we provide a descriptive comparison of student characteristics in this school and in the NYC school district as a whole. Our study school had a higher proportion of males and Asian students and a lower proportion of females; black, white, or Hispanic students; students with disabilities; and English-language learners when compared with all NYC students. Students at this school are higher achieving than the average for NYC, with higher weighted pass rates for the Regents Exams (with adjusted rates of passing the exams based on expected student growth since the eighth grade).[3] The school is, however, comparable to NYC schools overall in terms of the percentage of students qualifying for free or reduced-price lunch, an indicator of low family income. Along with the demographic differences we observed in our study school, we expected that student career aspirations to be unique given the school's vocational focus. Our pilot evaluation focused exclusively on students within this school, comparing those who did and did not participate in the Startup Tech program.

[3] Regents Exams are New York's statewide standardized tests for high school students.

Table 2.1. School Demographics and Achievement

Student Characteristic	NYC Public Schools	Study School
Male (%)	51.4	65.3
Female (%)	48.6	34.7
Asian (%)	15.5	46.4
Black (%)	27.1	20.5
Hispanic (%)	40.5	22.6
White (%)	14.8	4.1
Other (%)	2.1	4.2
Students with disabilities (%)	18.7	11.8
English-language learners (%)	12.5	1.4
Poverty (free or reduced-price lunch eligibility) (%)	76.5	76.5
Weighted English Regents pass rate (high schools only)	0.99	1.08
Weighted math Regents pass rate (high schools only)	0.97	1.33

SOURCE: NYC public data retrieved from demographic snapshots in February 2016 (New York City Department of Education, 2016).
NOTE: Weighted Regents pass rates are pass rates were adjusted to reflect expected student performance based on eighth-grade exam scores.

In this school, two classrooms with a total of 39 high school seniors from the web design subtrack were slated to take the new Startup Tech course in the 2015–2016 school year as a nonelective course. Aside from Startup Tech, these students did not take any other courses specific to their track that year (i.e., their other courses consisted of classes taken by all 12th graders, in the areas of history, reading, math, and the like). Both Startup Tech classrooms were taught by the same teacher. As described in our analysis plan (see Chapter Four), we evaluated the possible impacts of the Startup Tech program by comparing outcomes for the students in these two classrooms relative to those of other students at the same school, while using statistical techniques to account for preexisting differences in students' course tracks, demographics, and academics that might influence our outcomes of interest.

In addition to the school-wide data we used to conduct our primary analyses, we administered the survey in four other Startup Tech classrooms in three other schools across NYC. In these cases, however, surveys were not administered to the other, non–Startup Tech students in the schools, and as a result we lack a valid point of comparison to help contextualize students' responses. Given these limitations, we do not include those data in this report.

In the following chapter, we describe the data that we use in our evaluation of Startup Tech.

3. Data

We used two primary sources of data for our evaluation of the Startup Tech program: (1) administrative data about students, including their prior standardized-test scores and attendance, demographics, and current high school courses, and (2) survey data from an instrument we developed to assess students' self-efficacy and college and career plans. We obtained deidentified individual-level data of both types for all students at our study school across grades nine through 12.

Administrative Data

The New York City Department of Education provided a variety of administrative data about individual students at the study location. For each student, we had access to demographic characteristics, including race/ethnicity, gender, low-income status, and individualized education plan (IEP) status. In addition, we obtained a range of data related to students' current and prior academic performance. These data included standardized-test scores from middle school, rates of absence from school, and the current courses students were enrolled in during the 2015–2016 school year.

We used data on students' course enrollments to identify which of the six school admissions tracks students were in, as well as which of the 12 targeted subtracks students ultimately specialized in. The six admissions tracks for students when they initially enter the school are visual arts, information technologies, electrical installation, automotive technologies, robotics/STEM, mechanical technology, and medical careers. Each of these tracks represents a distinct admissions pathway with separate application materials and criteria. The 12 subtracks represent subsets of these six admissions tracks, and they include the following areas: graphic design, commercial arts, and web design (all as part of visual arts); Cisco networking, computer repair, and computer forensics (as part of information technologies); and automotive technology and collision repair (as part of automotive technologies). The admissions tracks of mechanical technology, electrical installation, medical careers, and robotics/STEM each map to just a single subtrack.

For approximately 33 percent of students at the high school, we were unable to determine vocational subtracks based on course enrollments. This primarily occurred for the majority of ninth-grade students, whose course loads did not yet map onto a specific school vocational subtrack. For this reason, in our analyses, we limited our sample to students who were in the tenth, 11th, or 12th grade in school year 2015–2016.

Survey Instrument and Data

Survey Instrument

RAND researchers designed the study survey to measure students' college and career aspirations, as well as their confidence in their ability to succeed (known as *self-efficacy*)[4] in two areas: academic achievement in general and in STEM in particular. The survey was designed to assess outcomes related to our key research questions, detailed in Chapter One. The survey borrows substantially from previously validated instruments from prior research. The appendix contains a full version of the survey instrument.

To assess college and career aspirations, students were asked five questions regarding their future educational and career plans. Three of the items ask about planned terminal degrees, planned career fields, and length of interest in those career fields. Items were pulled from existing surveys and mirror commonly asked college and career plan questions administered to high school students around the country by states and national education organizations (e.g., National Center for Education Statistics, 2002; Bernstein, Wade, and Loeb, 2004). The career field item was altered to collapse a few similar career areas together and provide examples targeted toward the vocational high school population. An additional item asked about students' own confidence in their college and career plans to gauge how students' responses may vary by how sure they are of their plans. Lastly, we included an item asking students whether they had discussed their plans with peers, parents, or school staff.

To measure general self-efficacy, we included Chen, Gully, and Eden's (2001) eight-item general self-efficacy (GSE) scale. According to Chen, Gully, and Eden, "GSE captures differences among individuals in their tendency to view themselves as capable of meeting task demands in a broad array of contexts" (2001, p. 63). This measure of GSE has shown high internal reliability (Cronbach's alpha of 0.85 and above) and predictive validity with job and task performance outcomes (e.g., Lai and Chen, 2012; Yeo and Neal, 2006). Along with this measure of GSE, we included four measures of subject-specific self-efficacy for mathematics, computer science, science, and engineering. These measures were adapted from Kier et al. (2014), who established reliable subject-specific self-efficacy scales for STEM fields. Items from the mathematics, science, and engineering scales were not changed. However, the technology scale was adapted to computer science by replacing *technology* key words to *computer science* and *coding* key words. Additionally, two new items were included on each subject asking students if they knew what they had to do to prepare for a career in the respective subject. Finally, we also designed a two-item measure of complex problem-solving in an attempt to gauge any difference in students' confidence in solving complex problems. All of the scales are measured on a Likert scale from strongly disagree (1) to strongly agree (5).

[4] Formally, *self-efficacy* is defined as "belief in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands" (Wood and Bandura, 1989, p. 408).

We observe high survey reliability measures (Cronbach's alpha) for each of the self-efficacy constructs.[5] A self-efficacy scale will tend to have high reliability if the individual question items are highly correlated with one another, which suggests that there is consistency among student responses on the items. We observe reliability values of 0.88 for general self-efficacy, 0.89 for mathematics self-efficacy, 0.93 for computer science self-efficacy, 0.92 for science self-efficacy, and 0.97 for engineering self-efficacy. The two-item measure for complex problem-solving remains acceptable (at 0.71), and its lower reliability is likely due to the low number of items (two).

Survey Data

The same survey was administered by school staff to all students in our study school at two points during the 2015–2016 school year. We initially planned to conduct the survey at the start of the 2015–2016 school year and again in late spring 2016 to gauge possible changes in student responses before and after exposure to the Startup Tech curriculum. Unfortunately, logistical challenges related to survey implementation delayed our first administration of the survey until early January 2016, midway through the school year (i.e., roughly week 12 of the intended curriculum, shown in Figure 2.1). We completed our second survey administration on schedule in late April 2016. As a result, our survey data allowed us to assess changes in individual student responses in only the second half of the school year, following partial completion of Startup Tech by participating students. Across both survey administrations, student response rates were very high, with an average survey response rate of 90 percent school-wide. In the Startup Tech classrooms, 97 percent (38 out of 39) of students completed both surveys, and one enrolled student completed neither survey. We observed no significant or substantive differences between the observable characteristics of survey respondents and nonrespondents.

In the following chapter, we describe in detail the analytical methods that we used to evaluate the impact of the Startup Tech program. We also describe how we defined the specific outcome measures that we considered.

[5] Factor analysis confirmed that the additional items and the modification of the technology scale to computer science did not alter the latent structure of the scales, as all items load uniquely onto the four scales by subject area.

4. Our Approach to Evaluating Startup Tech

Methods

To assess the impact that participation in Startup Tech had on student outcomes, it is necessary to have a reliable estimate of what the outcomes might have been for the Startup Tech students if they had not participated. To provide context for interpreting our analysis of impacts, we first describe the background characteristics of students in Startup Tech and their peers. We also describe the extent to which survey responses in the school varied over time, as a function of student tracks or as a function of student demographic characteristics. These preliminary descriptive analyses provide an introduction to our data and help to illustrate the relevance of our chosen model specifications and controls.

We then use two methodological approaches to more rigorously assess the relationship between participation in Startup Tech and students' survey outcomes. Both approaches involved comparing the Startup Tech students with otherwise similar students who did not participate in the program. First, we employ a cross-sectional analysis to compare the end-of-year outcomes of Startup Tech students with other students who did not participate, while accounting for observable differences in student characteristics using doubly robust estimation. Then, we examine the *change* in individual students' survey responses between survey waves using a difference-in-differences regression methodology. We describe these statistical methods below and discuss the limitations of our analysis.

Cross-Sectional Analyses

In our cross-sectional analysis, we compare the spring 2016 survey responses of students who participated in the Startup Tech course with those of comparison students. This approach does not account for changes in students' survey responses between January and April. However, the cross-sectional comparison did add some value to our analysis, because sufficiently accounting for differences between Startup Tech and comparison students allowed us to pick up on impacts of the Startup Tech program even if they occurred prior to our first survey administration in January. The goal of the cross-sectional analysis was to directly control for all relevant differences and assess the program effects with a clean comparison between Startup Tech students and otherwise similar students. The characteristics available as controls were eighth-grade achievement test scores in math and English, race/ethnicity, gender, disability, poverty status, absences in the previous year, whether students were previously held back a grade, and whether they had previously enrolled in Advanced Placement courses.

To help ensure a fairer comparison, we employed a technique known as *doubly robust estimation* to adjust for observable differences between participating and nonparticipating

students that could have obscured the effect of Startup Tech (Bang and Robbins, 2005). The technique is "doubly robust" in the sense that it employs a combination of two methods and results remain consistent even if one of the methods contains misspecification. The technique first adjusts the nonparticipating students with weights that are calculated to remove systematic differences between the two groups. In statistical terms, the goal is for the weighted comparison students to have the same distribution of characteristics as the participating students:

$$f(Characteristics \mid ST = 1) = w(Characteristics) * f(Characteristics \mid ST = 0).$$

Ridgeway (2006) noted that solving for *w(Characteristics)* and applying Bayes' theorem leads to the following formulation for the weights, w_i :

$$w_i = \frac{\Pr(ST=1 \mid Characteristics)}{1-\Pr(ST=1 \mid Characteristics)}.$$

The conditional probability of being a participant in the second equation is also known as the *propensity score* (Rosenbaum and Rubin, 1983), and this weighting formulation is one of several ways to use propensity scores to adjust for group differences in characteristics (Imbens, 2004). Weighting nonparticipants by their odds of being a participant ensured that nonparticipants who were more similar to the Startup Tech students received higher weight.

A significant advantage of the weighting approach is that its only input is a single estimated value—the propensity score—and we are free to choose whatever estimated propensity scores best align the characteristics across the two groups. Therefore, instead of using a parametric regression model to estimate the propensity scores, we use generalized boosted models (McCaffrey, Ridgeway, and Morral, 2004). Boosting is a nonparametric statistical learning technique that is considerably more flexible than a parametric regression, because it iteratively explores the data by fitting thousands of simpler models. Once complete, we canvassed these simpler models for the set of propensity scores that minimized the differences in characteristics between the groups.

If the propensity scores are well estimated, the weighting alone could be sufficient to remove all systematic group differences in characteristics. Still, we took an additional step and estimated weighted generalized linear regression models to predict postprogram scores on the college and career survey. The regression controls represent the second layer of the doubly robust technique. In practice, the regression adjustment helps to pick up small differences in the characteristics that might remain after weighting, but the results are less dependent on the parametric form of the regression.

Identifying a group of nonparticipants who were similar to the Startup Tech students was complicated by the fact that the Startup Tech students were uniquely situated in some respects relating to their education. For example, only 12th-grade students took the Startup Tech course, and these students represented all of the students in the web design subtrack in the school. This

means that there were no 12th-grade web design students who did not take Startup Tech to use as comparison students, which made weighted comparisons on the combined dimensions of grade and track impossible. This is problematic, as it is likely that the grade and track that students are in would have some impact on students' survey-reported outcomes, especially their college and career aspirations.

To account for these concerns, we considered two versions of our generalized linear regression model. In the first, we included as potential comparison students all students in grades ten to 12 at the school, and we included fixed effects for grade levels and for subtracks. In this approach, we controlled for differences in survey results across grade levels, and we controlled for differences in survey results across student subtracks, both of which might have been associated with college and career interests and self-efficacy. However, because we had only one year of survey outcome data, we had to assume that students of all grades shared a common effect of being in a particular subtrack (e.g., web design), which we estimated from differences among nonseniors in school year 2015–2016. Thus, if there were differences that stemmed from the particular cohort that students were a part of, overall or within specific subtracks (e.g., if subsequent web design students have systematically different mind-sets than the 12th-grade web design students who took Startup Tech), this would introduce bias. This is of particular concern, given that nonparticipating comparison students in the web design track were only identifiable (based on unique courses that they take) in the 11th-grade cohort.

A second specification of the cross-sectional analysis that we considered is a comparison that is limited to students in the 12th-grade cohort at the school. In this model specification, we were unable to control for differences that might have stemmed from subtrack participation (because the subtrack perfectly determined Startup Tech participation), but we instead included fixed effects for students' six broad admissions tracks, which might have captured much of the differences in students' preexisting career interests. This approach eliminated some potential bias that could have arisen from unobserved cohort and cohort-by-subtrack effects. However, it might have limited our ability to fully control for differences in students' college and career aspirations and self-efficacy that correspond to student interest in the more-specific subtrack areas. This limitation could have resulted in attributing the effect of other aspects of the web design track to participation in Startup Tech.

Difference-in-Differences Analyses

In the cross-sectional analysis, we compared student responses from our spring 2016 survey while relying on regression controls and weighting on other student observables to help ensure a fairer comparison point. Such an approach assumed that these adjustments were sufficient to account for any differences in how Startup Tech students would have responded to the survey if they had not participated in the course. Although we lack a baseline measure of students' survey responses from prior to the start of the Startup Tech program, we do have data at two points—first, with the midyear survey wave, after students had only been exposed to a portion of the

Startup Tech curriculum, and again at the end of the year. These two waves presented an opportunity to measure the effect of Startup Tech by measuring the change in responses between the waves. While still imperfect, the validity of such an analysis is not as dependent on the assumption that adjusting for observable differences between participating and nonparticipating students is sufficient to correct for all potential sources of bias.

Instead, in our preferred modeling approach, we measured the effect of Startup Tech by testing whether Startup Tech students experienced more growth in any outcomes than non–Startup Tech students did between surveys. This approach used Startup Tech student responses in the first wave as a control group for responses in the second wave (when students had been exposed to more of the curriculum), and it used pre- and postdifferences in nonparticipating student responses to control for macro trends that might have affected all students over this period. Of course, a key limitation of this approach is that we were able to assess improvement over just the second half of the year and thus could account for possible improvement in student outcomes that occurred earlier in the school year. To implement this approach, we estimated regressions in the following form:

$$y_{it} = \alpha(wave_t * ST_i) + \beta_0 + \beta_1 wave_t + \beta_2 ST_i + \beta_3 track_i + \beta_4 grade_i + \beta_5 student_i + \varepsilon_{it},$$

where y_{it} is the outcome of student i in wave t (e.g., self-efficacy). The variables $wave_t$ and ST_i are indicators for the survey wave (either January or April) and whether the student participated in Startup Tech. Additionally, $track_i$, $grade_i$, and $student_i$ represent track, grade level, and student-specific fixed effects, respectively. Conditional on the other variables, the interaction of the participation indicator and the survey wave variables ($wave_{it}$*ST_i) measures the change in the outcome among participants, relative to the change among nonparticipants.

As in our cross-sectional analyses, we considered two different modeling specifications and sample restrictions. The first included students across grades ten to 12, with controls for grade level and individual and subtrack fixed effects. The second included only students in grade 12 and included controls for students' six admission tracks with individual fixed effects.

Key Assumptions and Limitations

A key limitation of our study is that students do not randomly participate in Startup Tech at this school. This nonrandom assignment of program participation could bias the results of our cross-sectional analyses, because students may differ in terms of their preexisting college and career aspirations and self-efficacy. Moreover, because we only observed student responses at two points, even in our preferred difference-in-differences specification, we could not assess whether Startup Tech students differed in their preexisting (or counterfactual) improvement trajectories with respect to those outcomes.

Students in different course tracks could also have experienced different instruction during the school year. Fortunately, since we observed that the students in the web design track who

were assigned to take Startup Tech were otherwise in school-wide, nontracked courses (e.g., history, math, English) in their senior years, we expected that no other track-specific courses uniquely influenced these students' college and career aspirations during the period of the study. Of course, participating students might still have been different with respect to other unobserved factors that we could not fully control for, such as parental influences on their mind-sets and career aspirations over the course of the school year.

The modeling approaches that we employed helped to address possible preexisting differences in student outcomes. This is particularly the case in our preferred modeling specification, difference-in-differences, which explicitly accounts any differences in student survey responses as of the first survey administration. Unfortunately, a limitation of this approach is that we had to focus our analysis on just the second half of the school year. If the Startup Tech program were to influence students' mind-sets based on their earlier experiences in the course, then we might have missed this portion of its effect. However, if we assumed that the exposure to the Startup Tech course influenced students in a gradual and cumulative fashion, then our difference-in-differences analysis should have picked up on at least a portion of the program's effects. Even though it was more subject to potential bias, we included our cross-sectional analysis because it offered an opportunity to detect any early impacts of the program.

Our analysis was also limited to just a single implementation of the Startup Tech program, taught by a single teacher to two classrooms in the same school. Although our survey data for this sample are very complete, we were unable to assess whether any results we observed are likely to be generalizable to other Startup Tech classrooms in other schools and contexts. In particular, it is possible that any effect we observed related to the Startup Tech program could instead be a function of the instructional skills or focus of the particular teacher who implemented the program in our study school. This same teacher would have taught these students a web design course, even in the absence of the Startup Tech program, and we could not observe the counterfactual of how the teacher's default instructional approach might have influenced students. Our concern about the generalizability of our findings is further exacerbated by our limited information about the success of the teacher training and implementation of the program in our study school or in other sites. The lack of more-detailed implementation data makes it more difficult to gauge how typical our study school scenario is or the conditions in which our study results are likely to be typical. In addition, our limited sample size for the study means we are not well powered to reliably detect any modest-sized effects of the program (i.e., impacts that are around one-third of standard deviation or smaller).

A final notable limitation of our analyses is that we were evaluating the impacts of Startup Tech on only some of the dimensions that we imagine might be influenced by the program. Although it is plausible that Startup Tech would influence students' college and career aspirations and self-efficacy in general and specific domains, it is also plausible that the course could influence students' skill development or academic performance in the short term and college and career attainment in the longer term. These additional outcomes are not in the scope

of our evaluation but should be considered in future research on the program. Any results that we observed related to our survey outcomes of interest do not necessarily imply or rule out additional effects of the program in other domains.

Study Outcomes

Our pilot evaluation of Startup Tech focused on survey-reported outcomes related to students' college and career aspirations and their general and subject-specific sense of self-efficacy. Although the program may have other impacts, such as on students' academic performance or their experiences following high school graduation, we focused on survey-reported outcomes related to students' mind-sets that could plausibly be affected in the year of instruction and for which we could collect data on both Startup Tech and comparison students at the same school. Both college and career aspirations and self-efficacy have been shown in prior research to be predictive of individuals' longer-run outcomes (Stajkovic and Luthans, 1998; Homel and Ryan, 2014; Schoon and Polek, 2011).

For some of our survey-reported outcomes, we dichotomized categorical variables to be binary outcome measures. We specifically considered the following outcomes:

- a binary indicator of whether students' planned level of education is a bachelor's degree or higher
- binary indicators (three) of whether students' primary career goals are in the areas of
  - business
  - computer science
  - STEM (this was a single response option)
- a binary indicator of whether the student had only recently become interested in their primary career areas (i.e., within the past year)
- a binary indicator of whether students reported having discussion of college and career plans with school staff in the past year
- a binary indicator of whether students feel that their current courses are preparing them for their careers (some, most, or all versus none or not sure)
- a continuous measure of students' general self-efficacy in academic areas and a measure of their self-efficacy with respect to solving complex problems
- continuous measures of students' subject-specific self-efficacy in computer science, math, engineering, and science.[6]

Each of these outcomes reflected student responses that we initially hypothesized might be influenced by exposure to the Startup Tech curriculum and instruction. In designing the survey,

[6] In accordance with reporting practices in prior research using our self-efficacy scales, composite scores for general self-efficacy reflect the average across multiple items ranging from 1 to 5, while composite scores for the subject-specific self-efficacy scales reflect a sum across multiple items and range from 9 to 45.

we anticipated that students might experience increased interest in the field of business, in computer science, or in in STEM fields more broadly. Students might also develop more-ambitious college and career plans in general. We also anticipated that they might report greater self-efficacy in general, in the area of problem-solving, in computer science, or in STEM fields more broadly. Finally, because Startup Tech is designed to encourage discussion between teachers and students about career plans and increase student readiness for their future careers, we were also interested in the extent to which students reported discussing college and career plans with educators and the extent to which they felt that their courses were relevant to their plans.

In the next chapter, we describe the results of our analyses with respect to student outcomes in each of the areas described above.

5. Results

In this chapter, we present a series of analyses comparing Startup Tech students with other students at their school. We begin with a descriptive summary of the background characteristics of students in Startup Tech and school-wide. We then investigate the extent to which student tracking at the school corresponds to differences in student survey outcomes. In a third descriptive analysis, we summarize changes in students' responses to our survey between survey administrations. Finally, we present correlations between our survey results and various student demographic characteristics.

Following our presentation of those descriptive results, we provide the results from our statistical analyses. In this section of the results, we first share a cross-sectional comparison of spring 2016 survey results for Startup Tech and other students and conclude with results from our more stringent specification—the difference-in-differences analysis of trends in individual students' survey responses between January and April 2016.

Descriptive Analyses

Startup Tech Students and Their Same-School Peers

Table 5.1 provides a descriptive comparison of the demographic and prior-achievement characteristics of Startup Tech students relative to other students at their school. Startup Tech students appear quite similar demographically to other students at their school. However, they are somewhat less likely to be male than other 12th-grade students (55 percent versus 62 percent), and they have somewhat lower eighth-grade standardized math achievement test scores relative to the rest of the 12th-grade cohort (0.53 versus 0.65). We explicitly accounted for these observable differences in student characteristics in our subsequent analyses.

Table 5.1. Mean Characteristics of Students in the Startup Tech Program and of Other Students in the Same School

Student Characteristic	Startup Tech Students	All Students Grades 10–12	All Grade-12 Students
8th-grade math achievement	0.53	0.55	0.65
8th-grade English-language arts achievement	0.43	0.46	0.42
Male (%)	55	64	62
Eligible for free or reduced-price lunch (%)	82	78	77
Has an IEP (%)	8	11	12
Asian (%)	50	49	50
Hispanic (%)	26	23	25
Black (%)	16	20	20
White (%)	5	4	3
Other race (%)	3	4	2

NOTES: Math and English-language arts test scores are eighth-grade test scores standardized relative to eighth-grade test scores across NYC (mean of 0 for NYC eighth graders, with a standard deviation of 1). The Startup Tech students in this study are all 12th-grade students.

Student Tracking and Survey Outcomes

Table 5.2 examines the extent to which students' admission tracks and vocational subtracks appear to be related to differences in students' prior achievement outcomes or their responses to our survey. Overall, tracking is clearly associated with differences in both student achievement and reported self-efficacy, which reinforces our use of controls for students' tracks in our analyses. For example, students from the visual arts admissions track (which includes Startup Tech students) have a score of approximately 25 on the engineering self-efficacy scale on the spring survey, while students in the more engineering-focused admissions track of robotics/STEM score a mean of around 37 on this dimension (more than one standard deviation higher). In an analysis of variance across groups, we found statistically significant differences in each of our outcome measures across both admissions tracks and subtracks. Although some of the largest differences in achievement and self-efficacy scores are apparent across admissions tracks, there are also some substantive differences in scores between subtracks within the same admissions track. These results reinforce the importance of controls to help account for the possible influence of student tracks in our analyses.

Table 5.2. Self-Efficacy Scores and Prior Test Scores of Students by Admissions Tracks and Subtracks

Student Characteristic	Admissions Track						
	Visual Arts	Information Technologies	Electrical Installation	Automotive Technologies	Robotic/ STEM	Mechanical Technologies	Medical Careers
Prior math scores	0.51	0.67	0.32	0.37	0.57	0.63	1.13
Prior English-language arts scores	0.49	0.58	0.21	0.27	0.44	0.50	0.89
General self-efficacy	3.90	4.04	3.92	4.07	4.05	3.97	4.10
Math self-efficacy	28.49		28.89	28.32	33.75	28.25	26.47
Computer science self-efficacy	29.86	32.87	33.15	33.02	34.02	33.37	32.98
Science self-efficacy	30.23	33.39	31.65	32.50	33.10	32.14	35.72
Engineering self-efficacy	24.96	30.00	33.32	33.54	36.90	32.18	24.90
N	246	384	58	304	65	140	141

Student Characteristic	Subtrack											
	AG	AV	AU	TE	TS	TT	RF	RA	RR	RV	TD	SQ
Prior math scores	0.54	0.48	0.54	0.77	0.52	0.66	0.32	0.32	0.57	0.57	0.63	1.13
Prior reading scores	0.57	0.51	0.40	0.64	0.47	0.61	0.21	0.25	0.37	0.44	0.50	0.89
General self-efficacy	4.18	3.84	3.87	4.07	3.96	4.08	3.92	4.06	4.15	4.05	3.97	4.10
Math self-efficacy	28.59	27.73	29.82	34.36	32.37	33.82	28.89	28.23	28.67	33.75	28.25	26.47
Computer science self-efficacy	31.72	28.79	31.07	33.64	31.88	32.37	33.15	33.05	32.88	34.02	33.37	32.98
Science self-efficacy	27.85	30.84	30.20	34.16	32.04	33.54	31.65	32.68	31.83	33.10	32.14	35.72
Engineering self-efficacy	23.00	24.73	26.40	31.67	29.43	26.88	33.32	33.74	32.70	36.90	32.18	24.90
N	48	134	64	191	118	75	58	240	64	65	140	141

NOTES: Test scores are standardized relative to eighth-grade scores across NYC (mean of 0, standard deviation of 1). Standard deviations for self-efficacy scores as follows: general self-efficacy, 0.60; math self-efficacy, 7.80; computer science, 6.88; science, 7.22; engineering, 9.04. Course tracks are as follows: AG = graphic design; AV = commercial arts; AU = web design; TE = networking; TS = computer repairs; TT = computer forensics; RA = automotive tech.; RR = collision repair; TD = mechanical technology; and SQ = medical assisting.

Student Characteristics and Survey Outcomes

In addition to the relationship between student survey responses and tracking, we also observed significant correlations between students' preexisting characteristics and their survey responses. We present these results in Table 5.3. Several student characteristics are correlated, to a significant degree, with students' self-efficacy, either overall or in specific STEM subject areas. For instance, males are more likely to report self-efficacy in several subject areas, although less likely to plan on receiving a bachelor's degree or higher. Students with IEPs reported lower self-efficacy in multiple areas, as did students with more prior-year absences. Students' grade levels in this school were also predictive of some differences in subject-area self-efficacy, and students in higher grade levels were less likely to report plans to achieve a bachelor's degree or higher. Overall, these results confirmed the importance of including our controls for observable student characteristics in our subsequent analyses. They also provide evidence that our survey instrument is capable of picking up on differences in mind-sets across different groups of students.

Table 5.3. Statistically Significant Univariate Associations Between Student Characteristics and Survey Outcomes

	Have an IEP		Prior-Year Days Absent		Grade Level		Gender (male = 1)	
Student Characteristic	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
General self-efficacy	−0.21**	0.06	−0.01**	0.00				
Problem-solving self-efficacy	−0.22**	0.07	−0.01**	0.00				
Math self-efficacy			−0.11***	0.02	0.98***	0.25		
Computer science self-efficacy					−0.98***	0.29	2.23***	0.48
Science self-efficacy								
Engineering self-efficacy			−0.07*	0.03			6.63***	0.52
Education plan: Bachelor's or higher	−0.33***	0.04	−0.01*	0.00	0.11***	0.01	−0.13***	0.03

NOTES: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results reflect coefficients from ordinary least squares regressions predicting survey-reported data with student characteristics. We also investigated, but found no significant associations between, students' eligibility for free lunch and these survey outcomes.

Changes in Student Survey Responses over Time

Students' individual survey responses varied over time. In Table 5.4, we show the mean of student responses in January and April in each area of the survey. We show these results for Startup Tech students alongside the average results for other students in the school and for other students in the same grade. Respondents in both Startup Tech and the school as a whole reported similar survey responses in each period. However, Startup Tech students showed a substantial increase in the percentage of students reporting in April being primarily interested in business careers, relative to their interest as of January (14 percent versus 24 percent) and relative to the average for all 12th-grade students (13 percent in both periods). In addition, Startup Tech students more frequently reported developing an interest in their primary career focuses within the past year, with an increase between January (44 percent) and April (51 percent) of 7 percentage points. Finally, it is notable that the percentage of students who reported a primary career interest in business and who also reported recently developing their interest doubled between the two survey administrations for Startup Tech students (8 percent to 16 percent), with no apparent change among other students at the same school.

Table 5.4. Descriptive Summary of Mean Results Across Survey Administrations and Samples

	Startup Tech Students		All Students, Grades 10–12		All Students, Grade 12	
Student Characteristic	**January**	**April**	**January**	**April**	**January**	**April**
College and career plans						
Career plan: business	0.14	0.24	0.10	0.10	0.13	0.13
Career plan: computer science	0.11	0.11	0.17	0.16	0.16	0.17
Career plan: STEM	0.08	0.11	0.16	0.15	0.18	0.15
Education plan: bachelor's or higher	0.84	0.89	0.72	0.75	0.82	0.85
Recent career interest (<1 year)	0.44	0.51	0.25	0.27	0.27	0.28
Discussed with school staff	0.42	0.42	0.22	0.26	0.35	0.37
Courses prepare me	0.76	0.81	0.81	0.82	0.79	0.86
Recent interest in business	0.08	0.16	0.04	0.04	0.06	0.05
Self-efficacy scores						
General	3.99	3.86	3.98	4.01	4.03	4.02
Problem-solving	4.01	3.86	3.90	3.95	4.02	3.99
Math	31.47	31.56	32.04	32.48	33.53	33.84
Computer science	28.29	28.52	29.72	30.04	29.21	29.28
Science	31.38	29.61	32.63	32.62	32.98	32.52
Engineering	26.21	25.72	30.19	29.99	30.07	29.73
N	38	38	1,400	1,407	457	466

NOTE: Standard deviations for self-efficacy scores are as follows: general, 0.60; problem-solving, 0.71; math, 7.80; computer science, 6.88; science, 7.22; engineering, 9.04.

Statistical Analyses

Cross-Sectional Comparison

We began our analyses of the possible effects of Startup Tech by examining cross-sectional differences between Startup Tech student outcomes and those of other students, when adjusting for propensity weighting and additional control variables. In Table 5.5, we show results for our two cross-sectional specifications. These include (1) a comparison of Startup Tech students to students across grades ten to 12, with controls for grade and subtrack fixed effects, and (2) a comparison of Startup Tech students to other grade-12 students, with controls for admissions track fixed effects. For each outcome, we present results for Startup Tech students and for the comparison students who did not take Startup Tech. When showing comparison students' survey responses, we show unweighted means for the whole comparison sample; weighted means that include our propensity matching on student characteristics; and then weighted, adjusted means that include our controls for tracks and grade-level fixed effects.

In these cross-sectional analyses, our results varied as a function of our model specification. In our model, that includes subtrack controls; Startup Tech students have significantly lower adjusted scores in their reported self-efficacy in computer science and engineering relative to other students. However, in our model, that includes admissions-track controls and is limited to peer students in grade 12, so the differences between the two groups are not significant and are in the opposite direction. The differences between Startup Tech students and comparison students across these two models stem largely from our controls for track fixed effects, which indicated that the results are sensitive to those adjustments.

It is possible, but unlikely, that the lower self-efficacy scores in our first modeling specification reflect a causal effect of Startup Tech on students' self-efficacy in computer science and engineering. If the program reduced student self-efficacy in these areas, it is not apparent in Startup Tech student responses between January and April (shown in Table 5.4), and thus any causal impact would have had to occur prior to our first survey administration in January. It seems more likely that our cross-sectional models do not reflect the impact of the program on student self-efficacy but instead picked up on cohort biases specific to our controls that adjust based on the responses of students in the 11th grade who were also in the web design subtrack.

We also observed in our first model specification a marginally significant ($p = 0.07$) and substantial difference between Startup Tech students and comparison students in terms of the proportion of students who reported that they only recently (i.e., in the past year) became interested in their identified primary career interests. This difference is directionally the same but not statistically significant in our second model specification. We observed a smaller increase in the percentage of Startup Tech students who indicated a more recent career interest between January and April, which suggests that if the Startup Tech program were the cause of this difference, at least some of the impact likely occurred prior to our first survey administration in January.

Table 5.5. Doubly Robust Propensity Weighted Cross-Sectional Comparisons of Startup Tech Students to Other Students, by Model Specification

	Model 1: Subtrack Controls, Grades 10–12						Model 2: Admissions-Track Controls, Grade 12					
Student Characteristic	**ST Mean**	**Non-ST Mean**	**Weighted Non-ST Mean**	**Weighted, Adj. Non-ST Mean**	**Diff.**	***P*-Value**	**ST Mean**	**Non-ST Mean**	**Weighted Non-ST Mean**	**Weighted, Adj. Non-ST Mean**	**Diff.**	***P*-Value**
College and career plans												
Career plan: business	0.24	0.10	0.09	0.17	0.08	0.59	0.24	0.12	0.12	0.19	0.06	0.59
Career plan: computer science	0.11	0.16	0.14	0.11	0.00	1.00	0.11	0.17	0.13	0.07	0.04	0.60
Career plan: STEM	0.11	0.15	0.13	0.18	−0.07	0.48	0.11	0.14	0.16	0.16	−0.05	0.63
Education plan: bachelor's or higher	0.89	0.75	0.81	0.91	-0.02	0.80	0.89	0.84	0.88	0.94	−0.05	0.45
Recent career interest (<1 year)	0.51	0.27	0.26	0.27	0.24	0.07	0.51	0.26	0.28	0.38	0.13	0.34
Discussed with school staff	0.42	0.26	0.29	0.30	0.12	0.39	0.42	0.36	0.38	0.49	−0.06	0.60
Courses prepare me for career	0.81	0.82	0.80	0.88	−0.07	0.51	0.81	0.86	0.83	0.90	−0.09	0.29
Recent interest in business	0.16	0.03	0.03	0.15	0.01	0.94	0.16	0.04	0.04	0.14	0.02	0.84
Self-efficacy scores												
General	3.86	4.02	4.00	3.69	0.16	0.37	3.86	4.04	4.02	3.91	−0.06	0.70
Problem-solving	3.86	3.96	3.94	3.78	0.08	0.64	3.86	4.00	3.98	3.90	−0.04	0.85
Math	31.56	32.51	32.52	32.25	−0.76	0.64	31.56	34.09	33.64	32.45	−0.92	0.59
Computer science	28.52	30.09	29.73	32.31	−3.76	0.04	28.52	29.36	28.66	26.77	1.80	0.33
Science	29.61	32.71	32.20	30.35	−0.87	0.67	29.61	32.80	32.16	27.21	2.30	0.33
Engineering	25.72	30.10	28.84	29.07	−3.78	0.03	25.72	30.09	28.48	24.60	0.61	0.74
N	2,455						805					

NOTE: ST = Startup Tech.

Difference in Differences

Differences in student survey responses that we detected in our cross-sectional analyses may indicate impacts of the Startup Tech program, but they may alternately relate to bias associated with unobserved preexisting differences between Startup Tech and non–Startup Tech students. In light of this, we have more confidence in results that focus on changes in individual students' responses across the two waves of our survey. In the following model specification, we examine the extent to which student survey outcomes changed between January and late April 2016 and whether these changes appear to be related to participation in Startup Tech. These results provide our best evidence of possible impacts of the Startup Tech program on survey outcomes, although they are conservative, because we are unable to measure impacts that might have occurred prior to January of the 2015–2016 school year. As we did in our cross-sectional analyses, we considered two different samples and model specifications: In the first (model 1), we included controls for subtracks and grade-level fixed effects across students in grades ten through 12. In the second (model 2), we controlled for admissions tracks and restricted our sample to just grade-12 students. Results are shown in Table 5.6.

Our analysis indicates that Startup Tech might have increased students' interest in a career in business. We found a statistically significant differential increase over time in the percentage of students in the Startup Tech classrooms who both reported that they identified their primary career interest within the past year and reported business as their primary career interest. In other words, Startup Tech students disproportionately increased their interest in business careers between January and April, while also reporting that their interest in business first appeared within the past year. This finding is illustrated in our descriptive summary in Table 5.4 showing an 8 percentage point increase in the proportion of Startup Tech students reporting both a primary interest in business and that their primary interest was developed within the past year. The results are also consistent with a marginally significant differential increase in business interest among Startup Tech students overall, regardless of when they said that they first identified their identified primary career interest ($p = 0.07$; 0.10).

We do not find evidence of any other significant differential changes in student responses between the two survey administrations, including in the areas of computer science career interest and self-efficacy. Aside from increased interest in business as a career field, our difference-in-differences analyses do not indicate any other apparent impacts on student career interests, self-efficacy, or perceptions that courses have prepared students for their careers.

Table 5.6. Difference-in-Differences Analysis of Changes in Survey Scores Between January and April, Comparing Startup Tech and Non–Startup Tech Students

	Model 1: Subtrack Controls, Grades 10–12 Sample			Model 2: Admissions-Track Controls, Grade 12 Sample		
Student Characteristic	**Diff-in-Diff**	**Standard Error**	***P*-Value**	**Diff-in-Diff**	**Standard Error**	***P*-Value**
College and career plans						
Career plan: business	0.08	0.04	0.07	0.08	0.05	0.10
Career plan: computer science	0.01	0.05	0.77	0.00	0.05	0.95
Career plan: STEM	0.01	0.06	0.89	0.02	0.06	0.74
Education plan: bachelor's or higher	0.00	0.07	0.99	0.00	0.06	0.98
Recent career plan (<1 year)	0.08	0.08	0.33	0.10	0.08	0.24
Discussed with school staff	−0.05	0.08	0.58	−0.03	0.10	0.73
Courses prepare me	0.04	0.07	0.54	0.00	0.08	0.97
Recent interest in business	0.10	0.04	0.02	0.11	0.05	0.04
Self-efficacy scores						
General	−0.06	0.09	0.52	−0.05	0.09	0.59
Math	−0.89	1.10	0.41	−1.08	1.23	0.38
Computer science	−0.36	1.30	0.78	−0.31	1.45	0.83
Science	−1.79	1.29	0.17	−1.44	1.48	0.33
Engineering	−1.25	1.47	0.39	−0.79	1.57	0.61
N		2,455			805	

NOTE: Difference-in-difference estimates were calculated using a linear regression including track, grade-level, and student effects, with cluster robust standard errors.

We conclude in the following chapter by summarizing our findings and their implications, including discussion of what might be driving the results that we observe.

6. Summary and Implications

If students graduating from U.S. high schools are to be successful in an increasingly global labor market, educational programs that can encourage student interest and development of skills in high-demand fields may be essential. The Startup Tech program is built around an innovative, applied curriculum that aims to teach creative problem-solving and self-confidence in the context of developing and pitching a new business idea. The curriculum also encourages student learning in technical areas through practice in coding and web design. The curriculum is designed to be implemented in a scalable fashion in regular high school settings, and it utilizes a train-the-trainer model in which classroom teachers are trained to implement the new curriculum. Our pilot evaluation of the Startup Tech program is intended as a first step in assessing whether and how this unique program yields beneficial impacts for students.

For the most part, our pilot evaluation of the Startup Tech program did not identify evidence of program effects on students' survey-reported self-efficacy or generic college and career aspirations. However, we did find evidence that the program is effective at increasing recent student interest in business as a primary career path. Although our sample size of Startup Tech students is small, the overall increase in business careers was substantial in this group, with 14 percent of students reporting interest in January and 24 percent in April, and the percentage of students who reported a recently developed primary interest in business rose from 8 percent in January to 16 percent in April. These changes over time were not typical of other survey respondents in the school. It is certainly plausible that the Startup Tech program will affect students' career plans in this way, since the program curriculum focuses heavily on entrepreneurship and business planning. Future research encompassing a larger and more representative sample would help to confirm these findings and could also be used to investigate whether there was any commensurate increase in students' business-related skills.

We did not see any similar trend in terms of increased student interest or self-efficacy in computer science, in spite of the inclusion of coding related to web design in the Startup Tech curriculum. Previous research indicated that it is possible for individual programs to increase students' reported self-efficacy and interest in specific STEM fields (Carpi et al., 2016; Berk et al., 2014), but the Startup Tech program might not be having these kinds of impacts on student mind-sets. The apparent lack of impact on student interest in computer science careers may stem from the fact that, in this administration of the course, students did not receive as much computer science instruction as was intended in the initial curriculum. It is also possible that because we only asked students about their *primary* career interests, we might have failed to detect any accompanying secondary increases in these students' interest in other fields.

Overall, our pilot evaluation of Startup Tech indicated that the program might have influenced students' college and career aspirations. Nevertheless, it is important to keep in mind

the limitations of this small-scale study. First, our students were not randomly assigned to take the course, and we could not tell for sure whether students who participated were unique in unobserved ways. For instance, they might have unobserved differences in the school or parental supports students received concurrently. Second, our evaluation took place in just one school and one implementation of the Startup Tech program, and therefore we have limited confidence as to whether our results will generalize across a wider range of teachers, students, and school contexts. Third, our evaluation considered only survey-reported outcomes, and we did not assess possible impacts in other areas, including any potential impacts on students' academic learning as a result of the course. Finally, our data did not include a pretreatment baseline measure of individual student outcomes, and so we cannot rule out the possibility that students might have been affected by the program more or differently over the full school year than we observed via changes in student survey responses in the second half of the school year. As a consequence, it is possible that our estimates of the program's impact are overly conservative or miss one-time impacts that occurred when students were first introduced to the program. For all these reasons, this study is best characterized as exploratory in nature.

The results of this study can inform future investigation and hypothesis-generation related to the potential impacts of Startup Tech and other programs like it that aim to encourage student interest in and mastery of promising career paths. In addition, the survey instrument we developed to gauge students' college and career interests appears to be sensitive to differences in mind-sets across student subgroups and changes over time within groups. It may prove valuable in future studies that aim to examine differences in or changes to students' self-efficacy and college and career plans.

Appendix. Survey Instrument

Student Survey

This survey is for research purposes. Participation is voluntary and you may choose not to take this survey. All responses are strictly confidential.

- Use a No. 2 pencil or blue or black ink pen only.
- Do not use pens with ink that soaks through the paper.
- Make solid marks that fill the oval completely.
- Make no stray marks on this form.

CORRECT ● INCORRECT ✓ ✗ ◒ ⊙

Post-Secondary Plans

1. **What level of education do you think you will obtain?**
   - (A) Some High School
   - (B) GED or High School Diploma
   - (C) A specialized training program at a technical, business, or trade school of less than two years
   - (D) Associates degree – 2 years
   - (E) Bachelors degree – 4 years
   - (F) Master's degree
   - (G) Doctorate or professional degree
   - (H) Undecided

2. **Please indicate the category that most closely represents the career or occupation you plan to pursue.**
   - (A) **Business** (Accounting, Business and Management Consulting, Finance, Sales, etc.)
   - (B) **Computer Sciences** (Information Technology, cyber security, networking, etc.)
   - (C) **Construction and Development** (Auto repair/mechanic, Electrician, Carpentry, Plumbing, Heating, Construction, etc.)
   - (D) **Design** (Graphic Design , Electronic Media, Web Design, Computer Aided Design, etc.)
   - (E) **Healthcare** (Nurse, Doctor, EMT, clinician, administrative medical assisting, etc.)
   - (F) **Education and Social Services** (Early Childhood/Education, Higher Education, Social Work, Child Welfare, Social Services, etc.)
   - (G) **Science, Technology, Engineering, or Mathematics** (Civil/Mechanical/Other Engineer, Robotics, Applied Mathematics, Biotechnology, etc.)
   - (H) **Law, Government, Public Safety** (Police, Legal Services, Military/ROTC, Public Administration/Government, etc.)
   - (I) **Undecided**

3. **In the past year, have you discussed your educational or employment plans for after high school? (Mark all that apply)**
   - (A) Yes, with friends
   - (B) Yes, with parents/guardians
   - (C) Yes, with a school counselor, teacher, or administrator
   - (D) Yes, as part of a program, course, or regular meeting focused on college or career options
   - (E) No, I have not discussed my future plans

4. **How long have you been interested in the career or occupation selected above?**
   - (A) Recently (this year)
   - (B) For a few years
   - (C) Since middle school
   - (D) Since elementary school
   - (E) For as long as I can remember

5. **How sure are you of your current career plans?**
   - (A) Completely sure
   - (B) Mostly sure
   - (C) Moderately sure
   - (D) Somewhat sure
   - (E) Not at all sure

6. **Please indicate how well you think your courses are preparing you for your career.**
   - (A) They provide *all* the knowledge and skills I need for my career
   - (B) They provide *most* of the knowledge and skills I need for my career
   - (C) They provide *some* of the knowledge and skills I need for my career
   - (D) They *do not* provide the knowledge and skills I need for my career
   - (E) I am *not sure* to what extent they provide the knowledge and skills I need

PROOF

The next sections will ask you a number of questions about yourself. There are no right or wrong answers. If you are not sure which answer to select, choose the one that is closest to what you think. There are some questions that are very similar to each other; this is not a trick. This type of survey needs to ask similar questions in slightly different ways.

Using the scale below, please rate your agreement or disagreement with the following statements.	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
I will be able to achieve most of the goals that I have set for myself.	⬭	⬭	⬭	⬭	⬭
When facing difficult tasks, I am certain I will accomplish them.	⬭	⬭	⬭	⬭	⬭

Using the scale below, please rate your agreement or disagreement with the following statements.	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
In general, I think that I can obtain outcomes that are important to me.	○	○	○	○	○
I believe I can succeed at most any endeavor to which I set my mind.	○	○	○	○	○
I will be able to successfully overcome many challenges.	○	○	○	○	○
I am confident that I can perform effectively on many different tasks.	○	○	○	○	○
Compared to other people, I can do most tasks very well.	○	○	○	○	○
Even when things are tough, I can perform quite well.	○	○	○	○	○
If I have enough resources, I can solve any problem.	○	○	○	○	○
I am able to work my way through complex problems.	○	○	○	○	○

The following questions refer to your views and experiences in the subject areas of Math, Computer Science, Science, and Engineering (which includes practical applications of math and science).

Using the scale below, please rate your agreement or disagreement with the following statements.	**Strongly Disagree**	**Disagree**	**Neither Agree nor Disagree**	**Agree**	**Strongly Agree**
I am able to get a good grade in math classes.	○	○	○	○	○
I am able to complete my math homework.	○	○	○	○	○
I plan to use mathematics in my future career.	○	○	○	○	○
I will work hard in my mathematics classes.	○	○	○	○	○
If I do well in mathematics classes, it will help me in my future career.	○	○	○	○	○
I am interested in careers that use mathematics.	○	○	○	○	○
I like my mathematics class.	○	○	○	○	○
I know what to do in high school to prepare myself for a career in mathematics.	○	○	○	○	○
I know what to do after high school to pursue a career in mathematics.	○	○	○	○	○
I am able to do well in activities that involve computer science.	○	○	○	○	○
I am able to learn new coding skills.	○	○	○	○	○
I plan to use computer science in my future career.	○	○	○	○	○
I will learn new computer science skills that will help me with school.	○	○	○	○	○
If I become proficient in coding with at least one language, it will help me in my future career.	○	○	○	○	○

PROOF

Using the scale below, please rate your agreement or disagreement with the following statements.	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I like my computer science class.	⬭	⬭	⬭	⬭	⬭
I am interested in careers that use computer science.	⬭	⬭	⬭	⬭	⬭
I know what to do in high school to prepare myself for a career in computer science.	⬭	⬭	⬭	⬭	⬭
I know what to do after high school to pursue a career in computer science.	⬭	⬭	⬭	⬭	⬭
I am able to get good grades in science classes.	⬭	⬭	⬭	⬭	⬭
I am able to complete my science homework.	⬭	⬭	⬭	⬭	⬭
I plan to use science in my future career.	⬭	⬭	⬭	⬭	⬭
I will work hard in my science classes.	⬭	⬭	⬭	⬭	⬭
If I do well in science classes, it will help me in my future career.	⬭	⬭	⬭	⬭	⬭
I am interested in careers that use science.	⬭	⬭	⬭	⬭	⬭
I like my science classes.	⬭	⬭	⬭	⬭	⬭
I know what to do in high school to prepare myself for a career in science.	⬭	⬭	⬭	⬭	⬭
I know what to do after high school to pursue a career in science.	⬭	⬭	⬭	⬭	⬭
I am able to do well in activities that involve engineering.	⬭	⬭	⬭	⬭	⬭
I am able to complete activities that involve engineering.	⬭	⬭	⬭	⬭	⬭
I plan to use engineering in my future career.	⬭	⬭	⬭	⬭	⬭
I will work hard on activities at school that involve engineering.	⬭	⬭	⬭	⬭	⬭
If I learn a lot about engineering, I will be able to do lots of different types of careers.	⬭	⬭	⬭	⬭	⬭
I like activities that involve engineering.	⬭	⬭	⬭	⬭	⬭
I am interested in careers that use engineering.	⬭	⬭	⬭	⬭	⬭
I know what to do in high school to prepare myself for a career in engineering.	⬭	⬭	⬭	⬭	⬭
I know what to do after high school to pursue a career in engineering.	⬭	⬭	⬭	⬭	⬭

PROOF

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