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Does Course Structure Increase STEM Employment for Women and Underrepresented Minorities in Technology Training Programs? Evidence from LaunchCode

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Abstract: We examine three coding bootcamps offered by LaunchCode (LC101, Women+, and CodeCamp) to understand *if* tailored structures within coding bootcamp programs—designed for underrepresented groups in Science, Technology, Engineering, and Math (STEM)—lead to increased program persistence for women, underrepresented minorities, and low-income individuals. We also examine if these tailored structures lead to increased economic benefits in relation to STEM employment. We find that Women+ participants were roughly twice as likely to complete both the course and the apprenticeship than similar LC101 participants, while CodeCamp participants were roughly five times as likely to complete the course and roughly twelve times as like to complete the apprenticeship. We find that non-completing CodeCamp students found a STEM job much faster than similar LC101 students, suggesting a propensity to secure a job before completing the course in an immersive setting. Conversely, while non-completing Women+ students found STEM jobs more slowly than similar LC101 students, we do not observe a disparity between Women+ completers and non-completing LC101 students or completers. This suggests the efficacy of gender-focused programming in reducing gender disparities in job finding. Also, we find that course-completers in CodeCamp and Women+ experienced greater rates of STEM employment after 36 months when compared to similar LC101 students, suggesting the importance of content knowledge and work experience for students with little-to-no background in computer science, as well as for Women and non-binary persons in a longer term. Our findings demonstrate the effectiveness of tailored structures within coding bootcamp programs in reducing disparities in STEM job participation among women and underrepresented minorities.

Keywords: Coding Bootcamps; Apprenticeships; STEM; Labor Market Returns; Gender; Underrepresented Minorities

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INTRODUCTION

The persistent mismatch between the skills needed by employers and the existing skills of the current workforce is referred to as the "skills gap" (Bessen, 2014). This gap is particularly pronounced in technology sectors, which have experienced rapid transformations in the number and type of skills demanded by employers spurred by recent advances in cloud computing, blockchain technology, and artificial intelligence (Theben et al., 2023). Previous research demonstrates that employers in the technology sector tend to be located in areas with large numbers of high-skilled workers (Takatsuka, 2011), especially when training costs are borne by the workers themselves (Almazan, DeMotta, & Pittman, 2007). Thus, filling the skills gap in the technology sector can have positive implications for communal prosperity. Moreover, science, technology, engineering, and math (STEM) occupations offer some of the highest wages and growth trajectories in the U.S. economy. As noted by Huang and colleagues (n.d.), STEM occupations had a median annual income of $89,780 in 2020 (compared to $40,020 for non-STEM occupations), as well as a projected job growth rate of 10.5% by 2030 (compared to 7.5% for non-STEM jobs) (U.S. Bureau of Labor Statistics, 2020). Therefore, filling the skills gap in the technology sector may also have positive implications for individual social mobility.

Given the higher STEM incomes and potential for job growth, it is unsurprising that interest in STEM careers is relatively high, particularly in computer science. In a 2021 Gallup poll of middle and high school students, 62% of respondents mentioned that were interested in learning more about computer science (Murray, 2021). Despite the increasing demand for STEM skills from employers and the rising interest in STEM careers among students, traditional STEM education pathways (such as 2- and 4-year degree programs) have notable limitations. For example, in 2023, there were 381,904 open computing jobs nationwide, yet only 90,942 computer science graduates entered the workforce that year (code.org, 2023). Furthermore, traditional STEM education pathways—particularly in computer science—are prone to substantial equity gaps: less than 20% of computer science graduates in 2023 were women and less than 10% were Black or Hispanic (code.org, 2023), which reflect broader trends in STEM education and employment (Fry et al., 2021a; Pantic & Clarke-Midura, 2019). As a result, stakeholders have created new talent preparation pipelines in STEM that exist outside of these traditional pathways (Jabbari et al., n.d.).

One of the largest areas of growth in alternative STEM education pathways has been the concept of "coding bootcamps", where students develop in-demand computer science skills in short, intensive programs designed to prepare them for local technology jobs (Jabbari, Chun, et al., 2023). Compared to other pathways, coding bootcamps often have fewer barriers to entry, shorter time commitments, lower tuitions, and direct connections to employment opportunities; thus, they are frequently seen as vehicles for both social mobility and racial equity (e.g., Jabbari, Chun, et al., 2023). Indeed, recent research has demonstrated that coding bootcamps can increase STEM employment and earnings, often through work-based learning (i.e. apprenticeship) components (e.g., Jabbari, Chun, et al., 2023).

Coding bootcamps have been shown to boost the participation of women and underrepresented minorities in STEM education pathways (Jabbari, Huang, et al., 2023). However, women and underrepresented minorities often face substantial barriers to persisting in these programs (Huang et al., n.d.). Additionally, the financial returns to these programs are not equally distributed across income groups (Jabbari et al., n.d.). Stemming from this research, additional program models have been created to ensure that women, underrepresented minorities, and low-income individuals can persist in these alternative STEM education pathways and reap the same benefits as other, more advantaged participants. For example, LaunchCode, one of the largest and longest-standing technology training providers in the U.S., originally created LC101—a part-time, evening coding program that includes 20 weeks of courses and 12-52 weeks of a paid apprenticeship at a local employer(LaunchCode, 2023).

Noting stubborn equity gaps, LaunchCode recently developed two new program models: Women+ and CodeCamp. Women+ focuses on women and non-binary persons, while CodeCamp focuses on underrepresented minorities and low-income students. Both programs are free, include paid apprenticeships, and last roughly 1 year (including the apprenticeship) and each program has unique elements of support and immersion. Women+ is a part-time program in which participants are grouped in cohorts and receive professional mentorship from women. CodeCamp participants are immersed full-time in local community colleges and are provided with student success coaches. These program structures at LaunchCode and other, similar organizations were designed with the intention of improving efficiency and equity; however, their effectiveness has not been examined.

In order to determine whether tailored program structures lead to increased persistence and economic benefits for women, underrepresented minorities, and low-income individuals within coding bootcamp programs, we examined the impact of three coding bootcamps offered by LaunchCode: LC101, Women+, and CodeCamp. This study builds on our recent impact analysis of LC101, which found that being accepted into LC101 was associated with increased earnings and higher rates of working in a STEM industry, primarily because of the apprenticeship component of the program (Jabbari, Chun, et al., 2023). The current study represents a substantial extension of our previous analyses. As before, we draw on longitudinal administrative employment data collected by Equifax. However, instead of focusing on a single program model, we compare both Women+ and CodeCamp applicants to similar LC101 applicants with respect to their program participation as well as employment outcomes. We explore the following questions:

1. Are tailored technology training program structures associated with greater rates of persistence?
2. Are tailored technology training program structures associated with faster rates of STEM employment?
3. Are tailored technology training program structures associated with greater rates of STEM employment for prolonged periods of time?

To answer the first question, we use detailed program and demographic data to examine if students experience greater rates of persistence in Women+ and CodeCamp, compared to similar LC101 students. To answer the second question, we employ survival modeling strategies to examine how long it takes Women+ and CodeCamp applicants to gain general and STEM employment compared to similar LC101 applicants. To answer the third question, we employ a lagged dependent variable approach to examine if Women+ and CodeCamp applicants experience greater rates of general and STEM employment across multiple time points, compared to similar LC101 applicants. In answering questions two and three, we conduct both intent-to-treat (ITT) and treatment-on-treated (TOT) analyses. Specifically, we leverage entrance exam scores as an instrumental variable in our ITT analyses to compare admitted versus non-admitted applicants. (1) applicants who were not admitted to (2) applicants who were admitted. Additionally, we leverage a robust array of pre-application information to generate multinomial propensity score weights that statistically balance two samples of applicants in our TOT analyses. The two applicant groups are: (1) applicants who were not admitted and admitted applicants, who did not complete the course, and (2) applicants who completed the course and applicants, who completed both the course and the apprenticeship.

In this study, we find that Women+ participants were roughly twice as likely to complete both the course and the apprenticeship as their LC101 counterparts, while CodeCamp participants were roughly five times as likely to complete the course and roughly 12 times as likely to complete the apprenticeship as the LC101 participants. We find that non-completing CodeCamp students secured STEM jobs much faster than their LC101 counterparts, indicating a tendency to obtain employment before finishing the course in an immersive setting. Conversely, while non-completing Women+ students took longer to find STEM jobs compared to similar LC101 students, there is no observed disparity in acquiring a job between completing Women+ students and both non-completing and completing LC101 students. This suggests that gender-focused programming effectively reduces gender disparities in job acquisition. Finally, students who completed courses and apprenticeships in CodeCamp and Women+ experienced higher rates of STEM employment compared to similar LC101 students at 48 months. This suggests the importance of tailored content knowledge and work experience for students in immersive programming, particularly for women and non-binary individuals in a long run.

BACKGROUND

Gender and Racial/Ethnic Disparities in STEM

The field of computer science is characterized by significant gender and racial disparities that begin in education and persist into the workforce (Fry et al., 2021b; Newsome, 2022; Ren, 2022). From secondary education through post-secondary education, women and racial minorities (particularly Black and Hispanic individuals) are markedly underrepresented in computer science. For example, in secondary education only a quarter of participants in AP computer science exams in 2023 were female (CollegeBoard, 2023). In post-secondary education, the disparities become even more pronounced. According to the National Center for Education Statistics (2021), women accounted for just 18% of the bachelor's degrees awarded in computer science, while Black and Hispanic students collectively received only 15% of these degrees. Moreover, the pathway to computer science tends to narrow over time in post-secondary education. For example, Black students are twice as likely as White students to leave STEM majors (Olson & Riordan, 2012; President's Council of Advisors on Science and Technology, 2012).

Given the trends of disparity in education, it is unsurprising that these disparities continue into the workforce, where women and racial minorities are substantially underrepresented in computer science. For instance, female workers comprise about 27% of the overall STEM workforce and are even less represented in computer science (25%) (National Science Foundation, 2021; US Census Bureau, 2022). Even when women are employed in computer science, disparities in outcomes persist, as they earn approximately 86.6 cents for every dollar earned by men in computer science roles (Sassler & Meyerhofer, 2023). Racial and ethnic minorities also encounter significant barriers within the computer science workforce. For example, Black workers make up 11% of all employed U.S. adults, but only 9% of the STEM workforce. Hispanic workers make up 17% of all employed U.S. adults, but only 8% of the STEM workforce (Auxier & Anderson, 2021; code.org, 2023). Similar to the underrepresentation of women, these racial disparities are magnified in computer science, as Black workers make up only 5% of workers employed in computer science (US Census Bureau, 2023).

Barriers in STEM Education and Employment

The barriers faced by women and racial and ethnic minorities are both distinct and interrelated, reflecting deep-rooted societal inequalities. These barriers begin early in education and persist into the workforce. In particular, research has underscored the significant role of K-12 educational experiences, such as participation in advanced STEM courses, in shaping future opportunities in STEM (Griffith, 2010). In this regard, such courses and opportunities are often less accessible to Black and Hispanic students (Wang & Hejazi Moghadam, 2017). Furthermore, despite having comparable interests in STEM, Black and Hispanic students can also lack encouragement and support from parents and peers in pursuing advanced STEM courses (Catsambis, 1994; Maltese & Cooper, 2017; Oakes, 1990; Riegle-Crumb et al., 2011). Similarly, despite having comparable institutional access to advanced STEM courses, women often face unique social hurdles, such as lower awareness of opportunities in computer science, diminished encouragement from parents and educators, and a lack of visible role models in STEM (Cheryan et al., 2017). Moreover, once in these courses, sexism and racism tend to devalue the identities of women and Black and Hispanic students, which make them less likely to persist in the courses (McGee, 2016; Robinson et al., 2016). For instance, "stereotype threat," defined as a situation where prevalent negative stereotypes threaten one's social identity (Spencer et al., 2016, pp. 416–417), has been found to reduce persistence in education broadly and in STEM education in particular, leading to negative individual outcomes.

In the STEM workforce, women and Black and Hispanic workers continue to face substantial barriers. These include discrimination, unwelcoming or hostile workplace cultures, and a lack of formal and informal mentors (Eaton et al., 2020; Moss-Racusin et al., 2012). In addition, Black and Hispanic STEM workers face substantial barriers in accessing influential professional networks, which can limit opportunities for career progression. Ultimately, these barriers can contribute to higher attrition rates in the STEM workforce for female, and Black and Hispanic workers (McGee, 2021; U.S. Census Bureau, 2021).

Efforts to Reduce Barriers in STEM Education and Employment

The above barriers that women and Black and Hispanic individuals face underscore the need for new educational and workforce development policies and programs in STEM targeting the participation and persistence of these individuals in STEM education and employment. To this end, extracurricular programs for K-12 students, such as hack-a-thons, workshops, and mentoring programs, have been designed to empower female, Black, and Hispanic students with the skills, experiences, and support needed to succeed in male-dominated STEM educational and employment settings (Alvarado & Dodds, 2010; Bruckman et al., 2023; Holland, 2001; Varma, 2010; Stoilescu & Egodawatte, 2010; Kelly et al., 2013; Main & Schimpf, 2017). For example, Black Girls Code engages young Black women with computer programming through interactive workshops, after-school programs, and summer camps. These programs foster students' technical skills and boost their confidence in computer science (Black Girls Code, 2023). Additionally, curricular efforts have also been designed to increase computer science relevancy and visibility for female, Black, and Hispanic students in STEM (Cheryan et al., 2009; Master et al., 2016; Varma, 2010; Alvarado & Judson, 2014).

Education programs also exist for post-secondary students. With noted limitations for scale in traditional post-secondary contexts, non-traditional STEM education programs offer post-secondary students additional entry points to education and employment, as they are not prone to some of the prerequisites that are often used to determine entrance into more traditional STEM education programs. Additionally, persistence in STEM education also requires general education persistence, as one cannot major in a STEM field without first getting into, attending, and ultimately, graduating from college (Jabbari, Huang, et al., 2023). Programs like the Meyerhoff Scholars Program at the University of Maryland, Baltimore County, and Stanford Women in STEM demonstrate successful strategies in traditional post-secondary contexts, in which they support a diverse student body through networking, career development, and community-building activities (Tsui, 2007; Valla & Williams, 2012).

One of the most prevalent non-traditional STEM education programs is coding bootcamps. While coding bootcamps can take on many forms, most of them embody three main components (World Bank, 2017): (1) intensive rapid skills training with a competitive selection process, typically lasting no more than six months; (2) teaching methods that follow a project-based, experiential learning approach; (3) curricula that reflect current industry needs, with teaching subjects adapted according to local demand.

By focusing mostly on the application of computer science (coding), coding bootcamps distill the key skills from more traditional degree-granting computer science programs in a condensed period of time, ensuring that students with little or no background in computer science are able to program after completing the bootcamp (Waguespack et al., 2018). Without the prerequisites found in more traditional computer science education programs, coding bootcamps allow for alternative entry points. Additionally, some coding bootcamps have structures in place, such as mentoring programs, that can increase persistence in program completion and help graduates secure employment in the workforce (LaunchCode, 2023).

Surveys on the effectiveness of coding bootcamps suggest that these non-traditional computer science programs can lower the barriers to STEM education and employment. According to a survey conducted by Course Report (a bootcamp industry monitor) on over 3,000 bootcamp graduates from more than 100 bootcamps, 79% of students were employed after completing a coding bootcamp and students, on average, experienced a 56% increase in earnings (Eggelston, 2020). Furthermore, coding bootcamps have substantially lower opportunity costs than traditional computer science programs: the average length for in-person bootcamps lasted 14.4 weeks (Eggelston, 2018) and the average tuition was $14,214 (Eggelston, 2020). Beyond these surveys, most of the empirical research on program persistence and effectiveness of coding bootcamps comes from LaunchCode. For example, Jabbari et al. (n.d.) merged LaunchCode program data with earnings and employment data from Equifax and found that both course and apprenticeship completers experience a similar, modest increase in STEM employment at 48 months. They also found that apprenticeship completers experienced an income increase that was nearly double that of those who only completed the course. In light of these results, the authors demonstrated how LaunchCode operates as a tool for advancing gender and racial equity in STEM for students who complete the course, and especially for those who complete the apprenticeships, as that can allow for smooth transitions to permanent jobs, while also facilitating new social networks (Jabbari et al., n.d.).

Limited research has also examined the impact of a coding bootcamp designed exclusively for women. Leveraging a randomized controlled trial of 802 Colombian and Argentinian women, Aramburu et al. (2021) found that program participation significantly increased employment for women in technological jobs in Buenos Aires, Argentina, and Bogotá, Colombia. However, without a comparison to a similar program for all genders, it is difficult to determine the degree to which the program structure (i.e., it is designed specifically for women) influenced these outcomes. While additional studies on coding bootcamps have emerged in recent years, a scoping review of coding bootcamps demonstrates that these studies are often descriptive in nature, rarely consider persistence in the coding bootcamps, and frequently lack a robust examination of core economic outcomes (Huang et al., n.d.).[1]

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[1] Similar descriptions of the Coding Bootcamps program appear in Jabbari et al., 2022; 2023 and Chun et al., 2023.

With fewer barriers to entry, lower opportunity costs, and more flexibility, coding bootcamps offer an additional, broader pathway into the computer science workforce. However, historically underrepresented students in computer science may still face barriers to persistence and, ultimately, success in coding bootcamps. For instance, Jabbari, Huang, et al. (2023) leveraged a natural experiment in which LaunchCode adopted more equity-focused admissions policies. While admission rates increased for Black and Hispanic students, as well as students with lower entrance exam scores, persistence rates only increased among individuals with lower entrance exam scores, and only did so during the coursework phase and not the apprenticeship phase. A follow-up mixed-methods study found that prior coding experience and mentorship were significantly associated with increased persistence within the LC101 program, and that course difficulty was one of the largest barriers to course completion (Huang et al., n.d.). Nevertheless, given the flexibility of coding bootcamps, new program structures have been developed that may increase persistence rates and improve employment outcomes for traditionally underrepresented students. These structures are often tailored to a specific group and sometimes include mentors and instructors with similar identities as the students. Thus, peer compositional effects and mentor/instructor identities might operate as potential mechanisms to address the aforementioned barriers for underrepresented students.

Potential Mechanisms in Reducing Disparities in STEM

Peer Compositions

Diversity in gender composition and other social identities could hold the key to mitigating stereotype threat in STEM fields. Specifically, higher compositions of female and racial/ethnic minority students in STEM could potentially improve STEM outcomes—particularly those related to persistence—by tempering gender discrimination and stereotyping. For example, Van Veelen et al. (2019) leveraged survey data from 807 Norwegian STEM college graduates and found that women facing a “gender identity threat” reported lower work engagement and career confidence and that higher women-to-men ratios reduced this “gender identity threat” for women in STEM fields. Gender composition also affects academic self-concept, which “pertains to one’s beliefs about ability in academic domain,” (Wu et al., 2021, p. 1750), and is linked to academic achievement (Wu et al., 2021). For instance, Ulku-Steiner et al. (2000) leveraged data on 341 doctoral students at a state university and found that women in programs with a higher male-to-female ratio had lower academic self-concept and career commitment. In addition, Cohoon (2006) utilized survey and enrollment data from 18 computer science departments across a variety of US universities and found that the percentage of students in these departments who identified as women was the greatest predictor of retention of women in STEM majors at a given university. Based on focus group responses, Cohoon (2006) suggested that the availability of same-gender peers for academic support could explain these results. Along with academic support, same-gender peers might also support female students’ academic self-concept when dealing with instances of bias. Utilizing survey data from over 300 women interested in pursuing STEM, Robnett (2016) found that, while experiences of gender bias were associated with decreased STEM self-concept, having supportive peers mitigated these effects.

In addition to studies on gender-based compositional effects, research has also examined race-based compositional effects. For example, Bottia et al. (2018) found that attending racially isolated, predominantly white high schools was associated with a decrease in STEM majors and with graduating with a STEM major irrespective of students' own race. Moreover, Hall et al. (2017) leveraged survey data from over 5,000 college freshmen and found that having more ethnically diverse friend groups in college played a role in mediating the effects of racial discrimination on participation in STEM.

Instructor and Mentor Identity

Instructor identity may also promote the persistence of female and underrepresented minority students in STEM fields. Recent research in undergraduate education suggests that same-gender professor representation can have positive effects on educational outcomes relating to both performance and persistence (Hoffmann & Oreopoulos, 2009). Mansour et al. (2022) studied the outcomes of students in the United States Air Force Academy eight years after graduation. They found that, for female students who scored highly on the SAT, having more female professors was associated with a higher likelihood of receiving a STEM undergraduate degree or Master's degree, as well as a greater likelihood of working in STEM. Similar findings were reported earlier by Carrell et al. (2010). Additionally, leveraging longitudinal administrative data from 14,448 Black students and 1613 Black faculty at 13 public universities, Price (2010) found that Black students are more likely to complete a STEM major if they have taken a STEM course taught by a Black professor. In addition to professors, same-gender mentors may also promote the persistence of women and underrepresented minority students in STEM fields. Dennehy & Dasgupta (2017) leveraged a longitudinal study of 150 engineering majors and found that women who had women as mentors reported higher levels of belonging, self-efficacy, and retention. Same-race mentors have also been associated with occupational choices (Kofoed, 2019), although few studies examine this relationship in STEM contexts.

Study Setting

LaunchCode is a 501(c)(3) non-profit organization that was founded in 2013 with a mission “to help people with nontraditional backgrounds find fulfilling, upwardly-mobile careers, and to help companies find skilled, new tech talent from all backgrounds and walks of life” (Jabbari, Chun, et al., 2023). LaunchCode’s flagship program is LC101, a part-time, evening coding program that includes 20 weeks of courses and 12-52 weeks of a paid apprenticeship with a local employer. LaunchCode students also develop a portfolio project and enter a “Lift-Off” phase after graduation, which includes resume building and interview preparation to help students prepare for their apprenticeships. As noted by Jabbari, Chun, et al. (2023), the apprenticeships facilitate a more efficient transition to the labor market for graduates, as students are able to take the skills they learned from LaunchCode and apply them in a real-world setting with a local employer. The apprenticeships also allow LaunchCode graduates to supplement their technical skills with professional skills in the workplace. Moreover, perhaps most importantly, part of the apprenticeship pay from employers is used to subsidize the cost of the education program, making it free for all students.

LC101 has historically used three main benchmarks for admission: (1) admitted students must express an interest in having a career that involves coding; (2) admitted students must have enough time to attend the once-per-week course and complete the accompanying assignments, which typically requires 15 hours/week; and (3) admitted students must demonstrate proficiency on the HackerRank test, which assesses both critical thinking and problem-solving skills related to computer science[2]. At the time of data collection, LC101 had two-course tracks: (1) a JavaScript track in which students learn foundational programming concepts and front-end programming and (2) a Java or C# track (also known as the "skills track") in which students learn to build web applications.

Apart from LC101, LaunchCode has developed two new programs in recent years with different formats: Women+ and CodeCamp. Women+ is a program that is exclusively offered to women or non-binary students. CodeCamp is a full-time program that is mostly housed in a local community college, often focusing on serving low-income and minority students between the ages of 16-24 with no background in technology. While these programs are offered to different types of participants and on different timelines from LC101, the curricula of these courses are nearly identical to LC101[3]. We describe the features of each program in Table 1.

*** **Table 1 is about here** ***

METHODS

In this study, we utilized quantitative methods to assess the degree to which tailored programs are related to participant persistence. Then, we examined the different levels of participation in three LaunchCode programs—LC101, CodeCamp, and Women+—and the varying effects of these programs on STEM employment.

Data

For the quantitative analyses conducted in this study, we made use of two datasets. The first dataset consists of applicant roster data obtained from LaunchCode's three programs, which includes the program participation level, details about each applicant's cohort, HackerRank scores, and various sociodemographic attributes. This data was merged with Equifax's longitudinal employment data obtained from Equifax's Ignite secure

[2] Similar descriptions of the LaunchCode program appear in Jabbari et al., 2022; 2023 and Chun et al., 2023.
[3] While the Women+ web development curriculum is identical to LC101, some cohorts have offered additional skill tracks.

data platform (EQFX-Ignite), which provides observed employment data to researchers while maintaining the privacy and anonymity of the data subjects.

Sample

Our analyses focused on applicants to three LaunchCode programs: LC101, CodeCamp, and Women+. Due to varying eligibility criteria for each program, we created two sets of comparisons: LC101 and CodeCamp applicants, and LC101 female applicants and Women+ applicants. In the dataset, we identified four levels of participation in each program: (1) applicants who were not admitted, (2) admitted applicants who did not complete the course, (3) admitted applicants who completed the course, and (4) admitted applicants who completed both the course and the apprenticeship. For the Intended-To-Treat (ITT) group analyses, we combined categories (2), (3), and (4) and used those who were not admitted as the reference group. For the Treatment on the Treated (TOT) group analyses, we combined categories (3) and (4), as the TOT group and (1) and (2) as the reference group.

Measures

We identified STEM employment by examining the North American Industry Classification System (NAICS) codes associated with each individual's employer. Specifically, we flagged individuals who work in STEM-related fields based on whether their employers' NAICS code begins with "54", which is the 'Professional, Scientific, and Technical Services' classification. Regarding the gender variable, we combined non-binary gender identification with women due to the limited number of non-binary students in the sample. Additionally, we categorized the race/ethnicity of program applicants into two groups: historically overrepresented groups (non-Hispanic white and Asian) and historically underrepresented groups (non-Hispanic Black, Hispanic, and other groups) in STEM, as the sample sizes for underrepresented groups were relatively small. Finally, we classified participants' educational attainment into four groups: individuals without any college, those with some college or an Associate's degree, those with a Bachelor's degree, and those with a graduate (Master's or Doctorate) degree. Table 2 provides a summary of the statistics of the above variables for LC101, CodeCamp, LC101 (women only), and Women+ participants.

*** **Table 2 is about here** ***

Empirical Model Design

This study aimed to examine 1) the heterogeneity of LaunchCode participation and 2) varying impacts on STEM employment across three LaunchCode programs—LC101, CodeCamp, and Women+. We employed three empirical approaches to investigate this relationship. Firstly, we analyzed the various program participation rates across the three programs while controlling for participants' socioeconomic and demographic characteristics. This analysis allowed us to understand the distribution of program participation. Next, we assessed how quickly LaunchCode participants secure STEM employment using a survival model analysis. Lastly, using the LDV approach, we explored the duration of program participants' involvement in STEM jobs by comparing short-term and longer-term employment rates. Both the intent-to-treat (ITT) and treatment-on-treated (TOT) impacts of program participation on general employment and STEM employment were measured using these approaches.

Multinomial Logistic Regression Analysis

Our multinomial logistic regression (MNL) study examined the variation in program participation among those admitted to a LaunchCode program. Specifically, we compared the participation rates across the three LaunchCode programs. Note that CodeCamp participants were compared to LC101 participants as a whole, while Women+ participants were compared to female LC101 participants. In order to mitigate any potential bias in our analysis, we leveraged propensity score weighting across a range of different program characteristics (i.e., age, race, gender [for CodeCamp], educational attainment, HackerRank scores) to ensure that participants in each of the three programs were similar on observed baseline characteristics. These characteristics were also included as covariates, along with yearly cohort fixed effects, to create a doubly robust model; this helps account for demographic characteristics and program intake periods. To express this mathematically:

$$Ln\left(\frac{Pr(completed)}{Pr(dropped\ out)}\right) = \alpha_0 + \beta_1 Prog_i + \boldsymbol{X_i^{demo}\Gamma_1} + \gamma HR_i + \boldsymbol{X_i^{cohort}\Gamma_2}$$
$$Ln\left(\frac{Pr(apprenticed)}{Pr(dropped\ out)}\right) = \alpha_0 + \beta_1 Prog_i + \boldsymbol{X_i^{demo}\Gamma_1} + \gamma HR_i + \boldsymbol{X_i^{cohort}\Gamma_2}$$

where $\Pr\ (Completed)$ and $\Pr(Appprenticed)$ represent the probabilities of completing a LaunchCode course and apprenticing, respectively. The relative risk (or probability) of completing (or apprenticing) a LaunchCode course is determined by program type (LC101 and CodeCamp/Women+) along with the demographic characteristics of a program participant (X^{demo}), the HackerRank score at the baseline (HR_i), and the cohort year

(X_i^{cohort}). Here, the exponentiated form of the program coefficient (β_1) represents the relative risk ratio of completing (or apprenticing) either CodeCamp or Women+ compared to participating in the reference LC101 program.

Survival Model Analysis

Our second analysis examined *when* LaunchCode participants found a (STEM) job. To answer this question, we used the Cox proportional-hazard regression model (Cox, 1972), which estimates the hazard function of an analytic sample over time. In our context, the Cox proportional-hazard model captures different speeds of finding a STEM job among participants across three programs (ITT and TOT), controlling for demographic characteristics (age, race, gender, educational attainment), as well as HackerRank scores at the baseline period. Since this survival model is concerned with the first employment after program participation, our analytic sample is limited to those who were not employed in STEM fields at the baseline period (at the beginning of the program start). The Cox proportional-hazards can be estimated as follows:

$$h_{ij}(t) = h_0(t)\, exp\big(f(\cdot)\big)$$
$$f(\cdot) = \beta_1 Prog_i + \beta_2 Part_i + \beta_3 Prog_i \times Part_i + \boldsymbol{X_i^{demo}\Gamma_1} + \gamma HR_i + \boldsymbol{X_i^{cohort}\Gamma_2}$$

where $h_{ij}(t)$ is the hazard function of the jth event at time t in program participant i, which is a function of the program (LC101, CodeCamp, Women+) and the participation level (not-admitted, dropped-out, completed, and apprenticed) along with demographic characteristics (X^{demo}), HackerRank score (HR_i), and cohort year (X_i^{cohort}). $h_0(t)$ is the baseline hazard that corresponds to the value of the hazard if all the predictors are zero. In this model, the exponentiated form of the coefficient of the interaction term (β_3) represents the relative hazard ratio of being employed in a STEM field after participating in a LaunchCode program compared to not being admitted to an LC101 course.

Lagged Dependent Variable Approach

In addition to the survival model approach, we also used a Lagged Dependent Variable (LDV) regression to analyze the impact of LaunchCode programs and participation on employment outcomes. In non-experimental settings, the commonly used approach for evaluating intervention or policy effects is Difference-in-Differences (DID). DID aims to provide unbiased estimates of the Average Treatment Effect (ATE) by comparing treatment and comparison groups over time. It assumes that, in the absence of treatment, both groups would have followed parallel trends in average outcomes. However, there is a risk of bias in DID approaches if the assumption of parallel trends is violated (Angrist &

Pischke, 2009). Due to constraints in our research context, in which it is not possible to observe and confirm parallel pre-treatment trend lines for an extended period of time, we proposed an alternative approach: a modified LDV regression. This method considers pre-treatment outcomes and covariates from the pre-treatment period. Among the various alternatives to DID approaches, the LDV approach is recognized for providing efficient and unbiased estimates (O'Neill et al., 2016).

While the survival model focuses on the speed at which program participants find jobs, the LDV approach examines how long participants stay in their jobs. Our LDV models assessed both the ITT and TOT impacts of program participation on STEM employment at +12, +24, and +36 months from the start of the program. These timeframes represent the short-term and long-term impacts of the program.[4]

Instrument Variable (IV) approach— To claim a plausible causal inference of ITT effects on employment and earnings, we employed an instrumental variable (IV) approach. The ITT model focuses specifically on the impact of program admission rather than program completion (Angrist & Pischke, 2009). In our IV with the two-stage least square (2SLS) model, we utilized HackerRank (HR) scores as instrumental variables for program participation. Following Jabbari, Chun, et al. (2023), which considered the moderate proficiency levels in the HR scores among LaunchCode applicants, we expected that performing reasonably well on the HR test alone is not a critical factor for most individuals who apply to LaunchCode with the goal of securing a STEM job. Instead, we hypothesized that the impact of HR scores on employment in STEM occurs only through the pathway of participating in a LaunchCode program. Given this rationale, the HR test result serves as a theoretically sound instrumental variable.[5] In mathematical representation, our IV model is as follows:

$$Part_i = \pi_1 HR_i^{IV} + \beta_1 Prog_i + \boldsymbol{X_i^{demo}\Gamma_1} + \boldsymbol{X_i^{cohort}\Gamma_2} + v_i \text{...eq1.1}$$

$$y_i^t = y_i^0 + \alpha_0 + \beta_1^t Prog_i + \beta_2^t \overline{Part_\iota} + \beta_3^t Prog_i \times \overline{Part_\iota} + \boldsymbol{X_i^{demo}\Gamma_1^t} + \boldsymbol{X^t{}_i^{cohort}\Gamma_2} + u_i^t \text{...eq1.2}$$

In the first stage model (*eq 1.1*), our endogenous ITT treatment dummy, $\mathrm{Part_i}$, is a function of the instrumental variable (HR_i^{IV}), along with program type ($Prog_i$), demographic characteristics (X_i^{demo}) , and cohort year fixed effects (X_i^{cohort}). The second stage model

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[4] For individuals who were not admitted and thus have never taken an LC101 program, we assume a pseudo-start month—a hypothetical start month when they would be admitted to an LC101 program, just as their application cohort.

[5] Statistically, through initial tests of endogeneity (accounting for both time and pre-treatment outcomes), our results suggest that entrance exam scores are also an empirically valid instrument for STEM employment.

assumes an outcome variable of interest—i.e., STEM employment (y_i^t) at t months prior/post the program start as a function of the fitted endogenous variable ($\overline{\mathrm{Part}_\imath}$) from the first-stage model, program type, demographic characteristics, cohort year fixed effects, and most importantly, STEM employment at the baseline (y_i^0). Here, β_3^t estimates the difference of ITT impact on STEM employment at t between two programs—i.e., a CodeCamp/Women+ admission as opposed to not being admitted to LC101.

Multinomial Propensity Score Weighting (MPSW)—To examine the TOT effects on STEM employment, we employed a multinomial propensity score weighting (MPSW). Estimating the TOT effects poses a challenge due to the non-random nature of participants' decisions to complete the program and apprenticeship. Unlike the enrollment offer, these decisions are not determined by easily accessible metrics, like the HackerRank score. To address potential endogeneity, we employed a matching technique to balance the four participant groups based on observable characteristics. In order to tackle the issue of multidimensionality, we leveraged machine learning techniques and generalized boosted regression. This allowed us to use the MPSW [6] to calculate the probability or propensity of individuals selecting a program (LC101 or CodeCamp/Women+) and reaching a participation level (not admitted, dropped out, completed, or apprenticed). In the MPSW stage, we subsequently balanced individuals across various observable characteristics, including gender, race/ethnicity, age, educational attainment, and STEM employment before LaunchCode program participation. Our propensity score weighting strategy aimed to achieve balance across these time-invariant and pre-application characteristics, which are theoretically linked to both treatment assignment and the outcomes under investigation.

Following MPSW, we estimated the TOT effects of various levels of LaunchCode participation and LaunchCode programs on STEM employment and earnings across each of three treatment groups: (1) similar individuals who were accepted but did not complete the course; (2) similar individuals who completed the course but not the apprenticeship; and (3) similar individuals who completed the course and the apprenticeship. These treatment groups were compared to the control group, that is, similar students who were not accepted. Here, the various "levels" of program participation can be seen as representing certain "doses" of the treatment. In mathematical representation,

$$y_i^t = y_i^0 + \alpha_0 + \beta_1^t Prog_i + \beta_2^t Part_i + \beta_3^t Prog_i \times Part_i$$

[6] For our MNPS strategy, we use RAND Corporation's Toolkit for Weighting and Analysis of Nonequivalent Groups (TWANG), developed by Ridgeway et al., (2013).

$$+X_i^{demo}\Gamma_1 + \gamma HR_i + X_i^{cohort}\Gamma_2 + MPSW_i + u_i^t;\ (t = +12\ and + 48\ months)\ldots eq.2$$

Here, β_3^t is associated with the TOT impact of a CodeCamp/Women+ participation on STEM employment at t as opposed to the not admitted to LC101. Note that we utilized linear modeling approaches—a two-stage IV regression model for the ITT analyses and Ordinary Least Squares/Linear Probability Models for the TOT analyses—for the analysis of the impact of LaunchCode participation on STEM employment. Linear Probability Models are appropriate for the STEM employment dummy, as it is well-balanced among the analytic sample (Wooldridge, 2010). The data analyses in this study were conducted using R (R Core Team, 2023), and we used thresholds of $\alpha = 0.10$, 0.05, and 0.01 to assess statistical significance.

FINDINGS

How Far People Participate in a LaunchCode Program

Table 3 presents the findings of multinomial logistic regression analyses, with dropping out from a LaunchCode course as the baseline outcome compared to LC101 participants. The results indicate that, compared with LC101 participants, CodeCamp participants exhibited higher completion rates, with a 5.0 times higher likelihood of completing the course ($p < 0.01$) and an 11.5 times higher likelihood of completing the apprenticeship programs ($p < 0.01$). Similarly, compared with women in LC101, Women+ participants were 1.7 times more likely to complete the course ($p < 0.01$) and 1.9 times more likely to complete the apprenticeship programs ($p < 0.01$).

*** **Table 3 is about here** ***

How Quickly People Find a STEM Job

Tables 4A and 4B (along with Figures 1 and 2) examine the cumulative STEM employment by comparing the ITT and TOT groups, respectively. It is important to note that the survival model samples included in each model comprise individuals who were not employed in STEM fields during the baseline period. As a result, the employment rate for each plot begins at zero during this period. In most cases involving the three LaunchCode programs, we generally do not observe any significant disparities between the ITT groups (Table 4A and Figure 1). However, there is one notable exception of a significant increase in the STEM employment rate among those who were not admitted to a CodeCamp course (Column 1). Compared to individuals who were not admitted to an LC101 course, individuals who were not admitted to a CodeCamp course found a STEM job more quickly (*HR(Hazard ratio)* = 1.912, $p < 0.01$) than their counterparts, although this difference was not statistically significant for those who were admitted.

As for the TOT effects (Table 4B and Figure 2), we observe that non-completing CodeCamp students found a STEM job more quickly (*HR* = 1.931; $p < 0.01$) than their non-completing LC101 counterparts. Conversely, individuals who did not complete a Women+ program found a STEM job more slowly (*HR* = 0.693, $p < 0.10$) than their non-completing LC101 counterparts. However, we do not observe any disparities in STEM job search between Women+ completers and both LC101 non-completers and completers.

*** **Tables 4A and 4B are about here** ***

*** **Figures 1 and 2 are about here** ***

How Long People Stay in the STEM Job

Using the LDV model, Tables 5A and 5B examine the short-term (+12 months) and long-term (+24 and +36 months) employment rates for STEM employment and compare the ITT and TOT groups, respectively. It is important to note that these employment rates differ from those measured using the survival model (Tables 4A and 4B) due to the fact that the LDV model captures the employment rate as a snapshot at 12, 24, and 36 months following the beginning of the program.

ITT Effects

We began the ITT group comparisons (Table 5A) using those in the "not admitted to LC101" group as the reference category. In the CodeCamp models (columns 1 to 3), non-accepted CodeCamp students experienced a significant increase in STEM employment at 12 (beta = +0.667, $p < 0.01$) and 24 months (beta = +3.678, $p < 0.10$); however, this increase was negligible by 36 months. On the other hand, applicants accepted into CodeCamp exhibited significantly lower STEM job rates in the first two periods (+12 months: beta = -2.396, $p < 0.01$; +24 months: beta = -3.638, $p < 0.01$), but this negative gap dissipated by +36 months. In the Women+ models (columns 4 to 6), non-accepted students experienced a significantly higher STEM employment rate at 12 months (beta = -0.896, $p < 0.01$), which dissipated by 24 months.

TOT Effects

Moving on to the TOT group comparisons (Table 5B), using a combination of those in the "not admitted to LC101" group and those in the “admitted but did not complete LC101” group as the reference category, we observe interesting findings. In the CodeCamp models (columns 1 to 3), students who completed LC101 experienced a significant increase in STEM employment at 12 months (beta = +0.054, $p < 0.001$), but its magnitude gradually lessened at 24 months (beta = +0.046, $p < 0.001$) and 36 months (beta = +0.026, $p < 0.01$). Furthermore, non-accepted and non-completing CodeCamp students experienced a significant increase in STEM employment at 12 months (beta = +0.065, $p < 0.001$), which had a moderate decrease at 24 months (beta = +0.038, $p < 0.001$) and completely dissipated by 36 months. However, while completing CodeCamp students experienced a significant decrease in STEM employment at 24 months (beta = -0.033, $p < 0.001$), by 36 months, these students experienced a significant increase in STEM employment (beta = +0.060, $p < 0.001$).

In the Women+ model (columns 4 to 6), students who completed LC101 experienced no significant effects on STEM employment. Non-accepted and non-completing Women+ students experienced a significant decrease in STEM employment at 12 months (beta = -0.020, $p < 0.01$) that completely dissipated by 24 months. On the other hand, completing Women+ students experienced a significant decrease in STEM employment at 12 months (beta = -0.023, $p < 0.001$). However, by 24 months, these students experienced a significant increase in STEM employment (beta = +0.042, $p < 0.001$), which decreased only slightly by 36 months (beta = +0.034, $p < 0.001$).

*** **Tables 5A and 5B are about here** ***

DISCUSSION

Summary of Findings

Starting with persistence, when comparing similar admitted students through propensity score weighting, we found that both Women+ and CodeCamp participants exhibited higher program persistence as opposed to LC101 participants. Specifically, in comparison to LC101, Women+ participants were roughly twice as likely to complete both the course and the apprenticeship, while CodeCamp participants were roughly five times as likely to complete the course and about twelve times as likely to complete the apprenticeship. While previous research found that equity-focused admissions policies could increase entrance rates for underrepresented minorities in STEM, these policies did little to increase persistence (Jabbari, Huang, et al., 2023). Rather, it appears that alternative course structures account for increased persistence rates for underrepresented minorities in STEM. While research supports certain program elements of Women+ and CodeCamp in explaining their effects on persistence (e.g. peer composition in both courses and mentor identity in Women+), it is possible that other, unobserved factors could also affect persistence. For example, Jabbari et al. (n.d.) found that, while some students had difficulty keeping up with the curriculum in the conventional LC101 course, these difficulties could be partially alleviated by an expanded course timeline, which is a feature of both Women+ and CodeCamp.

We also examined how quickly LaunchCode participants of varying levels find a STEM job through survival modeling. In doing so, we constructed a series of models demonstrating ITT and TOT effects. In the ITT models, we found that non-admitted CodeCamp students found a STEM job more quickly than LC101 participants as well as CodeCamp admitted. It appears that non-admitted CodeCamp students are at a relative advantage when compared to others. This could be the case because CodeCamp is a full-time program, and non-admitted students in this program may lack a full-time job and are thus more motivated to find STEM employment.

In TOT models comparing students who completed a LaunchCode program with those who were not admitted or did not complete, we found that non-completing CodeCamp students secured STEM jobs much faster than similar LC101 students. The full-time nature of the CodeCamp course may allow students to learn more material quickly, leading them to leave before graduating due to securing a STEM job. Conversely, while non-completing Women+ students found STEM jobs more slowly than similar LC101 students, we did not observe a disparity between Women+ completers and non-completing/completing LC101 students. Given the history of gender discrimination in the STEM workforce, Women+ students may be benefiting from the mentorship structures set in place during the apprenticeship component. This gender-focused programming may have reduced gender disparities in job finding.

Lastly, we explored employment duration by a series of LDV models at 12, 24, and 36 months. While we observe significant increases in employment for non-admitted CodeCamp students at 12 and 24 months, these increases dissipate by 36 months. This result suggests that, without the proper education and training, these individuals are not able to endure in STEM industries. As the CodeCamp program is full-time, it is possible that non-admitted applicants face a greater desire for this employment to be in STEM industries. Conversely, for Women+ not admitted, it could discourage their STEM job seeking, which initially decreases their STEM employment that, ultimately, dissipates over time. Indeed, non-admittance could reinforce certain stereotype threats in STEM that have been widely documented (Cadaret et al., 2017).

The results from our LDV analyses on TOT groups demonstrate the importance of program completion in STEM outcomes. In a long run (+36 months), both Women+ and CodeCamp program completers experienced the highest rates of STEM employment across all comparison groups—including LC101 course completers. This suggests that when comparing similar students, tailored programs provide more enduring benefits in STEM employment. Meanwhile, the STEM employment rate of its completers (compared to LC101 non-completers) shifts from negative at +12 months to positive at +24 months. This suggests that students who are newer to computer science may take additional time to secure employment in STEM industries. Similarly, the STEM employment trends shift from negative at +24 months to positive at +36 months for Women+ course completers, suggesting that students who have historically been underrepresented in STEM fields take additional time to locate employment in STEM industries. Furthermore, when considering the result that non-accepted and non-completing CodeCamp students experienced an initial increase in STEM employment, it is possible that some non-completing students find STEM employment before completing the course, but perhaps lack the education and training to persist in these industries (Huang et al., n.d.).

Implications

At the federal level, our findings lend support for the use of federal funds for alternative education programs in STEM, like LaunchCode. At the state level, our findings lend support for new partnerships between traditional educational institutions, such as community colleges, and alternative education programs, such as LaunchCode. While the flexibility of LaunchCode’s programs allows for tailored program structures, traditional education institutions can offer additional program supports (e.g., guidance counselors) to increase the efficacy of these programs. Furthermore, incentives, such as college credit or industry-recognized credentials, could be integrated into these programs more readily and easily when non-traditional education programs are able to partner with traditional education institutions (Jabbari et al., n.d.). At the local level, our findings inform leaders to find new mechanisms, such as grants and tax breaks, to incentivize businesses to partner with local education organizations in order to offer apprenticeships and create new training-to-employment pipelines (Jabbari, Huang, et al., 2023). Moreover, our findings suggest that alternative education providers should make concerted efforts to understand equity gaps in their programs, tailor their program structures in ways to promote equitable outcomes, and then test these tailored structures, so that they can be continually improved.

Additionally, our findings have implications for several theories surrounding education, while also offering future directions for STEM education. Specifically, our findings demonstrate how tailored program structures substantially increase STEM educational persistence, and in many cases improve STEM employment, both in terms of speed and endurance. While the exact nature of compositional or mentor identity effects is difficult to discern, our findings suggest that, in the case of Women+, the social identity of gender plays a significant role in promoting STEM field participation among women. Future research should identify and examine these mechanisms—tailored curricula designs and consideration of social identity—to better understand how they affect students. For example, peer gender compositions might reduce stereotype threats and improve self-concepts, while the gender identity of mentors may open new doors in employment settings. Stemming from representative bureaucracy theories (Keiser et al., 2002), increased minority representation may lead to increased advocacy for underrepresented students in STEM education and employment. In the case of CodeCamp, while peer effects may play a role in persistence and employment, so too might the condensed nature of the course, as well as the additional supports (e.g., guidance counselors) that are often present in community colleges.

Limitations

Our study offers several novel contributions; however, it is not without limitations. Concerning external validity, LaunchCode's program model, which includes an apprenticeship component, may be distinct from other coding bootcamp programs; this may limit the generalizability of our findings. As noted by Jabbari et al. (n.d.), the use of administrative earnings data also limits the external validity of our findings, as not all participants could be matched into the Equifax data. Concerning internal validity, while the use of MPSW effectively balanced the different treatments (e.g., LC101, Women+) and treatment components (e.g., course and apprenticeship completion) across a range of observable characteristics for our TOT analyses, it is possible that other, unobservable characteristics may be systematically related to the treatments and outcomes under study, and, thus, may bias our results. Therefore, we cannot establish causal effects in our TOT analyses. It is also important to note that due to our limited sample size and relatively low prevalence rates of STEM employment, we cannot disentangle the course and apprenticeship completion components in our STEM employment analyses. As apprenticeships have been found to be important predictors of STEM employment in previous research (Jabbari, Chun, et al., 2023), future research should not only consider randomizing these types of programs, but also randomizing elements (e.g., the apprenticeship component) within these programs. Finally, while we were able to identify the effects of multiple programs with unique structures that have some theoretical support (e.g., peer effects), we cannot verify the mechanisms of impact. For instance, the effectiveness of CodeCamp may be due to the condensed time, the unique setting (i.e., inside a community college), the student population, or a combination of these factors. Future research should leverage qualitative data to further identity and unpack these mechanisms.

CONCLUSION

Traditional STEM education programs are plagued with stubborn inequities—particularly as they relate to the experiences of women and persons of color. Such systemic disparities have collective consequences: lack of diversity in STEM employment settings can stifle creativity and limit group problem-solving ability (Rock & Grant, 2016). The lack of diversity in STEM education also makes it difficult to fill the growing skills gap in STEM, which can cause employers to relocate.

Non-traditional STEM education programs (e.g. coding bootcamps) are not bound by traditional enrollment pre-requisites, tuition rates, and course structures, which make them more accessible to historically excluded groups of students. Indeed, with fewer barriers to entry, lower opportunity costs, and greater degrees of flexibility, coding bootcamps are an additional, broader pathway into the computer science workforce (Jabbari, Huang, et al., 2023). However, even within these pathways, students from historically underrepresented groups in computer science, such as women and persons of color, may still face barriers to persistence and, ultimately, success in the STEM workforce. Taking advantage of their flexibility, non-traditional educational providers, like LaunchCode, have developed alternative program structures to boost persistence and improve outcomes for students who have been historically underrepresented in STEM. In the first study of its kind, we examined if these tailored programs could increase equity in STEM employment. As equity in STEM employment is not only a product of what outcomes program graduates experience, but also how many students graduate from the program, we explored both program persistence and the speed and endurance of STEM employment. Not only did we observe improved program outcomes for Women+ and CodeCamp program graduates, but we also observed increased persistence across both programs. Thus, these programs demonstrate strong promise to improve equitable outcomes in STEM employment for underrepresented students. Policymakers, practitioners, and researchers should continue to examine the ways in which alternative education providers can leverage their flexibility in program delivery to tailor program structures that improve outcomes for every student group.

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TABLES AND FIGURES

Table 1. Summary of LaunchCode Programs

	LC101	**CodeCamp**	**Women+**
Target	Students ages 18+	Low-income and minority students ages 16-24 with no technology background	Students who identify as women, transgender, non-binary, and gender nonconforming
Duration	Part-time, 20 weeks of courses + 12–52 weeks apprenticeship Meets 3 hours twice per week, with up to 15 hours of homework per week	Full-time, 14-17 weeks, depending on cohort	Part-time, 24-45 weeks, depending on skill track Meets 3 hours once per week, with up to 15 hours of homework per week
Location	LaunchCode	Local community colleges	LaunchCode

Table 2. Descriptive Statistics of Variables in Use

	LC101 (all)		CodeCamp		LC101 (Women only)		Women+	
	Untreated (n=3301)	**Treated** (n=751)	**Untreated** (n=217)	**Treated** (n=67)	**Untreated** (n=1408)	**Treated** (n=293)	**Untreated** (n=994)	**Treated** (n=270)
STEM Employment (%)								
pre1	10.12%	7.59%	13.36%	4.48%	11.15%	9.56%	11.97%	7.78%
post12	10.42%	9.32%	17.97%	4.48%	10.87%	11.95%	9.36%	8.52%
post24	11.43%	10.24%	20.00%	1.89%	11.58%	13.03%	11.70%	13.19%
post36	11.65%	8.95%	16.53%	5.00%	11.63%	10.88%	12.34%	13.79%
Age (Mean)	35.37	32.67	34.52	32.19	36.42	32.92	35.86	33.54
	(10.14)	(7.86)	(11.09)	(8.34)	(10.59)	(7.89)	(10.25)	(7.73)
HackerRank Score (Mean)	61.04	82.01	61.57	81.19	57.56	80.99	65.53	82.57
	(27.80)	(14.73)	(27.92)	(12.87)	(28.19)	(15.16)	(26.66)	(15.28)
Gender (%)								
<u>Men</u>	57.35%	60.99%	54.84%	41.79%	-	-	-	-
Women/Non-binary	42.65%	39.01%	45.16%	58.21%	100.00%	100.00%	100.00%	100.00%
Race (%)								
<u>White + Asian</u>	51.35%	61.25%	53.92%	50.75%	43.75%	63.48%	53.92%	75.19%
Black + Hispanic	48.65%	38.75%	46.08%	49.25%	56.25%	36.52%	46.08%	24.81%
Educational attainment (%)								
<u>High School or less</u>	10.97%	7.86%	11.52%	13.43%	9.30%	4.10%	7.75%	3.70%
Some College or Associate	41.47%	34.22%	45.16%	31.34%	37.78%	29.69%	32.60%	23.70%
Bachelor's	34.35%	42.08%	29.49%	41.79%	36.65%	46.76%	36.92%	47.40%
Master's or above	13.21%	15.85%	13.82%	13.43%	16.26%	19.45%	22.74%	25.19%
Cohort (%, year)								
<u>2016</u>	0.00%	0.00%	-	-	-	-	-	-
2017	0.00%	0.00%	-	-	-	-	-	-
2018	16.87%	25.97%	-	-	14.56%	17.06%	13.18%	20.00%
2019	26.57%	22.50%	34.56%	46.27%	27.34%	26.96%	16.40%	17.04%
2020	21.57%	19.97%	21.20%	13.43%	21.59%	21.84%	18.51%	16.67%
2021	15.57%	14.78%	13.36%	19.40%	16.83%	15.36%	30.78%	21.85%
2022	19.42%	16.78%	16.13%	13.43%	19.67%	18.77%	21.13%	24.44%
2023	-	-	14.75%	7.46%	-	-	-	-

Note: Reference categories underlined; Standard error in parentheses

Table 3. Multinomial logistic regression results (Program participation; Reference outcome=Dropped-out)

	LC101 vs CodeCamp		LC101 vs Women+	
	Completed (1A)	**Apprenticed (1B)**	**Completed (2A)**	**Apprenticed (2B)**
Program				
Women+			1.645***	1.639***
			(0.195)	(0.303)
CodeCamp	4.243***	9.131***		
	(1.346)	(4.097)		
AIC	513.99		2,622.61	
R2	0.1357		0.0791	

Notes: * p<0.10 ** p <0.05; *** p<0.01
Age, gender (for LC101 and CodeCamp comparison), race/ethnicity, educational attainment, HR score, and Cohort (yearly) fixed effect controlled but not reported

Table 4A. Survival analysis results (ITT)

	LC101 vs CodeCamp	LC101 vs Women+
	(1)	(2)
Program x Participation		
LC101 x Admitted	0.131	-0.006
	(0.149)	(0.236)
CodeCamp/Women+ x Not admitted	0.648***	-0.348
	(0.243)	(0.266)
CodeCamp/Women+ x Admitted	0.228	0.115
	(0.469)	(0.277)
Observations	4781	3,119
R2	0.010	0.008
Max. Possible R2	0.591	0.523
Log Likelihood	-2,113.26	-1,142.351
Wald Test (df = 14)	45.480***	22.300*
LR Test (df = 14)	47.448***	24.866**

Notes: * p<0.10 ** p <0.05; *** p<0.01
Age, gender (for LC101 and CodeCamp comparison), race/ethnicity, educational attainment, HackerRank score, and Cohort (yearly) fixed effect controlled but not reported

Table 4B. Survival analysis results (TOT)

	LC101 vs CodeCamp (1)	LC101 (Female only) vs Women+ (2)
Program x Treatment		
LC101 x Treated	0.020	-0.077
	(0.172)	(0.288)
CodeCamp/Women+ x Not completed	0.658***	-0.367*
	(0.219)	(0.208)
CodeCamp/Women+ x Completed	-0.603	0.422
	(0.715)	(0.263)
Observations	4781	3119
R2	0.010	0.009
Max. Possible R2	0.591	0.523
Log Likelihood	-2111.980	-1140.032
Wald Test (df = 14)	45.280***	27.420**
LR Test (df = 14)	49.999***	29.502***
Score (Logrank) Test (df = 14)	48.162***	28.474**

Notes: * p<0.10 ** p <0.05; *** p<0.01
Age, gender (for LC101 and CodeCamp comparison), race/ethnicity, educational attainment, HR score, and Cohort (yearly) fixed effect controlled but not reported

Table 5A. Instrumental variable (IV) model results (ITT)

	LC101 vs CodeCamp			LC101 (Female only) vs Women+		
	+12 mo	+24 mo	+36 mo	+12 mo	+24 mo	+36 mo
	(1)	(2)	(3)	(4)	(5)	(6)
Program x Participation						
LC101 x Admitted	0.182***	0.433*	4.281	0.573***	1.126	1.097
	(0.059)	(0.223)	(15.095)	(0.175)	(1.547)	(0.668)
CodeCamp/Women+ x Not admitted	0.667***	3.678*	30.988	0.896***	-6.284	2.125
	(0.248)	(2.146)	(110.164)	(0.334)	(16.539)	(2.171)
CodeCamp/Women+ x Admitted	-2.396***	-3.638***	-25.901	-0.171	-3.474	-0.542
	(0.695)	(1.371)	(92.775)	(0.146)	(6.670)	(0.467)
Observations	4,336	3,488	2,821	2,965	2,192	1,710
R2	2.069	2.344	0.653	0.197	1.392	0.646
Adjusted R2	0.150	0.126	0.419	0.657	0.238	0.422
Residual Std. Error	0.432	0.904	7.090	0.456	2.904	0.951
	(df = 4322)	(df = 3476)	(df = 2810)	(df = 2953)	(df = 2181)	(df = 1700)

Notes: * p<0.10 ** p <0.05; *** p<0.01

Age, gender (for LC101 and CodeCamp comparison), race/ethnicity, educational attainment, HR score, and Cohort (yearly) fixed effect controlled but not reported

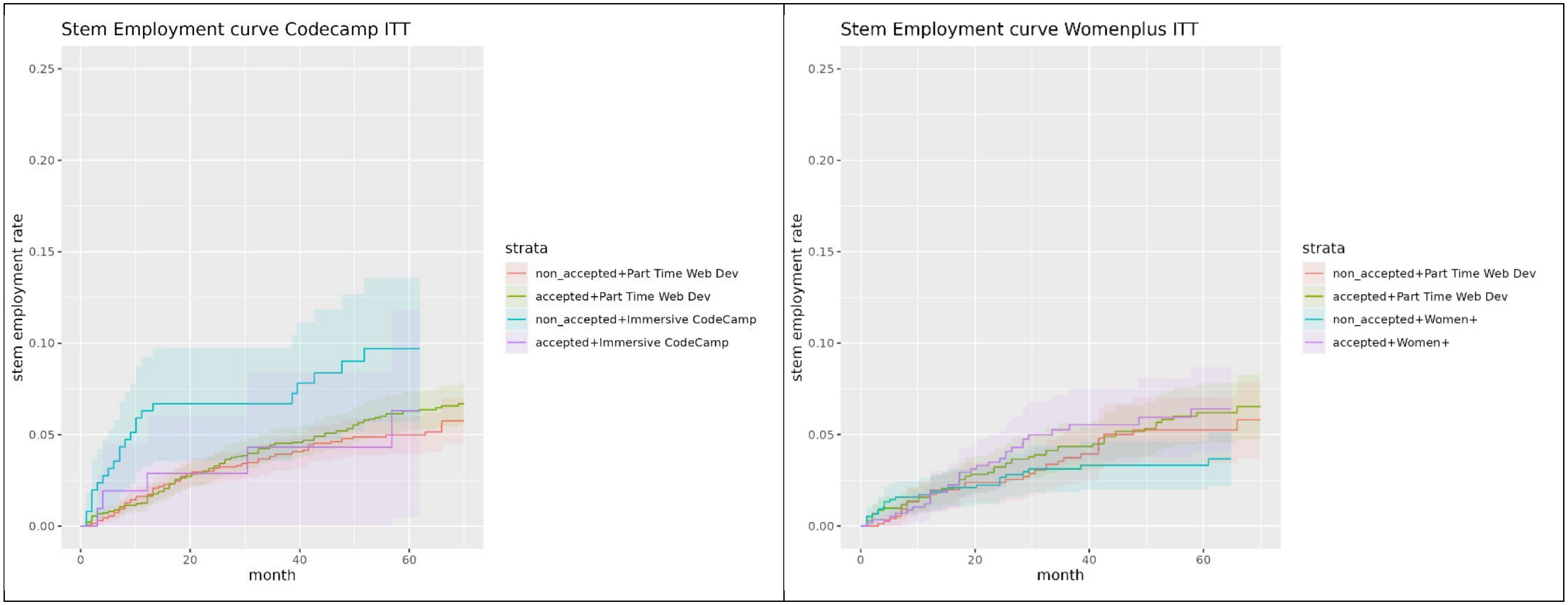
Table 5B. Multinomial propensity score weighting (MPSW) model results (TOT)

	LC101 vs CodeCamp			LC101 (Female only) vs Women+		
	+12 mo	+24 mo	+36 mo	+12 mo	+24 mo	+36 mo
	(1)	(2)	(3)	(4)	(5)	(6)
Program x Participation						
LC101 x Admitted	0.054***	0.046***	0.026**	0.017	0.018	-0.007
	(0.008)	(0.011)	(0.012)	(0.011)	(0.013)	(0.016)
Women+/Codecamp	0.065***	0.038***	0.011	-0.020**	-0.013	-0.012
x Not admitted	(0.009)	(0.011)	(0.013)	(0.010)	(0.012)	(0.014)
Women+/Codecamp	0.005	-0.033***	0.060***	-0.023**	0.042***	0.034**
x Admitted	(0.009)	(0.012)	(0.015)	(0.010)	(0.013)	(0.016)
Observations	4,336	3,488	2,821	2,965	2,192	1,710
R2	0.608	0.448	0.412	0.562	0.566	0.505
Adjusted R2	0.606	0.446	0.409	0.560	0.563	0.501
Residual Std. Error	0.356	0.404	0.425	0.358	0.379	0.401
	(df = 4319)	(df = 3473)	(df = 2807)	(df = 2950)	(df = 2178)	(df = 1697)

Notes: * p<0.10 ** p <0.05; *** p<0.01

Age, gender (for LC101 and CodeCamp comparison), race/ethnicity, educational attainment, HR score, and Cohort (yearly) fixed effect controlled but not reported

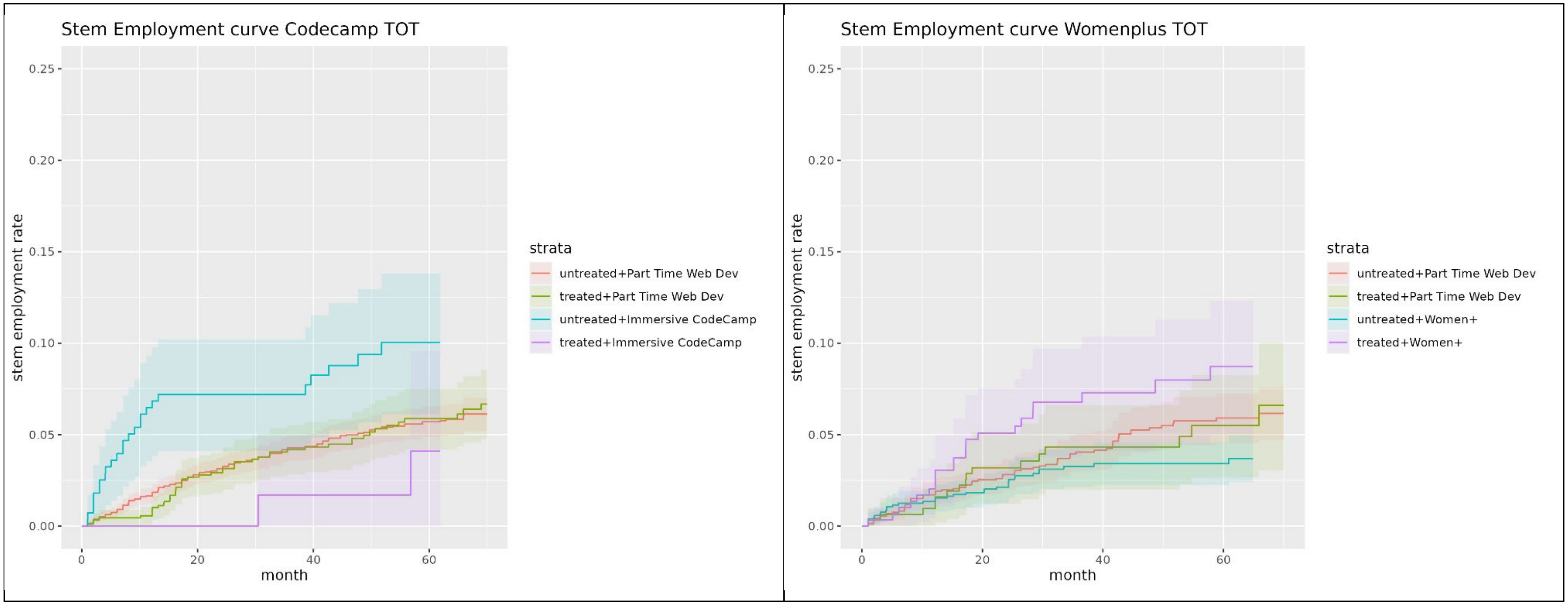
Figure 1. Survival model analysis (ITT impacts, Left—LC101 vs. CodeCamp ; Right—LC101 vs. Women plus)



Note: Left—STEM employment curve for LC101 vs. CodeCamp, showing non-accepted LC101 (red), accepted LC101 (green), non-accepted CodeCamp (blue), and accepted CodeCamp (purple) trends in STEM employment over time.

Right—STEM employment curve for LC101 vs. Women+, showing non-accepted LC101 (red), accepted LC101 (green), non-accepted Women+ (blue), and accepted Women+ (purple) trends in STEM employment over time.

Figure 2. Survival model analysis (TOT impacts, Left—LC101 vs. CodeCamp ; Right— LC101 vs. Women+)



Note: Left—STEM employment curve for LC101 vs. CodeCamp, showing not completed LC101 (red), completed LC101 (green), not completed CodeCamp (blue), and completed CodeCamp (purple) trends in STEM employment over time.

Right—STEM employment curve for LC101 vs. Women+, showing not completed LC101 (red), completed LC101 (green), not completed Women+ (blue), and completed Women+ (purple) trends in STEM employment over time.