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Technology Apprenticeships and Labor Market Outcomes: Mixed-Methods Evidence from the LaunchCode Program

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We leverage employment and earnings data from a large credit bureau, program data from LaunchCode—a free technology education, and in-depth interviews with applicants and instructors to examine if the LaunchCode program leads to economic benefits, who is most likely to experience these benefits, and how this program produces these benefits. We first conduct an intent-to-treat analysis by leveraging entrance exam scores as an instrumental variable. While we don't find a positive effect on STEM employment, we find large, significant effects on income after 48 months. We then conduct a treatment-on-treated analysis by leveraging multinomial propensity score weights to balance applicants across a range of program participation levels. We find that both course and apprenticeship completers experience a similar, modest, increase in STEM employment at 48 months; however, apprenticeship completers experienced an income increase that was nearly double that of those that only completed the course. Additionally, while LaunchCode appears to be a tool for advancing gender and racial equity in STEM, more complex findings were observed regarding social class. Finally, our qualitative findings highlight the potential for apprenticeships to allow for smooth transitions to permanent, full-time employment at the same employer, while also facilitating new social networks.

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Technology Apprenticeships and Labor Market Outcomes: Mixed-Methods Evidence from the LaunchCode program

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Abstract: We leverage employment and earnings data from a large credit bureau, program data from LaunchCode—a free technology education, and in-depth interviews with applicants and instructors to examine *if* the LaunchCode program leads to economic benefits, *who* is most likely to experience these benefits, and *how* this program produces these benefits. We first conduct an intent-to-treat analysis by leveraging entrance exam scores as an instrumental variable. While we don't find a positive effect on STEM employment, we find large, significant effects on income after 48 months. We then conduct a treatment-on-treated analysis by leveraging multinomial propensity score weights to balance applicants across a range of program participation levels. We find that both course and apprenticeship completers experience a similar, modest, increase in STEM employment at 48 months; however, apprenticeship completers experienced an income increase that was nearly double that of those that only completed the course. Additionally, while LaunchCode appears to be a tool for advancing gender and racial equity in STEM, more complex findings were observed regarding social class. Finally, our qualitative findings highlight the potential for apprenticeships to allow for smooth transitions to permanent, full-time employment at the same employer, while also facilitating new social networks.

Keywords: Coding Bootcamps; Apprenticeships; STEM; Labor Market Returns

INTRODUCTION

Educational attainment is one of the strongest predictors of income (Card, 1999) and social mobility. In 2021, for example, the median income for a year-round worker aged 25-34 with a high school diploma was $39,700, compared to $61,600 for a worker with a bachelor's degree (NCES, 2023). Unsurprisingly, the unemployment rate for those without a bachelor's degree was roughly three times higher than for those with a bachelor's degree (Federal Reserve Bank of New York, 2021). Despite college being seen as one of the primary pathways through which people can achieve the "American Dream," in reality only a minority of Americans ever attain this level of education. In 2021, only 37.9% of adults aged 25 and older had a bachelor's degree (Pew, 2022), and nearly 40 percent of all students that started a bachelor's degree program failed to graduate (National Center for Education Statistics, 2021). Moreover, these gaps are considerably larger for historically marginalized groups: only 28.1% of Black adults and 20.6% of Hispanic adults held a bachelor's degree in 2022 (Pew, 2022). While it is true that not everyone needs or wants a bachelor's degree, those without a bachelor's degree and who were not currently enrolled in school reported that high financial costs and the need to maintain employment were the main reasons for not having a bachelor's degree (Pew, 2022). This indicates that there is an unmet demand for access to higher education, training, or skill development programs.

While low rates of bachelor's degree attainment can have major implications for individuals' economic and social mobility, they can also impact the broader community. Previous research demonstrates that employers tend to locate to areas with large pools of high-skilled labor (Takatsuka, 2011) and that local sectors attract new firms when training costs are borne by workers (Almazan, DeMotta, & Pittman, 2007). Nevertheless, there is a persistent mismatch between the skills needed by employers and the existing skills of the broader labor force (Bessen, 2014), which is commonly referred to as the "skills gap". This gap is particularly pronounced in technology-intensive sectors where the accelerated innovation (e.g. cloud computing, blockchain technology, artificial intelligence, etc.) has led to rapid transformations in requisite skills 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). As noted by Huang and her colleagues (n.d.), STEM occupations offer some of the highest wages in the U.S. economy, with a median annual income of $89,780 in 2020, compared to $40,020 for non-STEM occupations. In addition to higher incomes, STEM occupations are projected to grow at faster rates than non-STEM occupations (e.g., 10.5% by 2030, compared to 7.5% for non-STEM jobs) (U.S. Bureau of Labor Statistics, 2020). However, while STEM occupations represent some of the most viable pathways to economic prosperity, these occupations are not equitably distributed in the population. Less than 20% of computer science graduates are women and less than 10% are Black or Hispanic (Code.org, 2023). These statistics reflect larger trends in STEM education, and research has consistently documented the severe underrepresentation of women (Pantic & Clarke-Midura, 2019) and Black and Hispanic individuals (Fry et al., 2018) in STEM.

In response to the growing demand for STEM careers from workers and a growing need for STEM skills from employers, as well as the limits of traditional education pathways (i.e., 2- and 4-year degree programs) to meet these demands, stakeholders have created new talent preparation pipelines in STEM that exist outside of these traditional pathways. As noted by Jabbari et al. (2023), one of the largest areas of growth in alternative STEM education pathways involves learning computer science skills through short, intensive programs where students develop in-demand computer science skills designed to prepare them for technology jobs;

programs often referred to as “coding bootcamps”. These coding bootcamps can simultaneously act as vehicles of social mobility and racial/ethnic and gender equity through their unique structure that circumvents some of the typical bottlenecks leading to inequity in traditional degree programs. They have fewer barriers to entry, shorter time commitments, lower tuitions, direct connections to employment opportunities, and resources to help students persist in the programs (e.g., Jabbari et al., 2023). Although coding bootcamps can fit within the larger body of non-degree credentials and apprenticeships, they are unique in that they exist in an occupation—computer science—that is typically filled with bachelor’s degree holders (Jabbari et al., 2023).

Despite the recent growth of coding bootcamps and the implications that these programs have for advancing social mobility and equity, as well their potential to help meet local labor market demands, little research exists on the outcomes of these programs. As a result, the quality of these programs has been called into question. Indeed, ongoing policy debates, such as those surrounding the Industry-Recognized Apprenticeship Program (IRAP) (U.S. Department of Labor, n.d.), have demonstrated the need for a more comprehensive understanding of these programs along 3 dimensions of outcomes —not only *if* these programs produce economic benefits, but also *who* is most likely to experience these benefits, and *how* these programs produce these benefits. As noted by the National Skills Coalition, demonstrating rigorous evidence of program efficacy is not only a major priority for increasing the quality of these programs, but also for increasing equity within these programs (Duke-Benfield et al., 2019). Otherwise, public investments will continue to be funneled almost exclusively to traditional, 2-year, 4-year, and graduate degree-granting programs, despite rapidly changing labor market conditions and the outsized proportion of individuals seeking a job *without* one of these degrees.

In order to understand *if* coding bootcamp programs lead to economic benefits, *who* is most likely to experience these benefits, and *how* these programs produce these benefits, we examine the impact of coding bootcamps offered by LaunchCode—one of the largest and longest-standing technology training providers in the U.S. LaunchCode offers technology certificate and apprenticeship programs that are free, include a paid apprenticeship, and serve a large share of individuals that are underrepresented in STEM. This research builds on an earlier exploratory analysis of the LaunchCode program, which used post-program surveys to explore the relationship between program participation and employment and earnings outcomes. This study found that being accepted to LaunchCode was associated with increased earnings and a higher probability of working in a STEM profession, and that these changes were primarily driven by the apprenticeship component of the program model. The current study represents a substantial advancement over our initial exploration. We draw on longitudinal administrative employment and earnings data collected by a large credit bureau, as well as in-depth, semi-structured interviews with LaunchCode instructors and applicants, to address the following questions:

1. What is the impact of being accepted into a technology certification and apprenticeship program on STEM employment and earnings?
2. To what extent do STEM employment and earnings differ between those who only receive the technology education component of the program and those who receive both the education and apprenticeship components? To what extent do these effects differ across students’ gender, race/ethnicity, prior employment status, and prior earnings?
3. How do students experience the apprenticeship program and how might these experiences help explain the overall study findings?

To answer the first question, we conduct an intent-to-treat analysis by leveraging entrance exam scores as an instrumental variable. To answer the second question, we conduct a treatment-on-treated analysis, leveraging entrance exam scores and a robust array of pre-application information to generate multinomial propensity score (MNPS) weights that statistically balance four samples of applicants: (1) applicants that were not admitted; (2) admitted applicants that did not complete the course; (3) applicants that completed the course but not the apprenticeship; and (4) applicants that completed both the course and the apprenticeship. To answer the third question, we employ in-depth, semi-structured interviews with LaunchCode instructors and applicants.

Although we find no significant effects of program acceptance on STEM employment, we find large, significant effects on income at 48 months after the start of the program. When considering similarities and differences between those who only receive the technology education component of the program and those who receive both the education and apprenticeship components, we find that both course and apprenticeship completers experience a similar, modest, increase in STEM employment at 48 months. However, apprenticeship completers experienced an income increase that was nearly double that of those that only completed the course. Additionally, concerning heterogenous treatment effects, while LaunchCode appears to be a tool for advancing gender and racial equity in STEM, more complex findings were observed regarding social class. Finally, in terms of the mechanisms at play within apprenticeships, our qualitative findings highlight the potential for apprenticeships to allow for smooth transitions to permanent, full-time employment at the same employer, while also facilitating new social networks.

BACKGROUND

Certificate Programs

There is a modest but growing body of research suggesting positive impacts of alternative education programs on employment and earnings. This literature often involves state-wide studies of programs offered by technical and community colleges or sector-based studies involving programs offered by non-profit organizations. For example, Jepsen, Troske, and Coomes (2014) utilized a fixed effects models with a sample of roughly 25,000 students from technical and community colleges in Kentucky, finding that certificates were associated with increased earnings and employment. Similarly, Bettinger and Soliz (2016) leveraged fixed-effects models with a sample of roughly 51,000 students from both technical and community colleges in Ohio, finding mostly positive impacts on earnings across multiple sectors. However, both studies reported heterogenous treatment effects: in Kentucky, certificates were only associated with increased employment for women; in Ohio men benefited more from short-duration certificates, while women benefited more from long-duration certificates. Moreover, Xu and Trimble (2016) leveraged fixed-effects models with a sample of roughly 230,000 students from 81 community colleges in Virginia and North Carolina to estimate the impact of sub-baccalaureate certificates, finding positive impacts on both employment and earnings. Furthermore, Minaya and Scott-Clayton (2022), leveraging fixed-effects models with roughly 92,000 students from community colleges in Ohio, found that the returns on a long-term certificate remained flat when compared to the returns on an associate degree, which grew over time. Most recently, Darolia, Guo, and Kim (2023) employed matching and fixed-effects models with roughly 108,000 students from community colleges in Kentucky and found significant impacts on employment and earnings, particularly for short-term certificates.

Sector-Based Training

Sector-based training programs tend to include direct connections to employers, often with formal apprenticeships and similar on-site training opportunities. In this regard, Maguire et al. (2010) leveraged an experimental research design with a sample of 1,014 individuals to understand the impacts of three sector-specific training programs. The authors found positive impacts on both employment and earnings across all the programs. Similarly, Schaberg (2017) used a randomized controlled trial with a sample of 2,564 individuals from four providers and found significant impacts on earnings after three years across all the programs.

Coding Bootcamps

"Coding Bootcamps" can take on many forms, but 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.

Representing their agility, coding bootcamps can offer a variety of computer science specializations, such as web or mobile application development, that are designed to meet the immediate and upcoming needs of local employers. As noted by Waguespack et al. (2018), coding bootcamps tend to focus on the application of computer science—coding—with less emphasis on some of the more theoretical aspects of the discipline. In doing so, coding bootcamps distill the key skills from more traditional degree-granting computer science programs to ensure that students with little or no background in computer science are able to program (Waguespack et al., 2018).

According to a survey with over 3,000 bootcamp graduates from over 100 bootcamps conducted by Course Report, a bootcamp industry monitor, the average coding bootcamp student is 31 years old, has 7 years of work experience, and has never worked as a computer programmer prior to starting the bootcamp (Eggelston, 2020). However, while bachelor's degrees are not required, holding one is fairly common across bootcamps graduates: 74% of students had bachelor degree prior to starting a bootcamp in 2020 (Eggelston, 2020). In terms of outcomes, 79% of students were employed after completing a bootcamp and students experienced a 56% increase in earnings (Eggelston, 2020). Considering opportunity costs, the average length for in-person bootcamps lasted 14.4 weeks (Eggelston, 2018) and the average tuition was $14,214 (Eggelston, 2020).

However, surveys like these rely on self-reported data and lack a comparison group, making them prone to selection bias. In this regard, Aramburu and her colleagues (2021) used a randomized controlled trial of 802 Colombian and Argentine women to explore the impact of coding bootcamps on employment, finding that program participation significantly increased employment in technological jobs. In the U.S. Context, much of the inferential work on coding bootcamps comes from LaunchCode. Implementing a retrospective survey design with roughly 1,000 LaunchCode applicants, Jabbari et al. (2023) used an instrumental variable design to conduct an intent-to-treat analysis, finding that program acceptance was significantly associated with increased probabilities of working in a STEM profession and increased earnings. The authors then used multinomial propensity score weighting to conduct a treatment on treated analysis, finding that these increases were primarily driven by the apprenticeship component. While additional studies on coding bootcamps have emerged, a recent scoping review of coding bootcamps demonstrates that these studies are often descriptive in nature, frequently lacking an examination of core economic outcomes, such as employment and earnings (Huang et al., n.d.).

STUDY SETTING

As noted by Jabbari et al. (2023), LaunchCode is a 501(c)(3) non-profit organization and 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." LaunchCode's flagship program is LC101, a part-time, evening coding program that includes 20 weeks of courses, and 12 to 52 weeks of a paid apprenticeship at a local employer. Students also develop a portfolio project and enter a "Lift-Off" phase after graduation that helps them prepare for their apprenticeships (this phase includes resume building and interview preparation). At the time of data collection LC101 primarily had two units: (1) a JavaScript unit where students learn foundational programming concepts and front-end programming and (2) a Java or C# unit (or "skills track") where students learn to build web applications. 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[1].

Additionally, LaunchCode has developed two new programs with different formats in recent years. Women+ is a program that is exclusively offered to students who identify as women or non-binary and CodeCamp which is a full-time program that is often housed in a local community college. While these programs are offered to different participants and in different timeframes from LC101, the curriculum and structure of these courses are nearly identical to LC101.

Finally, as noted by Jabbari et al. (2023), the apprenticeship program is perceived to 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. This also allows LaunchCode graduates to supplement their technical skills with professional skills in the workplace. 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.

METHODS

Study Design

We employ an explanatory sequential mixed-methods study design. Mixed-methods study designs capitalize on the strengths of quantitative and qualitative approaches to develop a more

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

robust and comprehensive understanding of social phenomena (Creswell & Plano, 2011; Padgett 2017; Ivankova, Creswell, & Stick, 2006). Explanatory sequential designs begin with quantitative data collection, analysis, and interpretation, which then inform qualitative data collection, analysis, and interpretation. Findings from both quantitative and qualitative components are then compared and triangulated to identify points of convergence and divergence (Ivankova, Creswell & Stick, 2006). In this study, our quantitative methods first examine the impact of the LaunchCode program on both STEM employment and income. Finding a substantial impact of the apprenticeship component, we then leverage qualitative methods to unpack these impacts, detailing the ways in which the apprenticeship may impact STEM employment and income. Given the variety of participant perspectives across race/ethnicity, gender, and social class, additional quantitative analyses methods are then employed to examine potential heterogeneous treatment effects.

Quantitative Data

For the quantitative component of this study, we utilize two data sources. First, we leverage applicant roster data from LaunchCode, which includes personally identifiable information (PII) of program participants, including four types of the program applicants: (1) those who were not admitted (not admitted); (2) those who were admitted but did not complete the course (dropped out); (3) those who completed the course but did not complete the apprenticeship program (completed); and (4) those who completed both the course and the apprenticeship program (apprenticed). In addition to the level of program participation, the roster data included cohort information (when each applicant applied for the LaunchCode program), Hacker Rank score, which measures both critical thinking and problem-solving skills related to computer science and is used to determine admission to the program, and a variety of sociodemographic attributes. This data was then merged with applicants' observed longitudinal income and employment data by from our partnering credit bureau through their secure data platform, where it is de-identified and shared back with the researchers.

Measures

For the gender variable, we collapsed non-binary gender identification with women identification due to the small sample size of non-binary students. We also dichotomized the race/ethnicity of the program applicants into groups that have historically been overrepresented (non-Hispanic white and Asian) and underrepresented (non-Hispanic Black, Hispanic, and other groups) in STEM due to small sample sizes among the underrepresented groups. Lastly, we categorize participants' educational attainment into four groups—those without an Associate or Bachelor's degree, 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.

To track earned income trends over time, we rely on our partnering credit bureau's "Gross Total Income" metric, which reflects the gross total compensation reported for the most recent year at the individual level. Also, we identify STEM employment by examining the North American Industry Classification System (NAICS) codes associated with each individual's employer. Specifically, we flag individuals who work in STEM-related fields based on whether their employers' NAICS code begins with "54" (Professional, Scientific, and Technical Services).

Sample

Figure 1 illustrates the process through which we arrived at the final analytic sample for the study. Initially, we received PII for 14,022 individuals from LaunchCode.[2] In Stage I, we extracted income and employment information from our partnering credit bureau data reservoir for 70.3% of the initial sample. Subsequently, in Stage II, we focused on LC101 participants, while excluding those who participated in either CodeCamp or Women+ programs–two other, relatively newer and smaller LaunchCode programs.[3] Finally, in the last stage, we retained individuals, with complete income and employment information, in the 48 months following their program participation. For individuals who were not accepted, we assumed their start period to be the month they would have started in the program if they had been accepted. After following these filtering stages, our final analytic sample included 2,141 individuals, which accounts for 15.3% of the initial participants in LaunchCode. Additional robustness checks were completed across complete cases at various time lengths (e.g., 6, 12, 18, 24, and 36 months), but results maintained similar relationships as those in our final analytic sample (For the full results of the robustness check results, see Appendices A and B).

***** Figure 1 is about here *****

Quantitative Analysis

In this study, we employ a Lagged Dependent Variable (LDV) regression approach to examine the impact of LaunchCode participation on changes in employment outcomes. In non-experimental settings, Difference-in-Differences (DID) approaches are commonly used to assess the effects of interventions or policies. The DID approach aims to provide unbiased Average Treatment Effect (ATE) estimates by comparing treatment and comparison groups over time. Specifically, it assumes that in the absence of the treatment, the average outcomes for both groups would have followed parallel trends. However, DID approaches may introduce bias if the parallel trends assumption does not hold (Angrist and Pischke, 2009). Given our research context, in which we cannot observe and therefore confirm parallel pre-treatment trend lines (due to time limits in our pre-treatment study period), we propose an alternative: a variation of the LDV regression approach. This method adjusts for pre-treatment outcomes as well as covariates in the pre-treatment period. Among a variety of alternatives to DID approaches, the LDV is known to provide the most efficient and least biased estimates (O'Neill et al., 2016).

Our LDV models measure both intent-to-treat (ITT) and treatment-on-treated (TOT) impacts of the program participation on STEM employment and total gross annual earned income at -6, +6, +12, +18, +24, +36, and +48 months from the program start.[4]

[2] It is important to note that the total number of records in the four participation groups exceeds 14,022 due to the possibility of duplications in program participations; an individual can have multiple records of participating in the LC program if they applied for multiple LaunchCode programs over time. To address this, we retained only the individual's most recent LC program participation for each duplicate record.

[3] Our decision to focus on LC101 in the quantitative analysis is based on having a sufficient sample size for students in the apprenticeship component. However, given the similar dynamics in the apprenticeship component across all LaunchCode programs, we did include qualitative data from all three programs.

[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.

Intent-to-treat (ITT) effects

Our ITT approach is focused on the impact of program admission rather than program completion. We use an instrumental variable (IV) approach to claim a plausible causal inference of ITT effects on employment and earnings (Angrist & Pischke, 2009). We specifically use HackerRank (HR) scores to instrument program participation in a 2SLS model. Our identification strategy assumes that the entrance exam scores would be associated with the outcomes of interest (i.e., STEM employment and income) solely through participation in the program. Following Jabbari et al., (2023), given the moderate levels of proficiency in the HR score among LaunchCode applicants, we assume that relatively adequate performance on the HR test *alone* will not be a critical factor for most individuals that apply to LaunchCode to find a STEM job (and by doing so, often increase their earnings). Rather, the impact of the HR score on STEM employment and earnings is assumed to occur through and only through participating in LaunchCode. For this reason, the HR test result serves as a theoretically sound instrumental variable. 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 both STEM employment (Wu-Hausman F Statistic = 17.228; p < 0.001) and income (Wu-Hausman F Statistic = 13.513; p < 0.001). In mathematical representation, our IV model is as follows:

$$d_i = \pi_1 x_i^{IV} + X_i \Pi_1 + v_i \ \ldots \ldots (eq\ 1.1)$$

$$y_i^t = \beta_0^t + y_i^{t0} + \beta_1^t \underline{d}_i + X_i B_2^t + u_i^t \ \ldots \ldots (eq\ 1.2)$$

In the first stage model (*eq 1.1*), our endogenous treatment dummy, d_i—0 for not admitted; 1 for admitted—is a function of the instrumental variable, x_i^{IV}, and a set of covariates, X_i, including cohort fixed effects, the outcome measure at the baseline (i.e., a month prior to the program participation), and demographic attributes (race/ethnicity, gender, age, education level before the LaunchCode). Then the second stage model (*eq* 1.2) assumes an outcome variable of interest, y_{it} (either STEM employment or earnings) at t months prior/post the program start as a function of the fitted endogenous variable, $\underline{d}_i$, from the first-stage model, the covariates vector, X_i, and the outcome measure at a month prior to the program start, y_i^{t0}. Here, β_1^t estimates the ITT impact of LaunchCode participation on post-LaunchCode earnings and STEM employment at t.

Treatment on the treated (TOT) effects

Our treatment-on-the treated (TOT) methodology looks at how different program participation levels impact STEM employment and earnings. One challenge with estimating this relationship is that the decisions to complete the program and apprenticeship are not random and, unlike the offer of course enrollment, are not a function of some readily observable indicator like the Hacker Rank score above. To account for this potential endogeneity, we employ a matching technique to balance the four multinomial participant groups on observable characteristics. Leveraging machine learning techniques and generalized boosted regression to deal with issues of multidimensionality, we use *multinomial propensity score weighting (MPSW)*[5], which calculates individuals' probability (or propensity) of attaining a given program participation level and then balances individuals with different participation levels across a range of observable characteristics (McCaffrey et al., 2013). Specifically, our propensity score weighting strategy

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

attempts to balance participants across the following time-invariant and pre-application characteristics that are theoretically related to both treatment assignment and the outcomes under study: gender, race/ethnicity, age, educational attainment before LC, STEM employment before LC, previous coding hours, yearly income before LC, and entrance exam score. As seen in **Table 1,** our MNPS technique was able to achieve balance across nearly all observed characteristics[6].

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

Then, we estimate the treatment effects of various levels of LaunchCode participation on STEM employment and earnings across each of the three treatment groups (similar individuals who were accepted but did not complete the course; similar individuals who completed the course but not the apprenticeship; and similar individuals who completed the course and the apprenticeship), compared to the control group (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,

$$y_i^t = \beta_0^t + y_i^{t0} + D_i \mathrm{B}_1^{\mathrm{t}} + X_i B_2^t + u_i^t \quad \dots\dots (eq\ 2)$$

where D_i is a multinomial treatment variable—0 for not admitted; 1 for admitted but did not complete the course; 2 for completed the course; and 3 for completed the course and the apprenticeship.

Heterogeneous treatment effects

In addition to examining the average treatment effects between the ITT and TOT groups, we explore heterogeneous treatment effects based on gender, race/ethnicity, and pre-treatment income and employment categories:

- *Gender*: We divided the treatment and comparison groups into two categories: men and women/non-binary.
- *Race and Ethnicity*: We combined non-Hispanic white and Asian individuals into one category, and Black, Hispanic, and other racial/ethnic groups into another category. In doing so, we compare racial/ethnic groups that are over-represented in STEM to racial/ethnic groups that are underrepresented in STEM (NCSES, 2023).
- *STEM Employment*: We divided our sample based on whether individuals had prior employment in STEM fields before applying to the LaunchCode program.
- *Income Quartile*: We divided our sample based on income quartiles prior to applying to LaunchCode. Those with zero income were excluded from these groupings.

These analyses aim to shed light on how various groups that are historically underrepresented in STEM, such as women/non-binary individuals and Black/Hispanic/other groups—respond differently to participating in LaunchCode, while also examining the degree to which LaunchCode can act as a pathway towards occupational attainment and social mobility for those from non-STEM backgrounds and those with lower incomes.

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[6] In addition to the descriptive statistics of each variable, we report the standardized effect sizes of the variation between each of the dropped out, the completed, and the apprenticed, and the not-admitted program participant types. Following Cohen's effect size guideline, d = 0.2 is considered a "small" effect size, 0.5 represents a "moderate" effect size and 0.8 a "large" effect size (Cohen, 1988, 1992).

For consistent specifications across empirical models, we employ 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 both STEM employment and income. Linear Probability Models are appropriate for the STEM employment dummy, as it is well-balanced among the analytic sample (Wooldridge 2010). Lagged DVs were not used in heterogenous treatment effects across pre-LaunchCode STEM employment and income quartiles, as this variation is captured in the groupings. The data analysis in this study was conducted using R (R Core Team, 2023), and we used thresholds of $\alpha = 0.10$, 0.05, 0.01, and 0.001 to assess statistical significance.

Qualitative Data

The data informing the qualitative portion of this study come from 3 semi-structured interviews with LaunchCode instructors and 23 semi-structured interviews with LaunchCode students who were enrolled in a LaunchCode program between 2020 and 2021 (see Table 2). Interview participants were recruited via email. The researchers were given a full list of LaunchCode students and narrowed down the participant recruitment by identifying students who varied in their gender and race/ethnicity in order to have a diverse group of participants across multiple identities. Each interview lasted approximately 30-60 minutes. The interviews were conducted on Zoom, and participants were awarded a $40 gift card for their participation in the study.

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

Qualitative Analysis

The analysis for the qualitative portion of the study was done using Delve online coding platform for collaborative projects. Transcripts were uploaded to the Delve platform after being professionally transcribed. The research team utilized an iterative process to sort and order data into units of meanings, categories, patterns, and themes (Creswell, 2009). The first step of data analysis involved open coding to identify themes within data sources and to develop categories. The second step of data analysis involved axial coding to generate subcategories, which allowed the research team to form more precise and complete explanations. The final stage involved selective coding (Strauss & Corbin, 1990) to systematically relate and refine categories and subcategories into theoretical constructions. Data triangulation was achieved by comparing instructor and student interviews. The qualitative research team met after each round of coding to discuss processes, build consensus, and make meaning.

Given the quantitative findings on the importance of the apprenticeship component in securing STEM employment, many of our interview questions focused on participants' experiences in securing the apprenticeship and their experiences within the apprenticeship—particularly in their relationship to gaining STEM employment. A list of the questions asked during the interview is provided in Appendix C.

FINDINGS

Quantitative Findings

Descriptive findings

Figures 2A and **2B** provide visual representations of the variations in STEM employment rates and earned income among the four TOT groups within the LaunchCode program, both before and after the program start. **Figure 2A** focuses on the changes in STEM employment rates. Throughout the study period, the dropout group consistently maintained the highest rate of STEM employment, followed by the non-admitted applicants. Notably, both of these groups experienced a rapid increase in STEM employment during the earlier stage of the analysis (pre 12 months to post 6 months). The STEM employment rate among the students who dropped out increased from 7% to 13%, and from 4% to 13% among the non-admitted students. On the other hand, the completed and apprenticed groups exhibited upward but relatively slower increases in STEM employment over time. It is important to note that the differences in STEM employment changes across the four groups may be attributed to group heterogeneity and potential selection bias, factors that our subsequent empirical models account for.

Figure 2B highlights more pronounced discrepancies in earned income changes across the four groups. One year prior to the start of LaunchCode, both the non-admitted and dropout groups had significantly higher average earned income compared to the course-completed and apprenticed groups. The income trends of the not admitted and dropout groups were relatively parallel and exhibited slow growth. In contrast, the apprenticed group experienced the steepest increase in earned income. Four years after participating in the LaunchCode program, the income gap between the apprenticed group and the other three groups widened to approximately $8,000. However, these difference may be attributed to group heterogeneity and potential selection bias–factors accounted for in our empirical models.

ITT effects

Table 3 presents the results of our instrumental variable (IV) model, capturing the intent-to-treat (ITT) effects of LaunchCode on STEM employment (Panel A) and annual income (Panel B) outcomes. Throughout most of study period, we did not observe any significant effects on STEM employment in the ITT group (composed of dropouts, course completers, and apprenticeship completers), compared to the non-admitted group. Furthermore, we observed a negative ITT effect at 36 months after the program starts (β=-0.078; $p<0.10$). Nevertheless, the findings regarding earned income are noteworthy. Immediately after the program start (at post 6 months), the ITT group earned $4,365 less than its not-admitted counterpart ($p<0.10$). As time progressed, however, the income dynamics between the two groups change. From 18 months after program start, the income gaps became positive. Specifically, at 48 months, the ITT group earned $8,831 more ($p<0.10$), than the non-admitted group.

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

TOT Effects

Table 4 presents TOT effect estimates on STEM employment (Panel A) and annual income (Panel B) with propensity score (PS) weighting, which examines how the LaunchCode treatment effects vary by treatment levels, or "doses". In the short term (12 to 35 after program starts), we observed significantly higher rates of STEM employment among the dropout group compared to the non-admitted group (β=0.018-0.031, $p<0.10$). In the long term, we observed positive employment effects among course completers and apprenticeship completers. At 36-months after program start, both the dropout and course completion groups exhibited higher STEM employment rates by 3.1 percentage points ($p<0.05$) and 3.8 percentage points ($p<0.01$), respectively. At the 48-month mark, both course completers and apprenticeship completers exhibited higher STEM employment rates by 2.9 and 3.2 percentage points, respectively ($p<0.05$). These findings differ from the descriptive results presented in Figure 2, which showed that both non-admitted and dropped out applicants had higher rates of STEM employment than course completers at 48 months since program start, indicating that the descriptive differences we observed are explained by differential selection effects accounted for in our TOT models.

The effects of LaunchCode on earned income are more prominent. In the immediate period after the program ends (post 6 months), we observed higher average income levels among the dropout group (β=1,413.4, $p<0.05$) and the apprenticeship group (β=1,812.5, $p<0.05$). However, while the relative income level decreased among the dropout group, it increased among those who completed the course, as well as those who completed the apprenticeship. At 48 months after the program start, those in the course completion group and those in the apprenticeship group earned \$3,375.4 ($p<0.05$) and \$6,710.4 ($p<0.01$) more, respectively, compared to their non-admitted counterparts.

***** Table 4 is about here *****

Heterogeneous Treatment Effects

Additionally, we examined how the LaunchCode TOT effects vary across gender, race/ethnicity, and baseline STEM employment and income categories. Figure 3 panels plot the predicted probability of being employed in STEM by gender (Panel A; and Appendix D1, Panel A), race/ethnicity (Panel B; and Appendix D2, Panel A), and baseline STEM employment (Panel C; Appendix D3, Panel A). In Figure 3A, we can see that the TOT effect is more prominent among the women/non-binary group than the men group in the long term. Specifically, at 48 months after the program start, the STEM employment gap between those who were not admitted and those who completed the apprenticeship is 7.9 percentage points ($p<0.05$) among the women/non-binary group. On the other hand, the gap among men was only 0.4 percentage points, which is not statistically significant. Regarding racial/ethnic differences (Figure 3B), we do not observe any significant disparities across TOT groups. However, some within-TOT group changes are still noticeable; Black/Hispanic/Other participants who completed the apprenticeship show a significant increase in STEM employment at 48 months after the program start, with a difference of 8.5 percentage points ($p<0.05$).

Interesting findings regarding income gaps can be found in Figure 4A. When analyzing the gender gap in treatment effects, we observe that there is hardly any income gap across TOT groups among men participants throughout the study period. However, at 48 months after the program start, substantial income gaps are observed across TOT groups among women/non-binary participants. Specifically, women who completed the apprenticeship earned \$14,230 (or 1.6 times) more than their not-admitted women counterparts. It is also important to note that the annual income of women apprenticeship participants during this time period (\$37,545.4) was higher than that of men apprenticeship participants (\$31,114.6) ($p<0.10$).

Additionally, there are notable racial/ethnic gaps in income (Figure 4B). Among the Black/Hispanic/Other participants, we do not observe any significant income disparities across the four TOT groups throughout the study period. However, as to the within TOT group income changes, the apprenticeship completers exhibit the fastest increase in average income among the four TOT groups; a 2.3 times increase in income ($13,566 at 12 months after to $30,898 at 48 months after). On the other hand, among white and Asian participants, we observe substantial income gaps across the TOT groups at 48 months after the program start; while the not-admitted white/Asian group earned $26,516 at the 48-month time-point, their apprenticed counterparts earned, on average, $35,163 at the same time-point ($p<0.01$). This is due to substantial increases in income among apprenticeship completers; while the white/Asian apprenticed participants earned $17,955 at 12 months after the program start, their income doubled to $35,163 at 48 months after the program start.

Lastly, we have also examined the treatment effects based on the pre-LaunchCode income quartiles (Figure 4C). We found that there are no income disparities across the four TOT groups among the lowest (Q1) and highest (Q4) pre-LaunchCode income quartiles throughout the study period. However, income changes within TOT groups over time are noticeable. Among the lowest income group, we did not observe any income increases within a TOT group, indicating that their income rarely increased over time. However, we observed intriguing trends in the two middle-income groups. In the second-lowest income quartiles (Q2), income gaps across the TOT groups widened over time. At 12 months after the program start, the income disparities across the four groups were marginal. However, at 48 months after the start, participants who dropped out, completed the course, and completed the apprenticeship earned 1.3 times ($17,538; not significant), 1.8 times ($24,880; $p<0.10$), and 2.3 times ($32,382; $p<0.05$) more than their not-admitted counterparts, respectively. Conversely, we observed negative income disparities across the TOT groups for participants in the second-highest (Q3) income quartile, such that increased LaunchCode "doses" were associated with decreased income.

Qualitative Findings

The quantitative results of this study indicate that the primary driver of the income gains associated with LaunchCode is the apprenticeship program. To explore some of the mechanisms through which the apprenticeship model leads to STEM employment and higher pay, as well as the challenges and limitations of the apprenticeship model, we draw on 26 semi-structured interviews with LaunchCode students and instructors. Through these interviews, we identified the following themes: (1) challenges in the apprenticeship placement process, (2) varied experiences in transitioning from an apprenticeship to full-time employment, and (3) social capital, human capital, and the process of scale. We explore these themes through corresponding quotes from instructors and students.

Challenges in the Apprenticeship Placement Process

One of the main intended outcomes of participation in the LaunchCode programs is STEM employment. To successfully complete the *entire* LaunchCode program, students are expected to gain and complete a technology apprenticeship, which is theorized to create an onramp to successful, full-time STEM employment. The LaunchCode staff is responsible for placing all students who finish the LaunchCode course *and* the "Lift Off" component, which consists of interview preparation and a final project, in a technology apprenticeship. However, descriptive results demonstrate that the number of students who complete the LaunchCode *course* is far more than the number of students who complete the *apprenticeship*. While some students may locate full-time employment outside of the apprenticeship, it is clear that there are challenges in placing *all* interested students in apprenticeships. Our qualitative data provides insights into the challenges of the apprenticeship placement process.

While we interviewed a limited number of students compared to how many students complete a LaunchCode program in any given cohort, it is important to note that our participants often shared insights on the experiences of their classmates as well:

> *I felt like LaunchCode was really painting this good rosy picture of like, 'Yes, you're going to get an apprenticeship, just if you're somewhat competent', but it's still taking like a lot of my classmates still to—I don't know how long it's been, maybe like probably five months at this point that still haven't gotten any apprenticeship or anything like that (Drew)*

Here, Drew discussed the process of getting an apprenticeship as not being a "good rosy picture," implying that realistic expectations of the apprenticeship process—particularly in relation to the challenges that can arise—may not have been grasped by students or promoted by instructors. In particular, she discusses the extended length of time that it took some of her classmates to receive an apprenticeship.

Additional data suggests that local labor market conditions may further complicate the apprenticeship placement process. For example, given the volatility of the labor market during the COVID-19 pandemic, some students expressed feeling discouraged during the apprenticeship placement process. One student, in particular, mentioned having a strong interest in working in the finance sector during the height of the pandemic but was told by LaunchCode staff that getting placed in this sector might be difficult at that time:

> *And I had the opportunity to potentially interview and do those things, but I was kind of discouraged from it by the person at LaunchCode because they were basically saying, 'Well, we just don't know when they—if they chose to offer a position, we don't know when that would happen because of this freeze'. And on the one hand, I appreciate that. That's absolutely valid. We don't know how long I could have potentially been waiting for an offer there. (Christine)*

Data also suggests that not all students eventually receive an apprenticeship placement and are therefore forced to apply for an apprenticeship or a job independently:

> *And then people at LaunchCode go to companies and set up apprenticeships or paid entry-level jobs, and they'll send you interviews basically. So, I think I had one or two interviews in that 'apprenticeship pool' that I was in after I did the group project. And one of them, I think, I got through three interviews before it fell apart. And one of them, I think, was just not even an interview. It was just a few emails to figure out if it was the right fit. So, they were sending me stuff, but nothing was coming to you until I found a job on my own. (Brandon)*

This participant also expressed that during the time in which he participated in the LaunchCode program, he was working multiple part-time jobs in the food industry. As his earnings were not sufficient, he was seeking new employment using his recently developed skillset in coding. While he initially tried to get an apprenticeship through LaunchCode, the interviews and exchanges facilitated by LaunchCode did not lead to anything; thus, he applied for and received a technology job on his own.

Collectively, the stories shared by the participants highlight some of the challenges within the apprenticeship placement process. While many students receive an apprenticeship, some students have to wait several months to receive an apprenticeship, and other students—due to particular labor market constraints—must take an apprenticeship in sectors that do not match their preferences. Other students never receive an apprenticeship and must secure employment outside of the LaunchCode program.

Transitioning from Apprenticeship to Permanent, Full-Time Employment

The ultimate goal of the apprenticeship component of LC101 is for students to secure a permanent, full-time STEM employment position. Across multiple interviews, LaunchCode students noted a variety of experiences receiving support from LaunchCode during their apprenticeships, such as onboarding and mentoring support. These supports helped students have a successful apprenticeship, which can be especially important in helping them gain a permanent full-time employment position in the same firm as their apprenticeship. While the apprenticeship component can lead to a permanent, full-time employment position inside or outside the firm providing the apprenticeship, several LaunchCode students noted their desire to be placed in apprenticeship roles at firms where they hoped to eventually secure permanent, full-time employment. In these cases, apprenticeships can provide a unique "on-ramp" to employment at select firms. In this regard, John noted the ease of transition from an apprenticeship role to a permanent, full-time position at the same firm:

> *It could get confusing to think about the apprenticeship or the contract because the apprenticeship was like, you get apprenticeships with the hopes of being hired on. So, I finished the official programs, LC101 and Lift-Off, in September or October of 2021, and then the apprenticeship/contract started. And then I did that for six months and started getting good feedback and was like, "Okay, I think they're going to hire me." And then they eventually just hired me on. So, it was an easy transition. I just got hired to do the job I was already doing but was officially employed by [my company].*

While John noted that his transition to a permanent, full-time employment position was 'easy,' he also indicated that he was performing well in his apprenticeship role, getting 'good' feedback, suggesting that—at least for those who want to stay at the same firm—demonstrating your performance can be important. While we did not interview employers, John's mention of doing the job "he was already doing" after the transition to a full-time role suggests that some employers use the apprenticeship as a trial run for a permanent, full-time role.

However, not every LaunchCode student's journey from apprenticeship to full-time employment was like John's. Rather, some students, like Alice, experienced uncertainty during their transition:

> *And [my internship] is three months. And I think about two weeks before my apprenticeship program finished, I got notified that my program will just finish, and they will not have me as an official employee. But a week later, they told me, 'Well, we actually had an opening for you. Yeah. Let's start the interview process.' And it was very quick. So I didn't even have vacation, any days off. They were like, 'Yeah, we are very flexible. We can continue your apprenticeship till you get officially being an employee, or you can start right now.' So yeah, actually, after the three months apprenticeship [was] over, I [became] the official employee. (Alice)*

Alice's transition experiences demonstrate some of the inherent uncertainties in apprenticeships, which are fundamentally temporary positions. While she was ultimately hired for a permanent, full-time position with a flexible start date, she nevertheless faced uncertainties in this process, which may cause some students stress.

Social Capital, Human Capital, and the Process of Scale

Some of the participants we interviewed were still working at the same firm where they were hired for their apprenticeship, and noted that these firms continued to hire apprentices from LaunchCode as permanent, full-time employees. This process often involved leveraging the networks of LaunchCode students, as noted by noted by Alice:

> *As I'm the first LaunchCoder in [my company], I know that my LaunchCode correspondent keep on–follow[ed] up with the CEO of my company, say, 'Hey, do you want to have more LaunchCoders?' because they think it's a success because I got—and yes, actually, right now my company has two LaunchCoders, as far as I know, that turn to full-time.*

Alice mentioned that LaunchCode kept in contact with her CEO due to her own success as an apprentice, which opened up doors for future LaunchCode students.

In addition to the logistical efficiencies that come with hiring, onboarding, and supporting multiple apprentices from the same training organization, there are also communal benefits. In particular, some students mentioned that having multiple LaunchCode apprentices at a given firm created an environment where apprentices could learn from and support each other, as noted by Michael:

> *And then when I joined [my company], there was a guy that was in my class that had already been with [my company] for a few months. So, from my experience, it was very, very quick. Yeah. And it could be quicker, and it could be slower, it seems like...So outside of the onboarding of [my company], which was great, they knew LaunchCode very well. They knew I needed a mentor, and they paired me with someone just so smart. I love that guy. Like I said, there was a guy in LaunchCode already in here. I made a point to reach out to him. He was in my cohort. We were already pretty friendly by that point. So he was really, really good about just bouncing stuff off in the early days. And then in [my company], since I joined, and I helped kind of get it going too, there's a LaunchCoder like,*

> *'Hey, we're all from LaunchCode. We know how much we know. We know, yeah, how much we actually end up going into [the company]. So if you feel stupid asking a really senior [developer] something, ask us. And yeah, it's safe here.*

Here, Michael notes that being paired with another LaunchCode alumnus as a mentor was helpful because the mentor knew from experience the type of training that Michael got from LaunchCode. Further, as more LaunchCoders began to work for the same company, they were able to create a work community where they could seek and offer others support—often in a low-stakes, learning-oriented environment. Here, social capital, which is built through various LaunchCode "ties" can be seen as increasing students' skills, and by doing so, building their human capital (Coleman, 1988). This process leads to the successful transition of LaunchCode apprentices to permanent, full-time employees, which ultimately leads the company to hire more LaunchCode apprentices and expand the community even more, representing the process of scale through apprenticeship placements.

DISCUSSION

The recent growth of coding bootcamps has the potential to advance individual economic mobility, social equity, and community prosperity through increasing the supply of local, high-skilled labor to meet growing employer demands. Despite this potential, very little rigorous research exists on the impacts of these programs (Huang et al., n.d.). Limited evidence on these programs' impacts may lead to underinvestment in these program models from policymakers, employers, foundations, and other stakeholders interested in fostering high-skill employment and economic equity. In addition, this lack of evidence may hinder the replication of successful programs, ultimately limiting the potential for these programs to operate across diverse geographic, social, and employment contexts. In this study, we contribute to the emerging body of work on technology training and upskilling programs by exploring *if* these programs produce economic benefits, *who* is most likely to experience these benefits, and *how* these programs produce these benefits. To do so, we merged novel program data from LaunchCode—a major U.S. provider of technology training—with administrative employment and earnings data from a large credit bureau to examine the extent to which this program model leads to increases in STEM employment and earnings. We then build on these findings through an explanatory sequential design, in which we examine the potential mechanisms underlying our quantitative findings through interviews with LaunchCode students and instructors.

Summary of Findings

We first construct intent-to-treat models, leveraging entrance exam scores as an instrumental variable, to understand the impact of LaunchCode program acceptance. Although we find no significant positive effects on STEM employment, we find large, significant effects on income at 48 months after the program start, with those admitted to the program earning $8,831 more than those not admitted. This lagged income effect for admitted applicants may be explained by the applicants moving from occupations with relatively low earnings growth, into relatively low-paid apprenticeship opportunities after completing their coursework, and ultimately finding employment opportunities with higher earnings growth potential than they would have had in the absence of the program.

We also explore the extent to which the LaunchCode coursework itself, as well as the apprenticeship component of the program, are driving changes in employment and earnings outcomes. To do so, we construct treatment-on-treated models by leveraging a robust array of pre-application information—including entrance exam scores—to generate multinomial propensity score weights that effectively balance applicants that were not admitted with admitted applicants that did not complete the course, that completed the course but not the apprenticeship, and that completed both the course and the apprenticeship. Both course and apprenticeship completers experience a similar increase in STEM employment: 2.9 and 3.2 percentage point increases at 48 months. While course completers experienced a significant income increase ($3,375), apprenticeship completers experienced an income increase that was nearly double that of those that only completed the course ($6,710). Similar to our previous research (Jabbari, Chun, Huang, Roll, 2023), these findings suggest that the apprenticeship is a key component in producing economic benefits. However, unlike our previous research, these findings also demonstrate that there are still economic benefits from the course component.

Through semi-structured interviews and thematic analyses with 23 LaunchCode students and 3 LaunchCode instructors, we observed that some students experience challenges in the apprenticeship placement process, which can delay their apprenticeship or—in some cases—force students to seek direct employment outside of the apprenticeship component. As multiple participants noted the importance of the selection process, it is possible that more advanced students receive apprenticeships, or do so more quickly, than less advanced students. While the "lift-off" phase can help level the playing field with interview preparation and independent project facilitation, it is possible that more advanced students still maintain a relative advantage over less advanced students during and after this phase. Indeed, across many of our models, we found that those with some college, a bachelor's degree, or a master's degree experienced an increase in STEM employment and income—net of treatment effects—when compared to those with a high school diploma or less. This was especially true in predicting income increases for those with a bachelor's or master's degree. Although it is true that these findings can represent additional educational stratification in a program that is intentionally designed to limit educational stratification (Jabbari et al., 2023), these findings can also represent a model of life-long learning in which individuals may seek short-term learning opportunities to increase their skills in a given industry or open up new doors to different industries.

Moreover, our heterogeneous treatment effect analyses demonstrate complex relationships in relation to equity and social mobility. For example, through the apprenticeship, women and non-binary students experience relative increases in employment and earnings relative to men students, while Black and Hispanic participants see early disadvantages dissipate over time relative to White and Asian students. However, while LaunchCode appears to be a tool for advancing gender and racial equity in STEM, findings were more complicated for social class, as those in the second lowest income quartile appear to receive a significant boost from completing the apprenticeship. While more must be done to understand these income dynamics, these findings may represent a situation in which lower-income participants have more room to "grow" their income, while—at the same time—participants with the lowest incomes face additional barriers in their pursuit of social mobility.

In terms of the mechanisms at play within apprenticeships, our qualitative findings highlight the potential for apprenticeships to allow for smooth transitions to permanent, full-time employment at the same employer. Here, apprenticeships allow firms to "test out" potential employees in a low-risk situation, while also allowing apprentices to understand the firm's expectations. In addition to the transition to permanent, full-time employment that can be facilitated by the apprenticeship component, apprenticeships can also facilitate new social networks. In the case of LaunchCode, social "ties" to other LaunchCode alumni can serve as sources of knowledge for new firm entrants. In doing so, the apprenticeship component can allow social capital to be converted into human capital (Coleman, 1988). At the same time, these social networks can benefit employers as well, which—through apprenticeships—can leverage placement alumni networks that can help attract and develop new talent.

Limitations

While our study offers several novel contributions, it is not without limitations. Concerning external validity, although LaunchCode is one of the first and largest coding and apprenticeship programs in the world, its program model is also distinct from other coding bootcamp programs, which may not include apprenticeships or other program components that drive the results we observe in this study. As such, these findings may not generalize to other coding programs. The use of administrative earnings data also limits the external validity of our findings, as not all participants could be matched into our credit bureau data. However, it is important to note that, based on previous research (see Jabbari et al., 2023), the analytic sample in this study closely resembles the larger pool of LC101 applicants in terms of gender, race/ethnicity, age, and education level.

Concerning internal validity, while use of entrance exam scores is both a theoretically and empirically sound instrument for our ITT analyses, other strategies should be considered in future research with larger samples, such as regression discontinuity designs. Finally, while the use of MNPS weights effectively balanced the different treatment "doses" across a range of observable characteristics for our TOT analyses, it is possible that other, unobservable characteristics may still drive some degree of selection bias in our estimates. As evidenced from our interviews, LaunchCode is matching students with apprenticeship opportunities, and ultimately, companies are selecting students for these opportunities. In turn, students are selecting both whether or not to pursue an apprenticeship opportunity, as well as which apprenticeship opportunity to pursue (Jabbari et al., 2023). As noted by Jabbari et al. (2023), companies may select the most talented students for these positions, and conversely, students may select the most prestigious companies. Thus, it is possible that our TOT analyses are subject to some selection bias. We therefore cannot establish causal effects in our TOT analyses. To address these issues, future research should not only consider randomizing these types of programs, but also randomizing elements (e.g., the apprenticeship component) within these programs.

Implications

These findings have implications for policymakers working across the federal, state, and local levels. At the federal level, our findings lend support for the use of funds for alternative education programs and apprenticeships, particularly, ones that include community-industry partnerships (Jabbari et al., 2023). At the state level, our findings may cause stakeholders to consider leveraging existing educational institutions, such as community colleges, to support more holistic workforce development programs that consist of both *learning* and *earning* components (Jabbari et al., 2023). By doing so, additional incentives, such as college credit or industry-recognized credentials, could be integrated into these programs. At the local level, our findings may cause leaders to find new ways, such as grants and tax breaks, to incentivize businesses to partner with local education organizations, potentially offering apprenticeships and creating new training-to-employment pipelines (Jabbari et al., 2023).

From a practical perspective, programs like LaunchCode should consider forecasting models and—potentially—additional participant screening tools to ensure that the appropriate number of apprenticeships are available for adequately trained students. The process of receiving an apprenticeship, which can be lengthy, could also be made more transparent at the outset of the program. Similarly, partnering employers can consider ways of introducing more transparency into the process of transitioning from an apprenticeship to a permanent, full-time role. More programs like LaunchCode should consider ways to leverage networks and alumni to help build students' social and human capital. While more work needs to be done to understand the reasons that students with the lowest incomes prior to LaunchCode do not see the same income gains from the apprenticeships as some of their higher-income counterparts, in the interim, techniques should be identified to provide these students with the necessary supports to benefit from these program models.

Additionally, our findings have implications for several theories undergirding the economics of education. Specifically, our findings demonstrate how social capital can help build human capital in the context of apprenticeships, which can help increase these programs' impact. Finally, our findings demonstrate the possibilities of leveraging credit agencies' employment data to understand the impact of educational, upskilling, and credentialing programs. While many studies rely on records from state unemployment insurance, these data are often confined to particular states, which can limit the ability to track individuals that move or take another job in a different state.

CONCLUSION

If achieving the traditional American dream continues to depend on bachelors degree attainment, it will continue to be out of reach for a majority of Americans. However, as we demonstrate in this study, achieving the American Dream does not have to depend on bachelors degree attainment. Through unique partnerships, LaunchCode apprenticeships provide opportunities for individuals to learn new, in-demand skills, while generating enough revenue to both pay participants for their time and subsidize the course component so that it remains free and open to all. As a result, LaunchCode provides opportunities for individual social mobility and equity, as well as communal prosperity by helping to fill critical skill gaps and improve labor market efficiency. Moreover, given the rising costs of traditional education pathways, the growing burden of student debt (Jabbari et al., 2022), the rapid technological transformations in our society spurred by artificial intelligence, and the growing precarity of labor markets (Howell & Kalleberg, 2019), programs like LaunchCode should not remain confined to the technology sector. Rather, a model that includes both courses that result in short-term certificates and paid apprenticeships could be adopted in a variety of other sectors. Indeed, alternative educational programs with fewer barriers to entry, shorter time commitments, less tuition, more flexible learning arrangements, and opportunities to build both hard and soft skills on the job, may represent a viable alternative for building human capital across multiple sectors. As the future of work continues to shift, so too must the future of learning.

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TABLES AND FIGURES

Table 1. Balance table (Pre- and Post-Multinomial Propensity Score Weighting)

	All	By group														
		Pre-MNPS							Post-MNPS							
		Not Admitted	Dropped out		Completed		Apprenticed		Not Admitted	Dropped out		Completed		Apprenticed		
Observation																
Gender																
Men	0.61	0.69	0.53	(0.321)	0.69	(0.000)	0.66	(0.063)	0.65	0.59	(0.136)	0.65	(0.014)	0.61	(0.087)	
Women/Non-binary	0.39	0.31	0.47	(0.321)	0.31	(0.000)	0.34	(0.063)	0.35	0.42	(0.136)	0.36	(0.014)	0.39	(0.087)	
Race																
White/Asian	0.52	0.56	0.42	(0.284)	0.65	(0.181	0.75	(0.388)	0.56	0.57	(0.142)	0.62	(0.131)	0.62	(0.131)	
Black/Hispanic /Others	0.48	0.44	0.58	(0.284)	0.35	(0.181	0.25	(0.388)	0.44	0.43	(0.142)	0.38	(0.131)	0.38	(0.131)	
Age																
Mean	35.08	35.86	35.44	(0.041)	33.80	(0.203)	31.94	(0.385)	35.07	35.08	(0.000)	33.84	(0.121)	33.83	(0.122)	
Std. Dev	10.16	10.28	10.72		8.78		7.39		10.16							
Educational attainment																
Highschool or below	0.09	0.10	0.10	(0.022)	0.08	(0.070)	0.06	(0.133)	0.10	0.10	(0.002)	0.08	(0.000)	0.04	(0.204)	
Some college or Associate's	0.39	0.41	0.42	(0.020)	0.33	(0.162)	0.32	(0.177)	0.38	0.40	(0.045)	0.34	(0.000)	0.38	(0.007)	
Bachelor's	0.37	0.34	0.34	(0.000)	0.43	(0.190)	0.49	(0.302)	0.37	0.36	(0.026)	0.41	(0.000)	0.40	(0.064)	
Master's or above	0.15	0.15	0.15	(0.009)	0.16	(0.023)	0.13	(0.058)	0.15	0.15	(0.025)	0.17	(0.000)	0.19	(0.092)	
HR Score																
Mean	58.7	49.9	55.6	(0.205)	74.7	(0.892)	81.0	(1.120)	55.8	58.8	(0.108)	63.6	(0.281)	70.9	(0.542)	
Std. Dev	27.799	29.517	27.198		17.946		13.627		27.799							
Cohort																
Jul 2017	0.16	0.08	0.18	(0.281)	0.23	(0.415)	0.27	(0.526)	0.15	0.17	(0.053)	0.22	(0.185)	0.22	(0.174)	
Sep 2017	0.05	0.07	0.04	(0.163)	0.07	(0.003)	0.04	(0.148)	0.07	0.05	(0.090)	0.05	(0.106)	0.03	(0.170)	
Oct 2017	0.07	0.10	0.04	(0.237)	0.09	(0.059)	0.04	(0.250)	0.08	0.06	(0.067)	0.06	(0.085)	0.04	(0.158)	
Jan 2018	0.12	0.07	0.13	(0.179)	0.16	(0.286)	0.22	(0.475)	0.12	0.12	(0.011)	0.14	(0.050)	0.18	(0.180)	
Jul 2018	0.23	0.30	0.21	(0.204)	0.18	(0.285)	0.20	(0.234)	0.30	0.24	(0.148)	0.26	(0.080)	0.25	(0.105)	
Aug 2018	0.06	0.04	0.06	(0.101)	0.07	(0.131)	0.06	(0.065)	0.07	0.06	(0.026)	0.06	(0.037)	0.06	(0.019)	
Nov 2018	0.05	0.02	0.06	(0.200)	0.05	(0.156)	0.04	(0.087)	0.04	0.05	(0.064)	0.05	(0.078)	0.04	(0.032)	
Jan 2019	0.13	0.32	0.04	(0.831)	0.08	(0.716)	0.13	(0.565)	0.17	0.11	(0.194)	0.08	(0.260)	0.17	(0.012)	
Feb 2019	0.12	0.00	0.23	(0.706)	0.06	(0.192)	0.00	(0.000)	0.00	0.13	(0.408)	0.07	(0.221)	0.00		
STEM Employment, Pre1																
Mean	0.074	0.059	0.099	(0.153)	0.054	(0.019)	0.044	(0.058)	0.062	0.043	(0.262)	0.068	(0.022)	0.091	(0.111)	
Std. Dev.	0.262	0.236	0.299		0.226		0.205		0.262							
Earned income, Pre1																
Mean	13,395	15,153	13,599	(0.073)	10,749	(0.208)	10,785	(0.206)	13,212	13,074	(0.007)	11,725	(0.070)	14,509	(0.061)	
Std. Dev.	21,181	23,428	21,310		16,835		18,953		21,181							

Note: Pre/Post-MPLS columns compares each of the three TOT groups (Dropped out, Completed, Apprenticed) with the comparison group (Not admitted);

Standardized effect size of the variation in parentheses (0.00 to 0.19: None/negligible; 0.20 to 0.49: Weak; 0.50 to 0.79: Moderate; 0.80 to 1.30: Large)

Table 2. Interview Participants

Name*	LaunchCode Program	Completion Status	Sex	Race/Ethnicity
John	LC101	Apprenticed	Men	White
Michael	LC101	Apprenticed	Men	Hispanic
Jillian	LC101	Apprenticed	Women	White
Christine	LC101	Apprenticed	Women	White
Michelle	LC101	Course completed	Women	Asian
Angela	LC101	Did not finish course	Women	Black
Craig	LC101	Did not finish course	Men	White
Amanda	LC101 Instructor		Women	
Bianca	Women+	Apprenticed	Women	Black
Sydney	Women+	Apprenticed	Women	White
Rebecca	Women+	Apprenticed	Women	Hispanic
Samantha	Women+	Apprenticed	Women	White
Tanner	Women+	Completed course	Women	Hispanic
Julie	Women+	Did not complete course	Women	White
Chantel	Women+	Did not complete course	Women	Black
Karina	Women+	Completed course	Women	White
Kyle	Women+ Instructor		Men	White
Alice	CodeCamp	Apprenticed	Women	Asian
Drew	CodeCamp	Apprenticed	Women	Hispanic
David	CodeCamp	Apprenticed	Men	White
Elise	CodeCamp	Apprenticed	Women	Asian
Brandon	CodeCamp	Completed Course	Men	White
Leslie	CodeCamp	Did not complete course	Women	Black
Marvin	CodeCamp	Did not complete course	Men	Black
Bailey	CodeCamp	Did not complete course	Non-binary/Gender non conforming	White
Charles	CodeCamp Instructor		Men	White

Notes: * pseudonyms are used.

Table 3. ITT effect (IV model; IV=HackerRank Score)

Panel A. STEM employment

	STEM Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ITT groups							
Admitted	-0.01	-0.026	-0.035	-0.049	-0.055	-0.078*	-0.063
	(0.013)	(0.023)	(0.031)	(0.034)	(0.037)	(0.041)	(0.044)
Pre LC outcomes							
STEM employed	0.963***	0.959***	0.947***	0.942***	0.935***	0.923***	0.912***
	(0.005)	(0.008)	(0.011)	(0.012)	(0.014)	(0.015)	(0.016)
Gender							
Women/non-binary	(0.005)	0.008	(0.002)	(0.001)	(0.002)	(0.002)	0.010
	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)	(0.011)
Race/Ethnicity							
Black/Hispanic/others	0.003	0.009	0.007	0.005	0.012	0.015	0.000
	(0.003)	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.010)
Age							
Age at course start	0.000	(0.000)	(0.000)	(0.000)	(0.000)	-0.001*	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Educational Attainment							
Some college or Associate's	0.001	0.018*	0.032**	0.028**	0.024	0.029*	0.018
	(0.005)	(0.009)	(0.012)	(0.014)	(0.015)	(0.017)	(0.018)
Bachelor's	0.003	0.012	0.026**	0.019	0.016	0.032*	0.023
	(0.005)	(0.010)	(0.013)	(0.014)	(0.015)	(0.017)	(0.018)
Master's or above	0.004	0.022**	0.024*	0.020	0.029	0.038*	0.030
	(0.006)	(0.011)	(0.015)	(0.016)	(0.018)	(0.020)	(0.021)
Constant	(0.002)	0.022	0.040	0.061	0.081*	0.124***	0.145***
	(0.014)	(0.026)	(0.034)	(0.037)	(0.041)	(0.046)	(0.049)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.955	0.862	0.773	0.735	0.690	0.636	0.605
Adjusted R2	0.955	0.861	0.771	0.733	0.688	0.633	0.602
Residual Std. Error (df = 2124)	0.064	0.118	0.157	0.173	0.191	0.212	0.224

Notes: Standard errors in parentheses; * p < 0.10; ** p < 0.05; *** p < 0.01

Panel B. Annual income

	Annual income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ITT groups							
Admitted	-2,273.52	-4,364.540*	-1,205.41	2,577.73	3,690.52	6,644.71	8,831.315*
	(1,574.585)	(2,230.238)	(2,807.081)	(2,922.773)	(3,683.901)	(4,348.823)	(5,309.764)
Pre LC outcomes							
Income	0.759***	0.938***	0.931***	0.926***	0.988***	1.018***	1.054***
	(0.008)	(0.012)	(0.015)	(0.016)	(0.020)	(0.023)	(0.029)
Gender							
Women/non-binary	499.6	106.3	-693.9	-916.6	-1150.8	-1,883.746*	-3,494.047***
	(380.013)	(538.250)	(677.466)	(705.387)	(889.079)	(1,049.553)	(1,281.468)
Race/Ethnicity							
Black/Hispanic/others	745.821**	883.028*	579.5	716.4	-402.0	-257.0	-1032.4
	(372.6)	(527.8)	(664.3)	(691.7)	(871.8)	(1029.1)	(1256.5)
Age							
Age at course start	65.345***	-20.765	43.103	-7.695	22.308	-45.387	-112.098*
	(18.986)	(26.892)	(33.847)	(35.242)	(44.420)	(52.437)	(64.024)
Educational Attainment							
Some college or Associate's	780.3	141.7	598.3	1415.1	1296.0	1196.5	2825.7
	(639.6)	(905.9)	(1140.3)	(1187.2)	(1496.4)	(1766.5)	(2156.9)
Bachelor's	403.7	1142.4	1359.4	2,196.938*	2,749.577*	4,398.918**	6,645.707***
	(656.2)	(929.4)	(1169.8)	(1218.1)	(1535.3)	(1812.4)	(2212.8)
Master's or above	1075.8	2,988.178***	4,661.035***	5,920.146***	7,334.108***	9,591.104***	13,104.480***
	(751.9)	(1065.0)	(1340.5)	(1395.8)	(1759.2)	(2076.8)	(2535.7)
Constant	-1365.7	6,013.668**	4699.2	1360.6	4194.6	7483.9	8788.4
	(1,742.870)	(2,468.597)	(3,107.090)	(3,235.147)	(4,077.621)	(4,813.607)	(5,877.249)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.806	0.755	0.663	0.640	0.564	0.496	0.416
Adjusted R2	0.805	0.753	0.660	0.637	0.561	0.492	0.411
Residual Std. Error (df = 2124)	8069.550	11429.690	14385.930	14978.840	18879.530	22287.170	27211.870

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 4. TOT effect (MNPS weightings applied)

Panel A. STEM employment

	STEM Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TOT groups							
Dropped out	0.003	0.005	0.018*	0.023**	0.022**	0.031**	0.021
	(0.004)	(0.006)	(0.009)	(0.010)	(0.011)	(0.012)	(0.014)
Completed	-0.001	0.004	0.014	0.015	0.014	0.038***	0.029**
	(0.005)	(0.007)	(0.009)	(0.010)	(0.011)	(0.013)	(0.015)
Apprenticed	0.005	0.002	0.008	0.002	0.012	0.011	0.032**
	(0.007)	(0.007)	(0.010)	(0.010)	(0.011)	(0.013)	(0.015)
Pre LC outcomes							
STEM employed	0.963***	0.969***	0.955***	0.951***	0.946***	0.937***	0.917***
	(0.005)	(0.008)	(0.011)	(0.012)	(0.013)	(0.015)	(0.017)
Gender							
Women/non-binary	-0.006**	0.009*	-0.004	-0.006	-0.002	-0.004	0.015
	(0.003)	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)
Race/Ethnicity							
Black/Hispanic/others	0.002	0.011**	0.000	-0.003	0.001	0.005	0.007
	(0.003)	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
Age							
Age at course start	0.0002*	-0.00001	0.0003	0.0004	-0.0001	-0.0005	-0.0005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Educational Attainment							
Some college or Associate's	0.001	0.021**	0.041***	0.037***	0.033**	0.042**	0.039**
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Bachelor's	0.003	0.008	0.022*	0.014	0.011	0.035*	0.023
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Master's or above	0.005	0.014	0.018	0.018	0.035**	0.040**	0.020
	(0.006)	(0.011)	(0.015)	(0.016)	(0.018)	(0.020)	(0.023)
HR test							
Score	0.000	0.000	0.000	0.000	0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0002*	(0.000)	0.000	0.000	(0.000)	(0.001)	(0.001)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.955	0.889	0.797	0.773	0.730	0.671	0.605
Adjusted R2	0.955	0.888	0.795	0.771	0.728	0.668	0.602

Residual Std. Error (df = 2124)	0.064	0.184	0.260	0.277	0.309	0.352	0.399

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annual income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
TOT groups							
Dropped out	715.0	1,413.389**	105.5	409.0	-1316.5	-1477.5	-802.4
	(477.3)	(667.2)	(816.9)	(883.9)	(1128.6)	(1345.8)	(1620.2)
Completed	7.3	-472.5	-1,471.397*	-716.1	-1611.9	669.9	3,375.432**
	(590.7)	(688.0)	(842.3)	(911.5)	(1163.7)	(1387.7)	(1670.7)
Apprenticed	1168.6	1,812.526**	-1043.9	1415.2	-79.8	2186.0	6,710.410***
	(839.7)	(788.4)	(965.2)	(1044.4)	(1333.4)	(1590.1)	(1914.3)
Pre LC outcomes							
Income	0.760***	0.955***	0.938***	0.931***	0.996***	1.043***	1.065***
	(0.008)	(0.012)	(0.015)	(0.016)	(0.020)	(0.024)	(0.029)
Gender							
Women/non-binary	223.3	-570.5	-522.2	-434.5	7.6	-547.6	-1306.8
	(371.7)	(514.8)	(630.3)	(682.0)	(870.8)	(1038.4)	(1250.1)
Race/Ethnicity							
Black/Hispanic/others	524.5	-56.6	145.3	513.8	-1459.8	-1475.2	-824.1
	(387.4)	(527.8)	(646.2)	(699.2)	(892.7)	(1064.6)	(1281.6)
Age							
Age at course start	68.907***	-2.8	63.224*	-33.0	23.7	-114.267**	-201.661***
	(18.431)	(27.877)	(34.129)	(36.931)	(47.151)	(56.226)	(67.690)
Educational Attainment							
Some college or Associate's	814.4	-366.9	176.9	1542.3	612.2	172.7	3433.4
	(636.2)	(948.0)	(1160.7)	(1255.9)	(1603.5)	(1912.1)	(2302.0)
Bachelor's	459.0	1,625.248*	972.3	2,431.846*	2441.2	5,269.574***	10,015.650***
	(656.3)	(962.4)	(1178.2)	(1275.0)	(1627.8)	(1941.1)	(2336.9)
Master's or above	1,305.600*	2,074.052*	1966.5	5,429.743***	4,293.104**	6,670.651***	11,419.010***
	(760.7)	(1093.3)	(1338.5)	(1448.3)	(1849.1)	(2205.1)	(2654.7)
HR test							
Score	-11.8	-29.319***	19.5	22.9	27.3	0.1	-0.5
	(7.5)	(10.7)	(13.1)	(14.2)	(18.1)	(21.6)	(26.0)
Constant	-3,191.476***	2,713.511*	3,448.192*	3009.3	9,064.075***	18,352.720***	18,331.260***
	(1,066.001)	(1,550.892)	(1,898.747)	(2,054.632)	(2,623.197)	(3,128.118)	(3,765.916)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.810	0.767	0.681	0.644	0.564	0.501	0.426
Adjusted R2	0.808	0.765	0.679	0.640	0.560	0.496	0.421
Residual Std. Error (df = 2124)	7,995.5	19,241.5	23,557.2	25,491.2	32,545.2	38,809.7	46,722.6

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Figure 1. Sample size waterfall

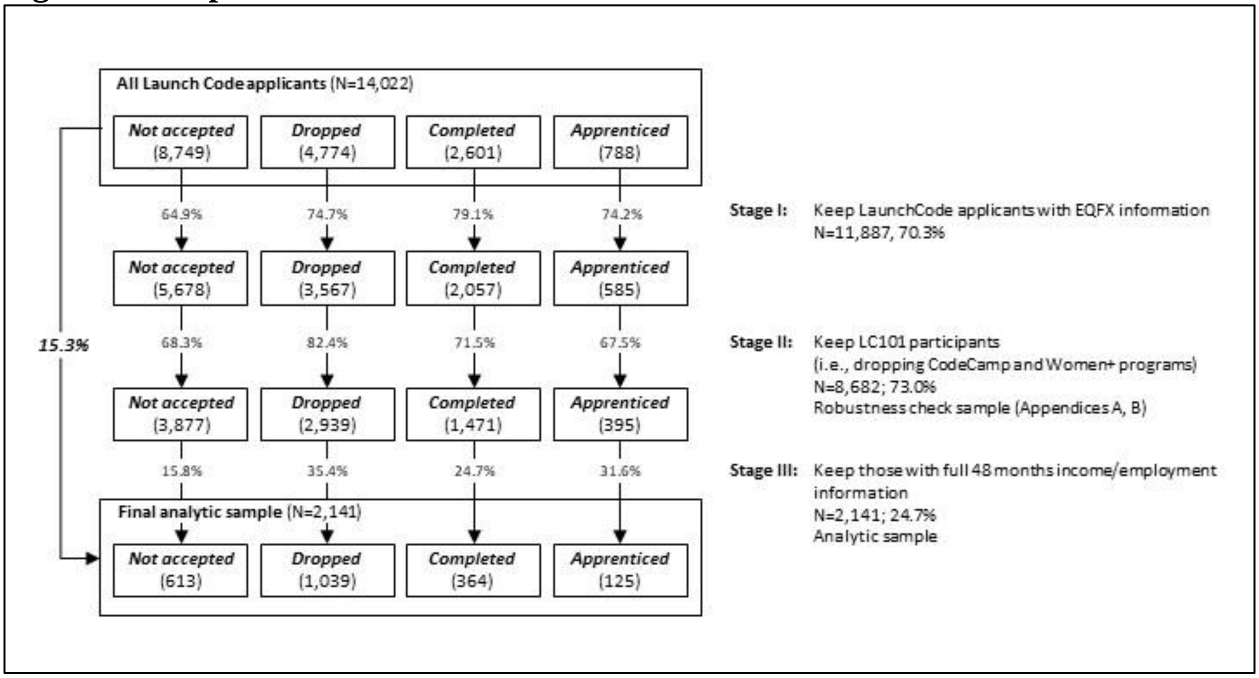
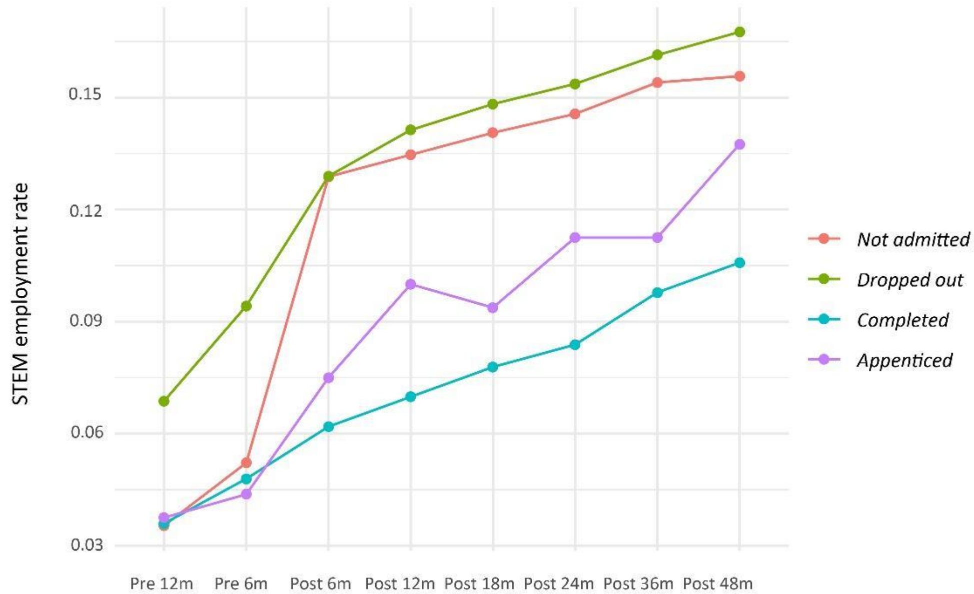


Figure 2. Descriptive plots of STEM employment (Panel A) and earned income (Panel B) by program participation

Panel A. STEM employment



Panel B. Earned income

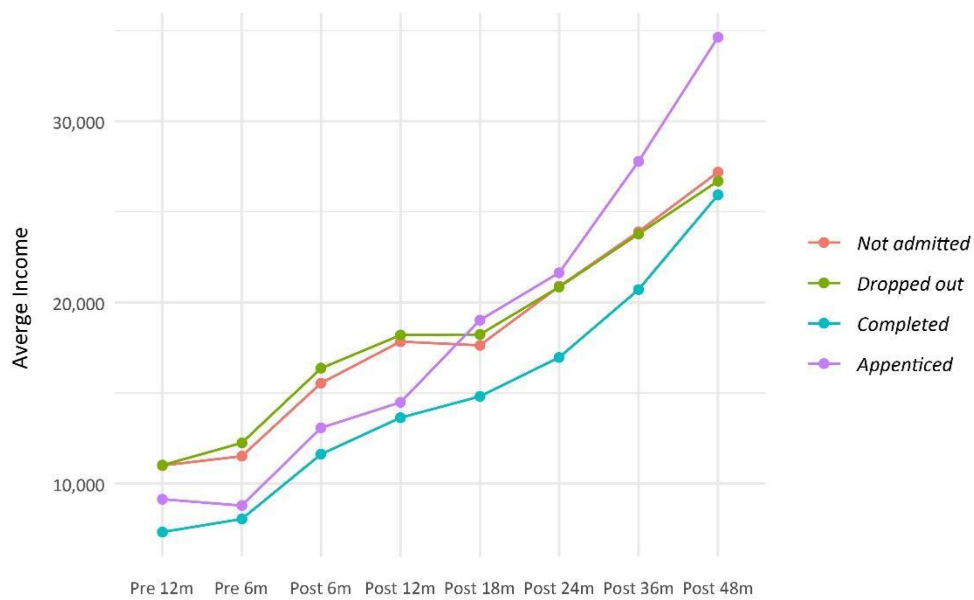
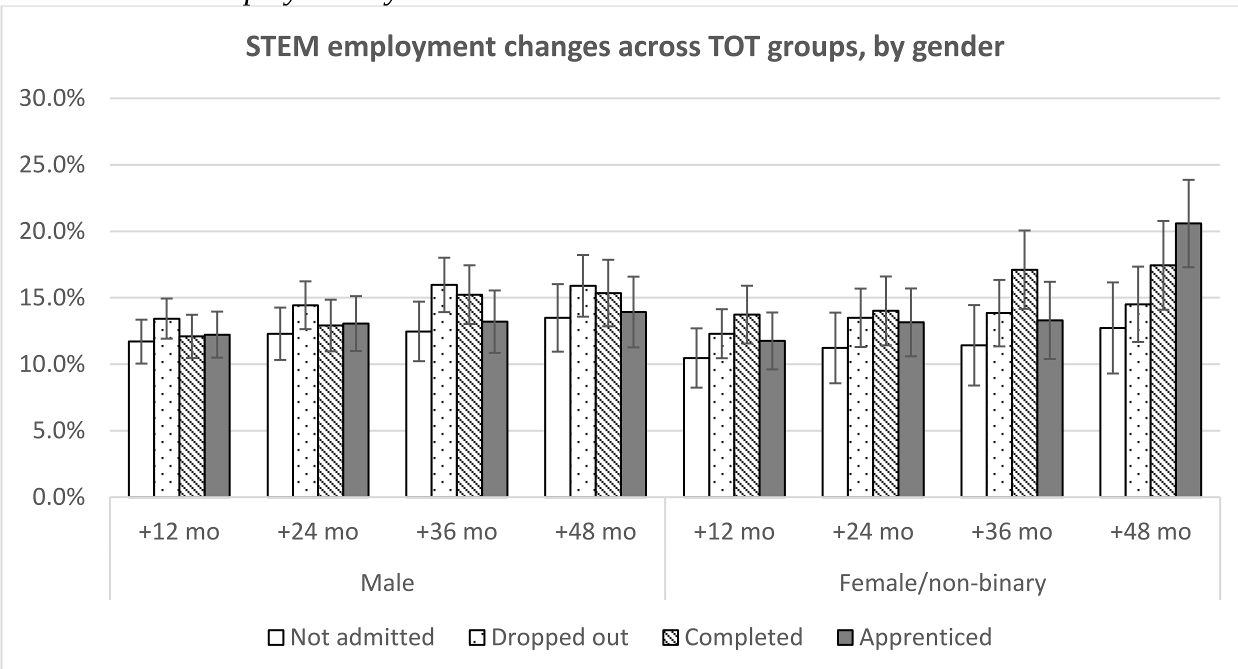


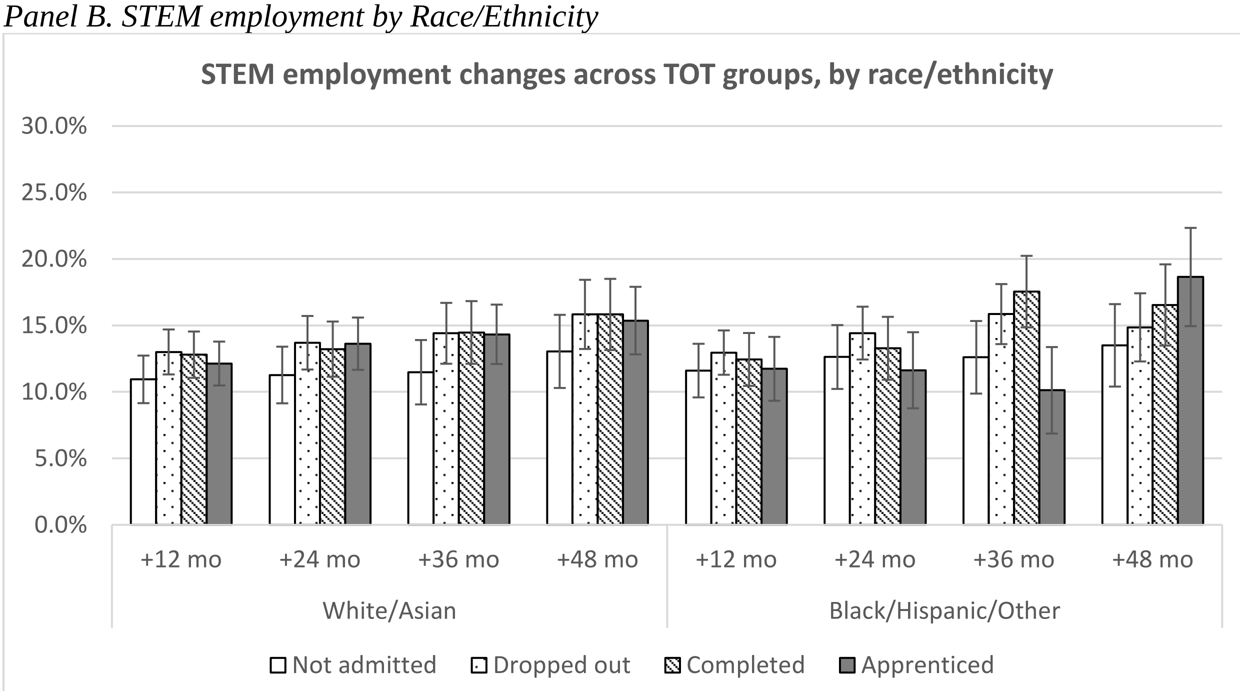
Figure 3. Heterogeneous LaunchCode Effects on STEM employment

Panel A. STEM employment by Gender



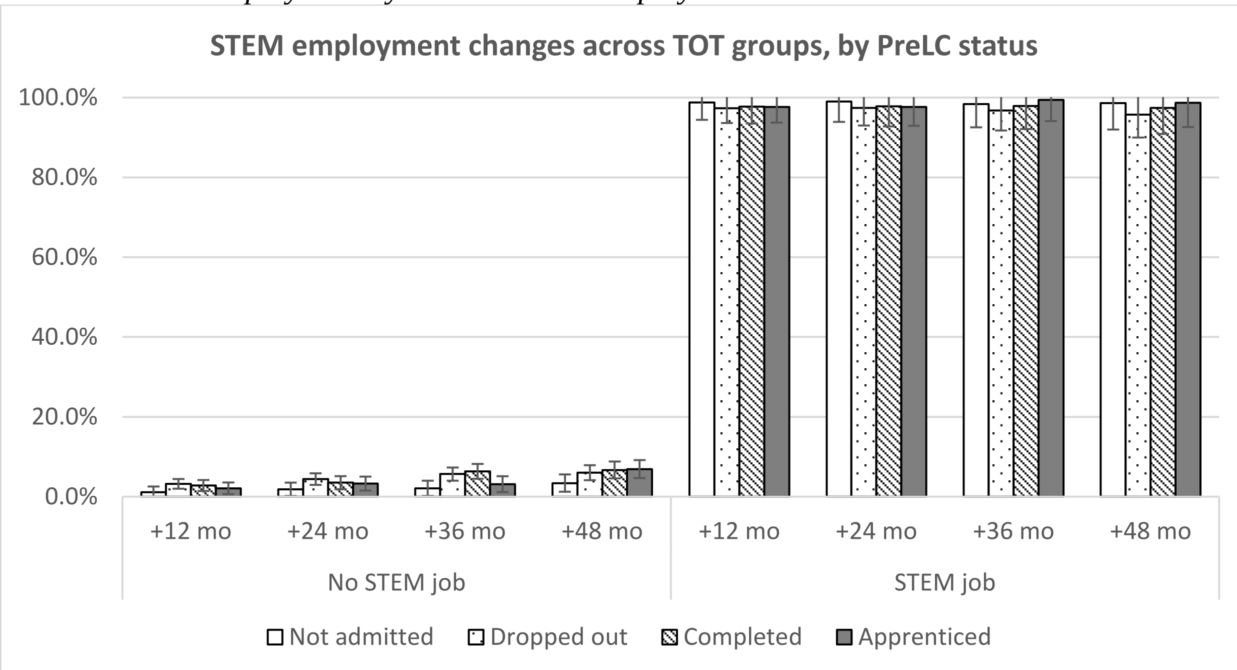
Notes: 95% levels of confidence intervals reported

Panel B. STEM employment by Race/Ethnicity



Notes: 95% levels of confidence intervals reported

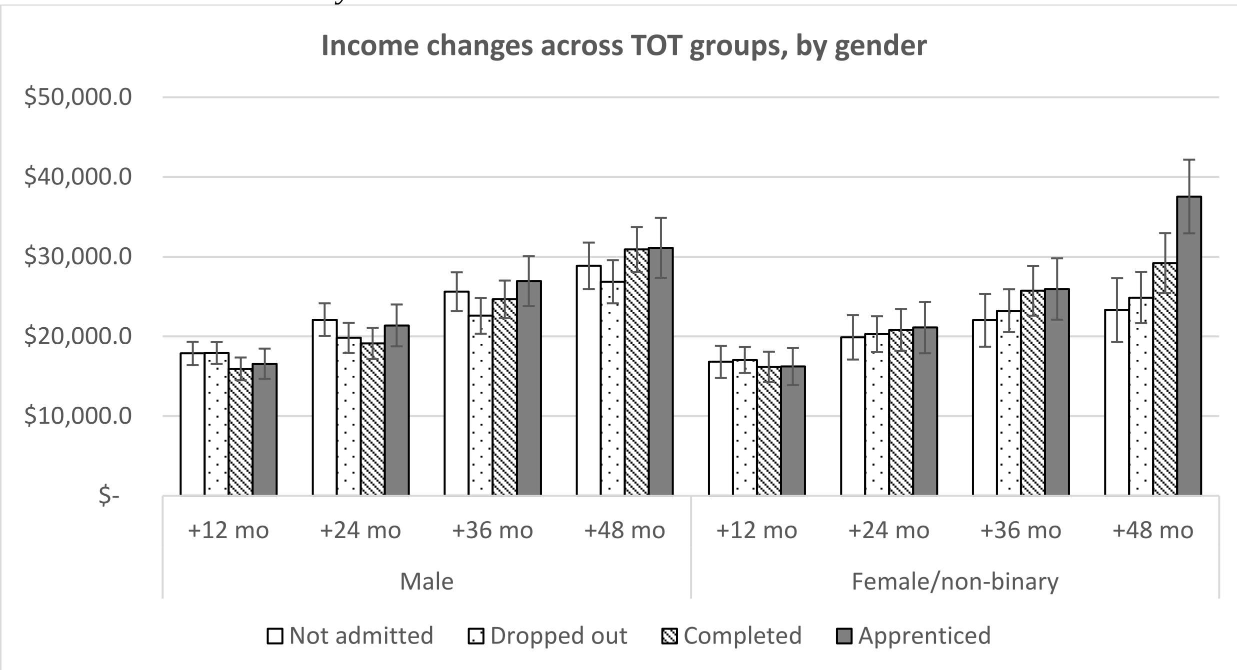
Panel C. STEM employment by Pre-LC STEM employment



Notes: 95% levels of confidence intervals reported

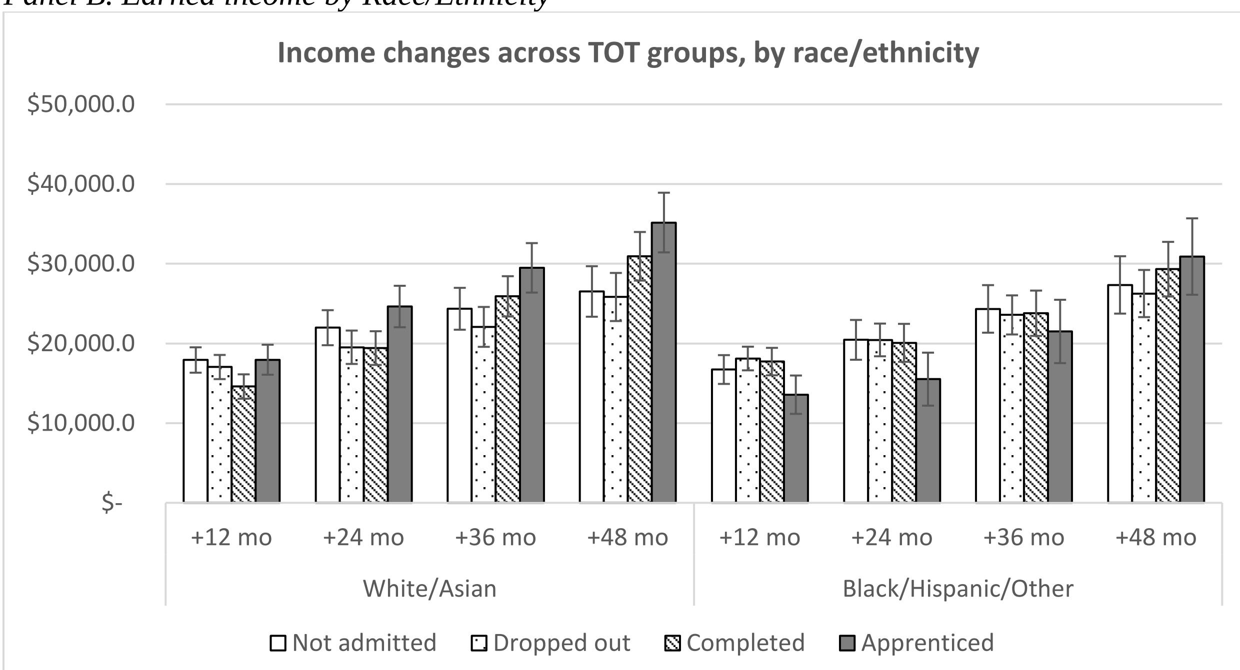
Figure 4. Heterogeneous LaunchCode Effects on Earned Income

Panel A. Earned income by Gender



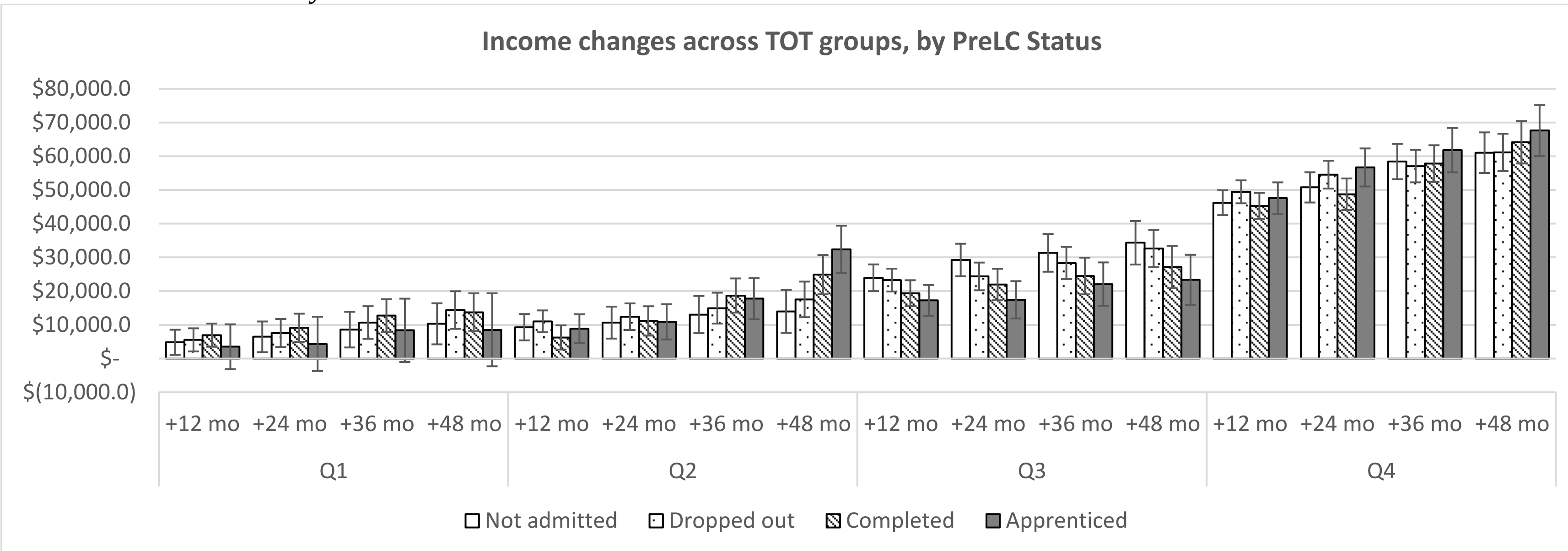
Notes: 95% levels of confidence intervals reported
For full TOT model results, see Appendix C1, Panel

Panel B. Earned income by Race/Ethnicity



Notes: 95% levels of confidence intervals reported

Panel C. Earned income by Pre-LC income



Notes: 95% levels of confidence intervals reported

APPENDICES

Appendix A. Robustness check (ITT effect; IV model; IV=HackerRank Score; Full-sample)

Panel A. STEM employment

	STEM Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ITT groups							
Admitted	0.0004	-0.023**	-0.023*	-0.016	-0.022	-0.032	-0.03
	(0.004)	(0.010)	(0.012)	(0.014)	(0.016)	(0.020)	(0.028)
Pre LC outcomes							
Employed	0.942***	0.953***	0.934***	0.931***	0.923***	0.916***	0.910***
	(0.003)	(0.007)	(0.009)	(0.010)	(0.011)	(0.014)	(0.019)
Gender							
Women/non-binary	0.000	0.008*	0.004	0.000	-0.003	-0.002	0.005
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)
Race/Ethnicity							
Black/Hispanic/others	0.001	0.007*	0.010*	0.008	0.015**	0.017**	0.016
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)
Age							
Age at course start	0.0002**	0.000	0.000	0.000	(0.000)	(0.000)	(0.000)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Educational Attainment							
Some college or Associate's	-0.002	0.004	0.009	0.010	0.016	0.017	0.007
	(0.003)	(0.007)	(0.009)	(0.010)	(0.011)	(0.014)	(0.018)
Bachelor's	0.000	0.001	0.008	0.008	0.009	0.014	(0.002)
	(0.003)	(0.007)	(0.009)	(0.010)	(0.012)	(0.014)	(0.019)
Master's or above	-0.002	-0.002	0.005	0.004	0.016	0.013	0.009
	(0.004)	(0.009)	(0.011)	(0.012)	(0.014)	(0.017)	(0.021)
Constant	(0.002)	0.022	0.040	0.061	0.081*	0.124***	0.145***
	(0.014)	(0.026)	(0.034)	(0.037)	(0.041)	(0.046)	(0.049)
Observations	7,116	6,881	6,380	5,968	5,435	4,399	3,144
R2	0.937	0.726	0.649	0.604	0.558	0.503	0.434
Adjusted R2	0.936	0.725	0.647	0.601	0.556	0.500	0.430
	0.070	0.167	0.196	0.212	0.230	0.251	0.271
Residual Std. Error	(df = 7076)	(df = 6842)	(df = 6344)	(df = 5934)	(df = 5403)	(df = 4373)	(df = 3124)

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annual income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
ITT groups							
Admitted	-695.13	-1,900.345**	-270.35	301.93	-1,517.02	1,272.29	9,858.218**
	(766.868)	(877.160)	(1,287.323)	(1,311.950)	(1,810.532)	(2,618.461)	(4,899.681)
Pre LC outcomes							
Income	0.844***	0.953***	0.943***	0.946***	0.970***	1.009***	1.097***
	(0.006)	(0.007)	(0.010)	(0.011)	(0.014)	(0.019)	(0.027)
Gender							
Women/non-binary	52.200	-356.400	-580.300	-947.988*	-1013.400	-1,504.467*	-3,433.230***
	(288.291)	(331.024)	(481.312)	(493.455)	(665.485)	(887.083)	(1,297.879)
Race/Ethnicity							
Black/Hispanic/others	369.4	606.105*	45.9	79.2	-588.5	-1180.2	-479.7
	(290.818)	(333.640)	(481.254)	(493.878)	(664.180)	(869.422)	(1,274.978)
Age							
Age at course start	96.677***	-23.1	17.1	-8.7	-24.3	-81.887*	-151.741**
	(15.521)	(17.978)	(25.897)	(26.320)	(35.219)	(46.313)	(67.666)
Educational Attainment							
Some college or Associate's	26.881	697.962	799.457	1,219.848	1,196.281	1,144.551	3,063.078
	(493.989)	(567.729)	(821.267)	(843.870)	(1,144.204)	(1,512.930)	(2,207.113)
Bachelor's	225.8	1,622.597***	2,635.036***	2,903.191***	3,975.700***	5,344.049***	7,451.235***
	(505.632)	(581.025)	(840.513)	(862.097)	(1,173.902)	(1,557.148)	(2,254.558)
Master's or above	633.245	2,012.360***	4,140.354***	4,836.220***	6,605.587***	9,566.266***	13,212.590***
	(588.721)	(676.435)	(975.972)	(1,001.380)	(1,354.675)	(1,807.431)	(2,595.923)
Constant	3,640.393***	2,335.927**	3,517.423**	1727.4	7,280.028***	10,811.850***	10,548.830**
	(1,007.866)	(1,171.251)	(1,661.193)	(1,674.339)	(2,197.793)	(2,804.909)	(4,170.763)
Observations	6,113	6,104	5,603	5,191	4,658	3,622	2,367
R2	0.782	0.767	0.634	0.628	0.535	0.468	0.437
Adjusted R2	0.780	0.766	0.632	0.626	0.532	0.465	0.433
Residual Std. Error	10,695.860 (df = 6076)	12,291.860 (df = 6067)	17,028.390 (df = 5569)	16,850.330 (df = 5159)	21,407.280 (df = 4628)	24,757.630 (df = 3598)	29,173.710 (df = 2349)

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Appendix B. Robustness check (TOT effect; MNPS weightings applied; Full-sample)

Panel A. STEM employment

	STEM Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TOT groups							
Dropped out	0.001	0.002	0.004	0.007	0.007	0.015	0.011
	(0.002)	(0.005)	(0.007)	(0.007)	(0.008)	(0.010)	(0.013)
Completed	0.000	-0.016***	0.000	0.002	0.008	0.028***	-0.012
	(0.002)	(0.005)	(0.007)	(0.007)	(0.009)	(0.010)	(0.014)
Apprenticed	0.004	-0.001	0.012*	-0.001	0.012	-0.005	0.0100
	(0.002)	(0.006)	(0.007)	(0.008)	(0.009)	(0.011)	(0.015)
Pre LC outcomes							
Employed	0.946***	0.961***	0.934***	0.940***	0.924***	0.921***	0.917***
	(0.003)	(0.007)	(0.009)	(0.010)	(0.011)	(0.014)	(0.018)
Gender							
Women/non-binary	-0.001	0.007*	-0.004	-0.013**	-0.01	-0.019**	0.008
	(0.002)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.010)
Race/Ethnicity							
Black/Hispanic/others	0.002	0.011***	0.018***	0.010*	0.022***	0.018**	0.013
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)
Age							
Age at course start	0.0004***	-0.00005	0.0004	0.0003	0.0001	0.0001	-0.00002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Educational Attainment							
Some college or Associate's	-0.004	0.017**	0.031***	0.030***	0.037***	0.039***	0.019
	(0.003)	(0.007)	(0.009)	(0.010)	(0.012)	(0.015)	(0.019)
Bachelor's	-0.001	0.009	0.019**	0.021**	0.019	0.030**	-0.003
	(0.003)	(0.007)	(0.009)	(0.010)	(0.012)	(0.015)	(0.020)
Master's or above	-0.001	0.004	0.008	0.009	0.016	0.021	-0.010
	(0.003)	(0.008)	(0.011)	(0.012)	(0.014)	(0.017)	(0.022)
HR test							
Score	0.000	0.000	-0.0002**	-0.0002*	0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0004***	(0.000)	0.000	0.000	0.000	0.000	(0.000)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Observations	7,116	6,881	6,380	5,968	5,435	4,399	3,144
R2	0.943	0.751	0.653	0.634	0.577	0.534	0.466

Adjusted R2	0.943	0.750	0.651	0.632	0.574	0.531	0.462
Residual Std. Error	0.114 (df = 7073)	0.275 (df = 6839)	0.343 (df = 6341)	0.350 (df = 5931)	0.388 (df = 5400)	0.425 (df = 4370)	0.458 (df = 3121)

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annual income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
TOT groups							
Dropped out	552.665	530.632	-341.412	-185.068	-1,572.498*	-1370.379	-17.389
	(345.267)	(397.233)	(582.697)	(609.164)	(819.378)	(1,117.178)	(1,649.530)
Completed	450.546	-1,275.698***	-2,096.280***	-1,465.875**	-2,886.609***	-126.595	4,138.458**
	(358.294)	(409.711)	(599.105)	(628.692)	(852.163)	(1,149.303)	(1,690.190)
Apprenticed	1184.704***	-907.709**	-3,085.058***	-1,610.890**	-2,079.441**	1509.140	7,340.114***
	(382.574)	(441.430)	(636.357)	(705.861)	(929.114)	(1,256.811)	(1,906.365)
Pre LC outcomes							
Income	0.857***	0.957***	0.940***	0.953***	0.968***	1.102***	1.208***
	(0.006)	(0.007)	(0.010)	(0.011)	(0.015)	(0.019)	(0.026)
Gender							
Women/non-binary	-454.648*	-337.093	148.460	-316.883	-21.967	-917.901	-1198.711
	(264.677)	(302.002)	(438.358)	(466.340)	(624.615)	(849.721)	(1254.564)
Race/Ethnicity							
Black/Hispanic/others	534.950**	162.102	662.813	319.070	-620.616	-1,838.185**	-1318.885
	(270.602)	(309.487)	(450.053)	(480.032)	(642.136)	(878.357)	(1278.653)
Age							
Age at course start	128.054***	-6.387	57.392**	-6.271	21.130	-67.169	-203.248***
	(15.265)	(17.463)	(25.244)	(26.752)	(35.592)	(48.506)	(69.889)
Educational Attainment							
Some college or Associate's	496.425	773.166	1049.392	1,836.813**	382.011	805.963	3410.418
	(477.7)	(544.7)	(787.0)	(840.6)	(1158.5)	(1582.1)	(2324.2)
Bachelor's	510.5	2,178.321***	2,874.238***	3,415.972***	2,924.016**	4,483.889***	9,131.320***
	(485.785)	(552.806)	(797.394)	(851.256)	(1172.465)	(1605.145)	(2348.311)
Master's or above	341.578	1,937.813***	3,159.511***	4,854.166***	3,541.367***	7,195.166***	10,219.100***
	(559.565)	(639.563)	(922.119)	(975.761)	(1331.157)	(1848.455)	(2675.970)
HR test							
Score	-14.644***	-12.038*	28.364***	25.507**	34.815***	2.870	12.773
	(5.845)	(6.620)	(9.659)	(10.135)	(13.410)	(18.788)	(26.395)
Constant	2841.886***	1983.3	823.1	-124.0	5,238.327**	12,476.140***	15,090.480***
	(984.126)	(1,212.727)	(1,729.665)	(1,788.656)	(2,336.730)	(3,051.961)	(4,127.414)
Observations	6,113	6,104	5,603	5,191	4,658	3,622	2,367
R2	0.775	0.758	0.630	0.597	0.499	0.528	0.517
Adjusted R2	0.774	0.756	0.627	0.594	0.496	0.524	0.512
Residual Std. Error	17410.620	20,006.610	27,945.590	28,067.690	35,570.620	42,611.820	49,963.460

	(df = 6073)	(df = 6064)	(df = 5566)	(df = 5156)	(df = 4625)	(df = 3595)	(df = 2346)

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Appendix C. Interview protocol

1. How did you find LaunchCode?
2. What led you to participate in a LaunchCode program?
3. Why are you interested in a career in STEM?
    a. Potential follow up: Why did you change your career?
4. How did they get here in your academic career?
    a. Potential follow up: how has your family dynamic shaped your educational experience?
    b. Potential follow up: What was your schooling experience like related to science and math?
5. What barriers have you faced in your journey of completing a LaunchCode program and apprenticeship?
6. How was the curriculum aligned with your needs as a learner?
    a. Potential follow up: How was it not aligned?
7. At what point during your time in the LaunchCode program did you decide not to continue?
8. What factors contributed to you not completing the program?
    a. Potential follow up: when did you decide not to continue with the LaunchCode program?
9. What was your previous experience with getting employment in STEM?
10. What was the process like for you finding employment after the LaunchCode program?
11. How if at all have your identities (i.e., race, gender, economic status) contributed to your experience completing the LaunchCode program?

Apprenticeship if they made it this far in the LaunchCode program (skip if needed):

1. What was the process like gaining an apprenticeship?
2. What support did you receive during your apprenticeship? (from the company, LaunchCode, family, friends)
    a. Potential follow up: What was the workplace culture at your apprenticeship like? Were they inviting to you as a career changer?

Final question:

1. Is there anything else you would like to share that you do not feel was covered based on my questions?

Appendix D1. Heterogenous LaunchCode Effects (TOT effect; by gender)

Panel A. STEM employment

	Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TOT groups							
Dropped out	0.001	0.002	0.017	0.019	0.021	0.035**	0.024
	(0.005)	(0.008)	(0.011)	(0.012)	(0.014)	(0.015)	(0.017)
Completed	-0.004	-0.010	0.004	0.004	0.006	0.028*	0.019
	(0.006)	(0.008)	(0.012)	(0.013)	(0.014)	(0.016)	(0.018)
Apprenticed	0.001	0.000	0.005	0.001	0.008	0.007	0.004
	(0.008)	(0.008)	(0.012)	(0.013)	(0.014)	(0.016)	(0.018)
Gender							
Women/non-binary	-0.011*	-0.005	-0.012	-0.018	-0.011	-0.010	-0.008
	(0.006)	(0.010)	(0.014)	(0.015)	(0.017)	(0.019)	(0.021)
Tot groups x Gender							
Dropped out	0.006	0.009	0.001	0.012	0.001	-0.011	-0.006
x Women/nonbinary	(0.007)	(0.013)	(0.018)	(0.020)	(0.022)	(0.025)	(0.028)
Completed	0.008	0.040***	0.029	0.030	0.022	0.029	0.028
x Women/nonbinary	(0.009)	(0.014)	(0.020)	(0.021)	(0.023)	(0.027)	(0.030)
Apprenticed	0.012	0.007	0.008	0.005	0.012	0.011	0.074**
x Women/nonbinary	(0.013)	(0.014)	(0.020)	(0.021)	(0.023)	(0.027)	(0.030)
Pre LC outcomes							
Employed	0.963***	0.967***	0.953***	0.950***	0.945***	0.936***	0.917***
	(0.005)	(0.008)	(0.011)	(0.012)	(0.013)	(0.015)	(0.017)
Income							
Race/Ethnicity							
Black/Hispanic/others	0.002	0.011**	0.000	-0.003	0.001	0.005	0.010
	(0.003)	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
Age							
Age at course start	0.0003*	0.000	0.000	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Educational Attainment							
Some college or Associate's	0.001	0.021**	0.041***	0.037***	0.033**	0.042**	0.038*
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Bachelor's	0.003	0.007	0.022*	0.013	0.011	0.035*	0.024
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Master's or above	0.005	0.013	0.017	0.017	0.035*	0.040**	0.022
	(0.006)	(0.011)	(0.015)	(0.016)	(0.018)	(0.020)	(0.023)

HR test							
Score	0.000	0.000	0.000	0.000	0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	(0.009)	(0.006)	(0.007)	(0.002)	0.010	0.041	0.059*
	(0.009)	(0.015)	(0.022)	(0.023)	(0.026)	(0.029)	(0.033)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.955	0.890	0.797	0.774	0.730	0.672	0.607
Adjusted R2	0.955	0.889	0.795	0.771	0.727	0.668	0.603
Residual Std. Error (df = 2118)	0.064	0.183	0.260	0.277	0.309	0.352	0.399
F Statistic (df = 22; 2118)	2,057.984***	777.027***	378.003***	329.128***	260.523***	196.921***	148.778***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annual income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
TOT groups							
Dropped out	101.971	1,745.842**	63.578	-594.51	-2276.941	-3,011.974*	-2000.179
	(576.153)	(833.296)	(1020.445)	(1103.108)	(1409.083)	(1680.117)	(2019.639)
Completed	-298.735	-722.386	-1,933.950*	-2,078.591*	-2,991.385**	-949.531	2053.215
	(696.017)	(849.386)	(1040.150)	(1124.408)	(1436.292)	(1712.560)	(2058.638)
Apprenticed	692.44	2,155.230**	-1,290.22	195.48	-729.81	1,327.43	2,269.67
	(1012.838)	(985.697)	(1207.075)	(1304.855)	(1666.791)	(1987.394)	(2389.012)
Gender							
Women/non-binary	-864.9	-310.443	-1040.283	-2,969.295**	-2228.799	-3,575.568*	-5,529.137**
	(711.712)	(1027.420)	(1258.169)	(1360.088)	(1737.343)	(2071.518)	(2490.135)
Tot groups x Gender							
Dropped out	1,647.367*	-878.00	161.95	2,820.48	2,667.98	4,206.53	3,556.81
x Women/nonbinary	(866.477)	(1,345.845)	(1,648.108)	(1,781.615)	(2,275.791)	(2,713.535)	(3,261.893)
Completed	940.862	675.299	1302.102	3,897.976**	3936.855	4649.317	3830.372
x Women/nonbinary	(1154.716)	(1345.845)	(1648.108)	(1781.615)	(2275.791)	(2713.535)	(3261.893)
Apprenticed	1,454.57	-904.75	705.70	3,460.97	1,958.15	2,587.73	11,959.860***
x Women/nonbinary	(1667.986)	(1602.368)	(1962.244)	(2121.198)	(2709.567)	(3230.746)	(3883.624)
Pre LC outcomes							
Employed							
Income	0.761***	0.955***	0.938***	0.932***	0.997***	1.044***	1.067***
	(0.008)	(0.012)	(0.015)	(0.016)	(0.020)	(0.024)	(0.029)
Race/Ethnicity							
Black/Hispanic/others	563.528	-60.949	161.469	583.397	-1399.114	-1395.715	-703.552
	(388.100)	(528.493)	(647.187)	(699.613)	(893.668)	(1065.563)	(1280.895)
Age							
Age at course start	69.452***	-3.114	64.312*	-29.135	26.355	-111.116**	-190.689***
	(18.452)	(27.928)	(34.201)	(36.971)	(47.226)	(56.310)	(67.689)
Educational Attainment							
Some college or Associate's	783.494	-356.219	159.478	1453.442	534.543	66.604	3281.685
	(636.617)	(948.825)	(1161.922)	(1256.044)	(1604.440)	(1913.051)	(2299.645)
Bachelor's	417.169	1,616.188*	957.871	2,359.198*	2342.524	5,133.189***	10,090.540***
	(657.531)	(963.644)	(1180.068)	(1275.661)	(1629.498)	(1942.929)	(2335.561)
Master's or above	1,256.898*	2,039.056*	1933.572	5,320.891***	4,139.639**	6,474.451***	11,559.280***
	(762.026)	(1095.533)	(1341.579)	(1450.255)	(1852.520)	(2208.849)	(2655.218)
HR test							
Score	-12.082	-29.224***	19.230	22.239	26.945	-0.153	-3.440

	(7.550)	(10.729)	(13.138)	(14.203)	(18.142)	(21.632)	(26.003)
Constant	1454.568	-2,785.787**	2,627.094*	3,614.110*	3,864.975*	9,851.165***	19,432.990***
	(1667.986)	(1,091.105)	(1,581.422)	(1,936.593)	(2,093.469)	(2,674.146)	(3,188.513)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R2	0.810	0.767	0.681	0.645	0.564	0.501	0.428
Adjusted R2	0.808	0.765	0.678	0.641	0.560	0.496	0.422
Residual Std. Error (df = 2118)	7,994.133	19,247.150	23,569.870	25,479.170	32,546.470	38,806.720	46,648.880
F Statistic (df = 22; 2118)	410.949***	317.727***	205.962***	174.544***	124.662***	96.806***	72.120***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Appendix D2. Heterogenous LaunchCode Effects (TOT effect; by race/ethnicity)

Panel A. STEM employment

	Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TOT groups							
Dropped out	0.001	0.008	0.021*	0.030**	0.024*	0.029*	0.028
	(0.005)	(0.009)	(0.012)	(0.013)	(0.015)	(0.017)	(0.019)
Completed	0.001	-0.001	0.019	0.018	0.019	0.030*	0.028
	(0.006)	(0.009)	(0.012)	(0.013)	(0.015)	(0.017)	(0.019)
Apprenticed	0.004	0.001	0.012	0.003	0.024	0.029*	0.023
	(0.008)	(0.009)	(0.012)	(0.013)	(0.014)	(0.016)	(0.019)
Race/Ethnicity							
Black/Hispanic/others	0.000	0.009	0.007	0.002	0.014	0.011	0.005
	(0.005)	(0.010)	(0.014)	(0.015)	(0.016)	(0.018)	(0.021)
Tot groups x Race							
Dropped out	0.004	-0.005	-0.007	-0.015	-0.006	0.003	-0.014
x Black/Hispanic/others	(0.007)	(0.013)	(0.018)	(0.019)	(0.021)	(0.024)	(0.028)
Completed	-0.004	0.012	-0.010	-0.006	-0.013	0.020	0.003
x Black/Hispanic/others	(0.009)	(0.013)	(0.019)	(0.020)	(0.023)	(0.026)	(0.029)
Apprenticed	0.005	0.002	-0.011	0.001	-0.034	-0.053**	0.028
x Black/Hispanic/others	(0.014)	(0.014)	(0.020)	(0.021)	(0.024)	(0.027)	(0.031)
Pre LC outcomes							
Employed	0.963***	0.969***	0.955***	0.951***	0.947***	0.939***	0.916***
	(0.005)	(0.008)	(0.011)	(0.012)	(0.013)	(0.015)	(0.017)
Gender							
Women/non-binary	-0.006**	0.009*	-0.004	-0.006	-0.003	-0.006	0.016
	(0.003)	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)
Age							
Age at course start	0.0002*	0.0000	0.0003	0.0004	-0.0002	-0.0010	-0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Educational Attainment							
Some college or Associate's	0.001	0.021**	0.041***	0.037***	0.034**	0.040**	0.039*
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Bachelor's	0.004	0.007	0.022*	0.013	0.012	0.036**	0.021
	-0.005	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Master's or above	0.005	0.013	0.019	0.018	0.038**	0.044**	0.016
	(0.006)	(0.011)	(0.015)	(0.016)	(0.018)	(0.020)	(0.023)
HR test							

Score	0.000	0.000	0.000	0.000	0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.010	-0.010	-0.013	-0.009	0.004	0.043	0.053
	(0.009)	(0.015)	(0.022)	(0.023)	(0.026)	(0.030)	(0.034)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R^2	0.955	0.889	0.797	0.774	0.730	0.672	0.606
Adjusted R^2	0.955	0.888	0.795	0.771	0.727	0.669	0.602
Residual Std. Error (df = 2118)	0.064	0.184	0.260	0.277	0.309	0.352	0.400
F Statistic (df = 22; 2118)	2,057.813***	773.586***	377.435***	328.812***	260.690***	197.626***	147.940***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annual income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
TOT groups							
Dropped out	320.9	1,486.735*	-882.7	-131.7	-2454.8	-2273.5	-692.5
	(629.5)	(899.6)	(1098.4)	(1190.4)	(1517.6)	(1812.7)	(2186.3)
Completed	-386.8	-1127.3	-3,330.026***	-1835.5	-2,558.806*	1558.0	4,413.620**
	(724.5)	(902.6)	(1102.1)	(1194.4)	(1522.7)	(1818.8)	(2193.7)
Apprenticed	1415.2	2,648.897***	35.4	2,889.195**	2656.3	5,134.991**	8,646.601***
	(973.4)	(1003.3)	(1225.1)	(1327.6)	(1692.5)	(2021.7)	(2438.4)
Race/Ethnicity							
Black/Hispanic/others	44.0	-61.0	-1195.6	118.5	-1526.3	-17.8	821.9
	(674.3)	(999.8)	(1220.8)	(1322.9)	(1686.6)	(2014.6)	(2429.8)
Tot groups x Race							
Dropped out	816.3	-102.1	2263.9	1230.4	2444.9	1518.4	-387.5
x Black/Hispanic/others	(842.8)	(1314.4)	(1604.9)	(1739.2)	(2217.3)	(2648.5)	(3194.4)
Completed	986.4	1522.0	4,327.802***	2599.8	2184.1	-2101.5	-2440.5
x Black/Hispanic/others	(1105.0)	(1367.2)	(1669.4)	(1809.1)	(2306.3)	(2754.9)	(3322.7)
Apprenticed	-1429.7	-2273.4	-3193.4	-4,119.091*	-7,586.640***	-7,963.819**	-5087.0
x Black/Hispanic/others	(1,791.8)	(1,595.0)	(1,947.6)	(2,110.5)	(2,690.7)	(3,214.0)	(3,876.4)
Pre LC outcomes							
Income	0.760***	0.953***	0.935***	0.928***	0.992***	1.039***	1.063***
	(0.008)	(0.012)	(0.015)	(0.016)	(0.020)	(0.024)	(0.029)
Gender							
Women/non-binary	226.4	-576.1	-507.7	-444.6	-34.4	-632.5	-1372.3
	(372.1)	(515.0)	(628.8)	(681.4)	(868.7)	(1037.7)	(1251.5)
Age							
Age at course start	68.669***	-0.5	67.514**	-30.5	23.9	-120.111**	-205.734***
	(18.4)	(27.9)	(34.1)	(36.9)	(47.1)	(56.3)	(67.9)
Educational Attainment							
Some college or Associate's	813.7	-422.2	58.7	1484.3	628.9	365.2	3572.9
	(636.5)	(949.1)	(1158.9)	(1255.8)	(1601.0)	(1912.4)	(2306.6)
Bachelor's	455.5	1,598.209*	904.1	2,443.758*	2611.5	5,648.719***	10,267.430***
	(656.8)	(965.2)	(1178.5)	(1277.2)	(1628.2)	(1944.9)	(2345.7)
Master's or above	1,304.900*	2,113.166*	2044.1	5,584.181***	4,713.720**	7,269.567***	11,782.180***
	(760.9)	(1097.5)	(1340.0)	(1452.2)	(1851.3)	(2211.4)	(2667.2)
HR test							
Score	-11.9	-28.535***	20.8	24.837*	31.395*	5.1	2.5
	(7.6)	(10.7)	(13.1)	(14.2)	(18.1)	(21.6)	(26.1)

Constant	-2,906.440***	2,765.113*	4,195.085**	3289.6	9,228.669***	17,732.470***	17,574.610***
	(1,109.6)	(1,603.3)	(1,957.7)	(2,121.5)	(2,704.6)	(3,230.7)	(3,896.5)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R^2	0.810	0.768	0.684	0.646	0.567	0.503	0.426
Adjusted R^2	0.808	0.765	0.681	0.642	0.563	0.498	0.420
Residual Std. Error (df = 2118)	7996.238	19228.630	23478.750	25443.580	32437.220	38745.920	46731.470
F Statistic (df = 22; 2118)	410.682***	318.525***	208.312***	175.302***	126.153***	97.412***	71.525***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Appendix D3. Heterogenous LaunchCode Effects (TOT effect model results, interact with pre-LaunchCode condition)

Panel A. STEM employment

	Employment outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TOT groups							
Dropped out	0.003	0.008	0.021**	0.027***	0.026**	0.036***	0.026*
	(0.004)	(0.007)	(0.010)	(0.010)	(0.011)	(0.013)	(0.015)
Completed	0.002	0.006	0.017*	0.017	0.017	0.043***	0.033**
	(0.005)	(0.007)	(0.010)	(0.011)	(0.012)	(0.013)	(0.015)
Apprenticed	0.004	0.003	0.010	0.004	0.014	0.010	0.035**
	(0.007)	(0.007)	(0.010)	(0.011)	(0.012)	(0.014)	(0.016)
Pre LC outcomes							
Employed	0.969***	0.983***	0.976***	0.974***	0.972***	0.963***	0.952***
	(0.008)	(0.016)	(0.023)	(0.025)	(0.027)	(0.031)	(0.035)
Tot groups x Gender							
Dropped out	-0.003	-0.027	-0.035	-0.040	-0.042	-0.051	-0.055
x Employed	(0.010)	(0.021)	(0.030)	(0.032)	(0.036)	(0.041)	(0.047)
Completed	-0.046***	-0.021	-0.027	-0.027	-0.029	-0.048	-0.045
x Employed	(0.015)	(0.023)	(0.032)	(0.034)	(0.038)	(0.044)	(0.050)
Apprenticed	0.025	-0.008	-0.02	-0.017	-0.029	0.00004	-0.034
x Employed	(0.026)	(0.022)	(0.031)	(0.034)	(0.037)	(0.043)	(0.048)
Gender							
Women/non-binary	-0.006*	0.009*	-0.003	-0.006	-0.002	-0.003	0.016
	-0.003	-0.005	-0.007	-0.007	-0.008	-0.009	-0.01
Race/Ethnicity							
Black/Hispanic/others	0.001	0.011**	0.000	-0.003	0.001	0.005	0.007
	(0.003)	(0.005)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
Age							
Age at course start	0.0002*	0.000	0.000	0.000	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Educational Attainment							
Some college or Associate's	0.001	0.021**	0.041***	0.037***	0.034**	0.041**	0.040**
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Bachelor's	0.003	0.008	0.022*	0.014	0.011	0.036**	0.023
	(0.005)	(0.009)	(0.013)	(0.014)	(0.016)	(0.018)	(0.020)
Master's or above	0.005	0.014	0.018	0.019	0.036**	0.041**	0.020
	(0.006)	(0.011)	(0.015)	(0.016)	(0.018)	(0.020)	(0.023)

HR test							
Score	0.000	0.000	0.000	0.000	0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	(0.011)	(0.012)	(0.013)	(0.008)	0.004	0.041	0.051
	(0.009)	(0.015)	(0.022)	(0.023)	(0.026)	(0.029)	(0.033)
Observations	2,141	2,141	2,141	2,141	2,141	2,141	2,141
R^2	0.956	0.889	0.797	0.774	0.730	0.672	0.606
Adjusted R^2	0.955	0.888	0.795	0.771	0.727	0.668	0.602
Residual Std. Error	0.064	0.184	0.260	0.277	0.309	0.352	0.400
F Statistic	2,068.429***	773.636***	377.654***	328.977***	260.551***	196.940***	147.873***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Panel B. Annualized income

	Income outcome						
	Pre6	**Post6**	**Post12**	**Post18**	**Post24**	**Post36**	**Post48**
	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
TOT groups							
Dropped out	4,083.53	1,197.97	739.57	2,337.23	1,119.50	2,101.03	4,083.53
	(4223.382)	(2324.056)	(2592.324)	(2580.840)	(3147.830)	(3666.196)	(4223.382)
Completed	3431.225	1787.957	2133.955	1553.770	2673.151	4145.739	3431.225
	(4218.171)	(2321.189)	(2589.126)	(2577.655)	(3143.947)	(3661.673)	(4218.171)
Apprenticed	-1,774.86	1,389.44	-1,286.00	1,600.60	-2,099.02	-195.65	-1,774.86
	(6335.799)	(3486.484)	(3888.932)	(3871.704)	(4722.287)	(5499.925)	(6335.799)
Pre LC outcomes							
Income-Q2	3663.777	4,512.603*	4,493.011*	4131.041	4209.633	4467.129	3663.777
	(4439.452)	(2442.956)	(2724.948)	(2712.876)	(3308.875)	(3853.760)	(4439.452)
Income-Q3	24,028.830***	14,899.810***	19,147.580***	18,550.930***	22,770.760***	22,771.690***	24,028.830***
	(4489.950)	(2470.744)	(2755.944)	(2743.735)	(3346.513)	(3897.596)	(4489.950)
Income-Q4	50,738.170***	42,654.120***	41,409.290***	44,322.360***	44,302.430***	49,837.370***	50,738.170***
	(4325.402)	(2380.196)	(2654.944)	(2643.183)	(3223.870)	(3754.757)	(4325.402)
TOT groups x Income							
Dropped out							
x Income Q2	-512.60	454.94	998.75	-355.73	634.62	-193.58	-512.60
	(5914.098)	(3254.429)	(3630.091)	(3614.009)	(4407.979)	(5133.858)	(5914.098)
x Income Q3	-5,793.44	1,011.23	-1,420.88	-3,039.64	-5,990.07	-5,122.58	-5,793.44
	(5996.118)	(3299.563)	(3680.434)	(3664.130)	(4469.111)	(5205.057)	(5996.118)
x Income Q4	-4,016.12	2,271.65	2,477.11	-585.53	2,652.36	-3,449.60	-4,016.12
	(5899.057)	(3246.153)	(3620.859)	(3604.818)	(4396.769)	(5120.802)	(5899.057)
Completed							
x Income Q2	7482.029	-3152.045	-5177.165	-778.393	-2181.073	1504.848	7482.029
	(6049.014)	(3328.671)	(3712.902)	(3696.454)	(4508.536)	(5250.975)	(6049.014)
x Income Q3	-10,631.950*	-722.446	-6,698.929*	-5185.829	-9,946.705**	-11,010.880**	-10,631.950*
	(6194.121)	(3408.521)	(3801.970)	(3785.127)	(4616.690)	(5376.939)	(6194.121)
x Income Q4	-339.615	-5047.333	-3096.320	-3788.992	-4720.547	-4772.544	-339.615
	(6073.928)	(3342.381)	(3728.195)	(3711.678)	(4527.106)	(5272.602)	(6073.928)
Apprenticed							
x Income Q2	20,190.870**	-255.09	830.08	-1,030.55	2,325.72	4,906.97	20,190.870**
	(7851.534)	(4320.568)	(4819.294)	(4797.944)	(5852.016)	(6815.691)	(7851.534)
x Income Q3	-9,208.13	599.06	-5,408.16	-7,039.43	-9,708.73	-9,080.01	-9,208.13
	(7949.527)	(4374.492)	(4879.443)	(4857.826)	(5925.054)	(6900.756)	(7949.527)
x Income Q4	8,344.27	7,126.64	2,669.54	1,320.14	8,002.79	3,584.81	8,344.27
	(7998.464)	(4401.421)	(4909.480)	(4887.731)	(5961.528)	(6943.236)	(7998.464)

Gender							
Women/non-binary	-2,944.309*	-2,253.618**	-1418.588	-1218.464	-631.471	-790.613	-2,944.309*
	(1,659.949)	(913.442)	(1,018.881)	(1,014.368)	(1,237.216)	(1,440.954)	(1,659.949)
Race/Ethnicity							
Black/Hispanic/others	-796.068	-654.018	-824.201	717.745	-2,424.222*	-2404.035	-796.068
	(1758.822)	(967.850)	(1079.570)	(1074.788)	(1310.910)	(1526.783)	(1758.822)
Age							
Age at course start	144.844	272.695***	389.122***	239.588***	325.951***	225.255***	144.844
	(94.852)	(52.195)	(58.220)	(57.962)	(70.696)	(82.338)	(94.852)
Educational Attainment							
Some college or Associate's	1806.499	794.646	1475.403	1769.259	367.032	-930.702	1806.499
	(3307.440)	(1820.029)	(2030.116)	(2021.122)	(2465.148)	(2871.093)	(3307.440)
Bachelor's	9,914.591***	2050.091	1462.571	2055.833	2144.470	4200.235	9,914.591***
	(3331.551)	(1833.297)	(2044.916)	(2035.856)	(2483.119)	(2892.024)	(3331.551)
Master's or above	10,387.860***	4,891.888**	4,219.082*	7,649.354***	5,192.287*	6,365.649**	10,387.860***
	(3731.438)	(2053.348)	(2290.367)	(2280.221)	(2781.168)	(3239.154)	(3731.438)
HR test							
Score	39.270	-6.529	55.666***	54.059**	55.778**	33.252	39.270
	(34.708)	(19.099)	(21.304)	(21.209)	(25.869)	(30.129)	(34.708)
Constant	1817.646	-7,558.064**	-9,759.165***	-8,927.736**	(3175.399)	4461.495	1817.646
	(6118.961)	(3367.162)	(3755.836)	(3739.197)	(4560.671)	(5311.694)	(6118.961)
Observations	1,596	1,596	1,596	1,596	1,596	1,596	1,596
R^2	0.321	0.538	0.470	0.484	0.415	0.363	0.321
Adjusted R^2	0.308	0.529	0.46	0.474	0.403	0.351	0.308
Residual Std. Error	53,125.640	29,234.150	32,608.670	32,464.210	39,596.350	46,116.840	53,125.640
F Statistic	24.694***	60.750***	46.304***	48.995***	36.932***	29.788***	24.694***

Notes: Standard errors in parentheses; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$