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Technical Job Placement Success of Coding Bootcamps

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Abstract
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Keywords
coding bootcamps, technical role, job placement, entry-level

Disciplines
Adult and Continuing Education | Curriculum and Instruction | Educational Assessment, Evaluation, and Research | Management Information Systems | Online and Distance Education | Technology and Innovation | Vocational Education

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TECHNICAL JOB PLACEMENT SUCCESS OF CODING BOOTCAMPS

By

Savi Joshi

An Undergraduate Thesis submitted in partial fulfillment of the requirements for the

JOSEPH WHARTON SCHOLARS

Faculty Advisor:

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THE WHARTON SCHOOL, UNIVERSITY OF PENNSYLVANIA

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ABSTRACT

Studies have addressed the inconsistencies and uncertainty of coding bootcamps despite the recent sensationalization of bootcamps as an opportunity to close the wage gaps. While high variability based on intensity, duration, and delivery exist, many of these bootcamps advertise high job placement rates and guarantee technical competency upon graduation. This study evaluates technical job placement rates for recent coding bootcamp graduates using public LinkedIn profiles, accounting for any technical experience prior to the bootcamp such as a technical undergraduate degree or previous employment. Through regression analysis and propensity-score matching, the study finds that while prior technical experience is the strongest predictor of technical employment, the lack of a technical background will not penalize a bootcamp graduate from landing a technical role in the future. The research shows that bootcamp attendees were not penalized for a non-technical undergraduate degree and that the bootcamp significantly positively increased their chances of success to obtain a future technical role. Furthermore, attending a bootcamp was shown to be unhelpful for participants who already had a technical undergraduate degree. Finally, the research suggests avenues for further exploration with regards to how levels of education (i.e. undergraduate, graduate, and/or bootcamp) impact recruiting for graduates.

Keywords

Coding bootcamps, technical role, job placement, entry-level

Discipline

Business, Operations

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1. INTRODUCTION

1.1 Motivation and Purpose

By 2030, nearly 14% of the global workforce will need to switch occupations as the "age of automation" changes the nature of human capital (Illanes, Lund, Moushed, Rutherford, Tyreman 2018). More importantly, low-wage jobs are most likely to be replaced: 83% of jobs that pay less than $20 hourly could be automated according to the U.S. Council of Economic Advisers. The rise of alternative employments, such as contractors, and the easing of job licensing complements the growth of alternative education (McAfee and Brynjolfsson 2016). As automation increases, the need for problem solvers who understand the programming and systems behind the robotics grows (Jong-Wha 2018). While some undergraduate schools have introduced data science curriculums, students who did not pursue a technical undergraduate degree are looking towards another type of school: coding bootcamps. However, many of these bootcamps, unlicensed and unaccredited, come with a high sticker price and no guarantee of successful placement into a technical role. This study serves as an objective third party evaluation of coding bootcamp placement success into entry-level technical roles.

1.2 Alternative Credentials

Overview of Alternative Credentials

Non-traditional studies have existed before the 1970s but were defined by the Commission on Non-Traditional Study in the 1970s as "more of an attitude than a system" with the aim to focus on the learning and its impact on the student rather than the time and location of the education (Cross 1976). Alternative credentials can be defined as "credentials that serve as alternatives to bachelor's and associate's degrees and alternative pathways to achieving an academic degree" (Brown et al. 2017). These degrees are offered through higher education institutions where a four-year degree is obtainable as well as private organizations that do not offer academic degrees such as coding bootcamps, MOOCs, and corporate training. The current landscape consists of five categories: certificate programs, work-based training programs, skills-based short courses, MOOC providers, and competency-based degree programs (Brown et al. 2017).

According to the U.S. Department of Education, more than 3,000 for-profit post secondary institutions serve 670,000 students each in short-term certificate programs. However, for most of these graduates, these certifications will serve as supplements to their undergraduate degrees. Research from the University of Pennsylvania found that 83% of students taking MOOCs have a post-secondary degree, with 79.4% having a Bachelor's degree of higher, with these trends more pronounced in developing countries (Christensen et al. 2013). In addition, the study found that most participants took the course for either "curiosity, just for fun" or to "gain specific skills to do my job better." Within types of courses, 54% of social science participants and 39% STEM course participants were aiming to gain job-specific skills compared to the 12% of humanities participants looking to do the same (Christensen et al. 2013). This paper will take a deeper look at skills-based short courses, the umbrella category for coding bootcamps.

Skills-Based Short Courses

Skills-based short courses date back to the late nineteenth century such as the University of Wisconsin-Madison's 12-week short course in farming education[1] and the University of Chicago's Meatpacking Institute classes[2] and have regained attention through the popularity of coding bootcamps. Anecdotally, skill-based short courses are selected because they provide

[1] "About FISC," Farm and Industry Short Course, College of Agricultural and Life Sciences, University of Wisconsin-Madison, https://fisc.cals.wisc.edu/about-fisc/.

[2] "Institute of Meatpacking: 1923–1928," University of Chicago University of Extension Records, https://www.lib.uchicago.edu/ead/pdf/ofcpreshjb-0052-002-03.pdf.

flexibility, are more practical, and enhance their value to their current employer or future similar to other alternative accreditations (British Academy of Media 2013). However, unlike their counterparts, skill-based short courses are designed to be less than one year, normally 12-16 week intensives, with a focus on a specific field or skill. By the end, students will have a compiled portfolio of work samples, with some courses providing certification and job placement guarantees. Coding bootcamps are the most-recent development of short courses that are 12-weeks and prepare their students for roles such as developers, designers, and data scientists (Brown et al. 2017).

1.3 The Rise of Coding Bootcamps

Origins of the Bootcamp

As university education focused heavily on theory and the demand for practical skills in the industry grew, the foundations of the first coding bootcamp rose. At the end of 2011, one person offered to teach six people to code on Hacker News. Then, based on this idea, two companies emerged: Hungry Academy (which would later become the Turing School of Software & Design) and Dev Bootcamp ("What happened to Hungry Academy" 2014). The goals of these bootcamps were to make participants ready for the workforce in an intensive, affordable manner compared to an undergraduate computer science degree. However, most students who enroll in a bootcamp hold a bachelor's degree or higher (See Appendix B).

Growth and Expansion Since Founding

Since two providers in 2012, there are now 95 in-person bootcamp providers and 13 online bootcamp providers as of 2018. Excluding scholarship and online revenue, ~220M in revenues are anticipated from tuition with over 20,000 graduates, compared to approximately 93,500 undergraduate computer science graduates from accredited US universities (Course

Report 2018). The most popular language is Full-Stack JavaScript, however, almost all languages appear to grow except for Ruby on Rails, which decreased from 31% in 2017 to 16.2% in 2018. Full-Stack Web Development continues to be the preferred career track selected by nearly 91% participants (Course Report 2017; Course Report 2018). Courses are tailoring their offerings to greater trends in the popularity of programming languages. Geographically, most bootcamps are in New York City and San Francisco as well as Seattle, Dallas, and Chicago. As of June 1, there are bootcamps located nationwide in 86 US cities and 44 states (Course Report 2018).

Future Trends

Intending to "close the gap," bootcamps have been presented as a method to increase diversity and inclusion in tech, with minority-specific bootcamps such as the Grace Hopper Academy and Black Girls Code (Course Report 2018). Currently, STEM continues to face a pipeline issue with only 19.2% of undergraduate computer science degrees held by women in 2015 and 36.1% by underrepresented students (DataUSA Computer Science). Structurally, bootcamps appear to as the solution: the average length is 15 weeks compared to 4 years of undergraduate, the average tuition is $11,400 compared to $30,000 per year for private college, and the rise of diversity scholarships have made bootcamps more accessible (Course Report 2018). Preliminary data supports these assumptions. Compared to the 19.2% of undergraduate computer science degrees held by women, 36% of coding bootcamp graduates were female. Furthermore, 20% of graduates were of Hispanic origin, compared to the 7.7% in universities. While the financial costs differ, starting salaries appear to be on par (Brown et al. 2017; Course Report 2015).

In addition, bootcamps are trending towards partnerships, both corporate and academic. In 2017, the Department of Education launched EQUIP (Educational Quality through Innovative Partnerships) to encourage partnerships between accredited colleges and universities and non-traditional education providers such as bootcamps (Office of Educational Technology). In 2018, 24 bootcamps worked with corporate partners to teach programming and collaborated to build industry assessments such as L'Oreal and General Assembly's "Digital Marketing Level 1 Assessment" (Course Report 2018; L'Oreal 2017).

Challenges of Coding Bootcamp

While many participants use bootcamps to start an alternate career path or as an alternative form of education, they face barriers during the recruiting and hiring process. According to Thayer and Ko, students mentioned five recurring criteria for employment: relevant educational credentials, software industry work experience, online portfolios, networking with employers and engineers, and interviewing abilities ("whiteboarding"[3]) (2017). To prepare participants in these criteria within 12 weeks, bootcamps, by definition, must be rigorous and intense. The bootcamps themselves require $10,000 and three months, with most students putting in 70-80 hours a week. Some participants claimed to set aside anything that was not directly tied to the bootcamp, including showering. After the bootcamp is over, the career switch can take up to a year for some students. One male interviewee stated, "During these nine-months, I pretty much devoted my time to [the bootcamp's] prescribed job hunting methods, which means financially, I have no money. I couldn't work because I really needed to do job searching full time. And that's a big sacrifice I made, which reflects on my family because no we're low on

[3] Whiteboarding can be defined as when an interview participant is asked to present a solution or write an algorithm on a whiteboard. Whiteboarding has been critiqued as a practice that favors those who can "cram code" and younger developers, does not test engineering aptitude, and depends on luck based on the algorithm lottery (Forbes 2018, Free Code Camp 2018).

funds" (Thayer and Ko 2017). In addition to time and the financial costs with a level of uncertainty around job placement, students also mentioned challenges to fitting in with the culture of bootcamps on dimensions such as, expected knowledge of developer jargon, stereotypes and subcultures (particularly gaming), demographics, and programming background. Many students discussed struggling with Impostor Syndrome[4] (Thayer and Ko 2017).

Taking into account the industry has conflicting views around the success of bootcamps, the paper explores an economic understanding of labor markets to develop a hypothesis around the efficacy of coding bootcamps on relevant job placement for self-reported graduates.

2. LITERATURE REVIEW

2.1 Demand Side Economics of Technical Labor Markets

Increased Demand in Technical Skills

The use of Artificial Intelligence is replacing and reducing the number of jobs, finding that "one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent," while introducing demand for analytical skills that require more preparation (Acemoglu and Restrepo 2017; Pew Research Center 2016). While the effect on the number of jobs remains unclear, the National Academy of Sciences found that "new jobs are likely to rely more heavily on analytic, cognitive, and technical skills...Despite the low unemployment rate, the overall U.S. employment rate remains near a 20-year low" (National Academy of Science 2017). While some of the effects are accounted for by an aging population, the decline in employment rate amongst younger, less educated individuals indicates the change in job demands and the need for further skills training

[4] Also known as the impostor phenomenon. Defined as "the idea that you've only succeeded due to luck, and not because of your talent or qualifications" (Time 2018).

(Davis and Haltiwanger 2014). Currently, open jobs still exists and remain tough to fill. According to TechHire data, IT jobs consists of 12% of the 5,000,000 jobs available (White House Archives 2015). LinkedIn conducted an analysis of the skills companies need the most and have the hardest time filling for 2018, including skills such as cloud and distributed computing, data mining, web architecture, and user interface design (LinkedIn 2018). The full list can be found in Appendix D.

In a non-scientific canvassing, the Pew Research Center found that 70% of respondents believed new educational programs would arise in the next 10 years to successfully train large numbers of workers. The shift to AI is expected to change the future of job training. The Pew Research Center and Elon University's "Imagining the Internet Center" outline optimistic major themes such as the migration to online classes through a hybrid or solely online model both self-directed and mandated by corporate, the rise of emotional intelligence and resilience as well as practical, experiential learning, the acceptance of alternate credentials. However, two concerning trends are that learning systems will not meet our needs by 2026 due to lack of necessary funding and motivation for self-directed learning and that technology will fundamentally change the number of jobs required (Pew Research Center 2017). While Ho et al. found that 5% of 840,000 participants received certificates of completions for Harvard and MIT MOOCs, CIRR found a 92% graduation rate from bootcamps for its 2016 Cohort (Ho et al. 2015, CIRR 2016).

Evaluating The Skills Gap

The rapid increase in technological advancements have given us more data than ever seen before. According to Bajaj and Ramteke, 2.5 quintillion bytes of data are created everyday, with "90% of the data in the world today has been created in the last two years alone" (2014). Given the heterogeneity of big data[5], an analysis challenge arises as analysis needs to be completed automated for effective large-scale analysis (Bajaj and Ramteke 2014). Database design becomes more important than ever and today is "an art...carefully executed in the enterprise content by highly-paid professional. We must enable other professional, such as domain scientists, to create effective database designs, either through devising tools to assist them in the design process or through forgoing the design process completely and developing techniques so that databases can be used effectively in the absence of intelligent database design" (Bajaj and Ramteke 2014). However, the skills-gaps goes beyond database designers. Complements, such as data scientists and big data statisticians, are crucial but not taught in traditional statistics courses (McAfee and Brynjolfsson 2012). Some U.S. universities have started offering big data analytics programs to ensure graduates are prepared growing demand in these skills, but demand continues to outpace supply (Al-Sakran 2015, Wixom et al. 2014). According to the McKinsey Global Institute, "by 2018, the United States alone could face a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts with the know-how to use the analysis of big data to make effective decisions" (2011). While sizeable, closing the gap and experiencing productivity growth is possible given investment in skill acquisition. Using the LinkedIn skills database, Tambe found that "from 2006 to 2011, Hadoop investments were associated with 3% faster productivity growth, but only for firms (a) with significant data assets and (b) in labor markets where similar investments by other firms helped to facilitate the development of a cadre of workers with complementary technical skills" (2014). While some employers and researchers claim a skills gap or shortage, others take a more nuanced view of a skills mismatch as employees are currently over-qualified for their current jobs (Cappelli 2015;

[5] Big data is distinguished by four characteristics: volume, variety, velocity, and veracity (Bajaj and Ramteke 2014).

Bartels et al. 2017). Furthermore, the growth rate of technology graduates exceeds that of the technology jobs even as technology job openings increase (Bartels et al. 2017). However, all of the authors reconcile that with higher job requirements, supply will be constrained and training is necessary. Peter Cappelli states the“obvious solution to the monopsony problem, and indeed to virtually all the skill problems reported by employers, is to increase training and produce the skilled workers they want themselves” (2015).

Shift in Recruiting Practices

Even though the existence of skills gap is contended, shifts in recruiting practices are proven. Participants are now expected to provide work samples or portfolios in addition to or in replacement of traditional interviewing methods. “A survey of employers conducted by the Chronicle of Education (2013) showed that work experience was the crucial attribute that employers wanted, even for students who had yet to work full-time, and that the relevance of coursework to the job in question was just not that important” (Capelli 2015). Rather than focusing on the buzz around a “skills-gap,” some researchers believe the focus needs to be on “knitting together the supply and demand sides of the labor market. Thinking about the real financial and institutional mechanisms necessary to make, say, apprenticeships work is far more productive than perennially sounding alarms about under-skilled workers” (Weaver 2017). Research from both perspectives of the skills-gap as well as change in recruiting practices highlight the need for a core component of bootcamps: practical experience.

2.2 Supply Side Economics of Technical Labor Markets

Accessibility of Coding Bootcamps

While coding bootcamps have been marketed for their accessibility, many of the elite bootcamps have acceptance rates around ~8-10%, similar to that of elite universities. The admissions process focuses less on previous technical experience, and screen candidates for traits such as commitment to learning, discipline, aptitude, grit, [and] the right motivation/passion (Lighthouse Labs 2018; Flatiron School 2018). Once students cross the selection hurdle, further financial and non-financial hurdles arise. Studies found that "success in computing programs depended on background experience, comfort level, sense of belonging and stereotypes (disproportionately negatively affecting women), view of self as an 'insider', and believed role of luck (Thayer and Ko 2017). When interviewing participants on determinants of success in their recruiting process, participants mentioned educational credentials such as a bachelor's degree in computer science and felt a "stigma" against bootcamp certificates (Thayer and Ko 2017). As discussed earlier, job placement was more contingent on work experience, online portfolios, networking, and "whiteboarding" rather than content learned and executed during the bootcamp. While bootcamps help participants build online portfolios and assist with work experience, informal boundaries of knowledge, identity, and belonging also took a role. Many of the programmers were expected to learn outside of the bootcamp through tutorials and StackOverflow, however, some participants were only exposed to this material through the bootcamp. Identity and belonging were discussed earlier with regards to the impostor syndrome and stereotypes around the "nerdiness" of software engineers (Thayer and Ko 2017). Although most bootcamps are more accessible than institutions, the most elite seem as exclusive as elite universities. Furthermore, underlying informal factors from the industry may decrease actual accessibility. Based on these findings, students with technical degrees will have better access to these programs, with regards to both applying to the program and attaining resources during the program.

Occupational Licensing & Credentials as a Job Market Signal

Similar to education, occupational licensing serves as a job market signal that often results in higher pay. Firms rely less on observable characteristics, such as race or gender, with occupational licenses. By extension, licensed minorities experience smaller wage gaps and higher labor market participation compared to unlicensed peers (Blair and Chung 2018; Bailey and Belfield 2018). Stackable credentials have also been shown to have a slightly positive return, however, the difference is indistinguishable from one post-secondary degree (Bailey and Belfield 2017). Coding bootcamp courses resemble stackable credentials rather occupational licenses. Furthermore, many schools lack accreditation unlike university education, which has proven to be a job market signal (Spence 1973). The combination of these may lead to penalties in hiring for diverse candidates such as women and other minorities or even non-technical undergraduates entering the field for the first time.

However, recruiters for technical jobs seem less focused on occupational licenses or accreditations. A recent article reviewed pre-existing articles and blog posts to postulate whether coding bootcamps prepare their participants for industry. In a survey by Indeed of 1,000 employers, 72% believed that "bootcamp grads are 'just as prepared' to be high performers as degree holders" (Indeed 2016). While employers are willing to higher bootcamp graduates, bootcamps should not be viewed as "an opposition" to the traditional university route to industry, as there are are abundant positions available"(Wilson 83-87). 41% of respondents stated they would hire rather hire a candidate with a computer science degree. Regardless, 98% of employers also wanted to see increased regulation and accreditation programs for these bootcamps (Indeed 2016). University graduates will still attain the developer positions in languages that cannot be easily taught within a 6 to 12-week bootcamp. Ultimately, while bootcamps are not suitable for everyone, they do help participants pass initial hurdles, such as having work samples or previous experience. However, for those who are less committed, a university entry-level course supplemented by industry experience would be the preferred method (Wilson 83-87).

3. SIGNIFICANCE

3.1 High Risk, High Reward Nature of Bootcamps

While coding bootcamps have been marketed as a way to break down the barriers that technical degrees face in college, such as financial hurdles or flexibility, coding bootcamp students still face a high uncertainty of employment. Most bootcamps range near $10,000 for a 12-week intensive without provide students security around their outcome. In addition, most bootcamps are unaccredited, therefore students are not eligible for a student loan. Instead, students must take private loans to pay for the program as well as computer equipment and additional software (Krishnan 2018). Similar to the MOOC study at the University of Pennsylvania, coding bootcamps tend to attract white males with at least a bachelor's degree (Christensen et al. 2013; Course Report 2018). The underlying question changes from whether coding bootcamps are worth their price in general to whether certain users stand to benefit from bootcamps more than others. When tracking the job outcomes of 26 participants, Thayer and Ko found that most students had additional education beyond the bootcamp such as online courses, in-person courses, or individual help between their previous unrelated job and reaching full-time employment. The researchers also noted that "at least four students happened to be married to programmers, and at least seven others had parents, siblings or other important people in their social circle who were programmers" (Thayer and Ko 2017). Only one participant attained full-time employment with a bootcamp and simultaneous unrelated job. This study aims to expand the work of Thayer and Ko and provide more context to both whether bootcamps placed the sample into technical jobs and whether a technical undergraduate degree has an impact.

3.2 Legal Implications of Unaccredited Universities

Many of these schools lack the same levels of regulations of accredited universities, with marketing material unaudited. Recently, multiple coding bootcamps have shut down, including coding bootcamp pioneer Dev Bootcamp, and two schools in particular, Coding House and Flatiron School, have been fined by their respective state education boards for misrepresentation and false advertising of placements and graduation rates (Bloomberg 2016; New York State Office of Attorney General 2017). According to a student at UT Austin, which partnered with Trilogy Education Services, Inc., "the success rate of these institutions is virtually unknown. All they provide is anecdotal evidence of a handful of successful individuals" (Krishnan 2018). The government and private organizations have intervened to increase transparency of bootcamps and collaboration between accredited universities and unaccredited camps. In March 2015, former president Barack Obama launched the TechHire initiative to help build tech pipelines across the country through a three-pronged approach: "(1) More than 20 communities with over 300 employer partners signed on to pilot accelerated training strategies; (2) large private-sector companies and national organizations committed to providing tools to support these TechHire communities; and (3) the President pledged $100 million in federal grant funding" (White House Archives 2015). EQUIP partnerships introduced in October 2017 promoted non-EQUIP partnerships as well. However, non-EQUIP partnerships, such as Lynn University and General Assembly's technology design course, still require students to pay separately for the courses, around $16,000 for 16 weeks (Brown et al. 2017).

With regards to job placement data integrity, CIRR (Council on Integrity in Results Reporting) was developed in March 2017, starting as a group of 17 bootcamps using a common framework for auditing and reporting outcomes, including cohort specific data. The granularity of these reports provides more realistic outcomes than the marketed values, such as 39% of students employed within 90 days and 73% within 180 days as opposed to the 99% marketed on the website (CIRR 2016). Even CIRR reporting has flaws, such as focusing on selective schools rather than accessible schools. Former employees have critiqued using hiring statistics as a metric as the measure promotes increasing hiring statistics through selective admissions, ultimately affecting the underserved groups it aimed to help (Noda 2017).

However, the validity of these interventions still stand contested. The Flatiron School, charged with a $375,000 fine for misrepresenting their job placement statistics, is a participator of the quality assurance task force by Entangled Solutions “with the goal of establishing quality assurance standards for non-traditional learning providers. It aims to drive industry-wide accountability and transparency in this exciting time of emergent, outcome-focused learning solutions” (EducationQA.org). This study aims to take an objective, outcome-based approach to understand a more representative job placement rate into a relevant field.

4. RESEARCH QUESTION AND HYPOTHESES

This study will determine whether specialized, intensive bootcamps can successfully fill a shortage in supply side of labor markets for technological skills by placing non-technical college graduates into technical roles upon completion of the bootcamp.

Research Questions:

- Are graduates of specialized bootcamps, such as General Assembly and Flatiron School, employed into technical roles?

- If bootcamps successfully place their graduates, can graduates who do not have a technical undergraduate degree or previous technical employment be hired into technical roles upon completion of the bootcamp?
- Does completion year have an effect on job placement? If so, what is the strongest predictor of placement into a technical role?

Hypotheses:

- Hypothesis 1: Given the importance of licensing and familiarity with the culture of technical environments, graduates of specialized bootcamps with technical experience, either undergraduate or previous employment will successfully place into technical roles.
- Hypothesis 2: Non-technical undergraduate degrees will still successfully place into technical roles but at a lower percentage compared to their technical peers.
- Hypothesis 3: More recent graduates will not have placed into technical jobs as explained by the longer recruiting process compared to slightly older graduates. However, the strongest predictor will be working in a previous technology role followed by undergraduates with a technical degree.

5. DATA AND RESEARCH METHODOLOGY

5.1 Data Overview

The data for this study will come from one primary source: LinkedIn School Alumni Tool. The alumni of the coding bootcamps “General Assembly” and “Flatiron School” will be manually collected.

Treatment Group

The LinkedIn Alumni Tool allows users to search Alumni of any institution recognized by LinkedIn as a “School”. The tool provides a list of recent graduate with filters by location, graduation year, and course based on the user's inputs in their respective "Education" section of their personal profile. The suggestions provided are based on LinkedIn's algorithm and are not manipulated by the researcher. Redirecting to their personal profile, LinkedIn provides the relevant education information for this study:

- Undergraduate School
- Undergraduate Major
- Undergraduate Graduation Year
- Bootcamp
- Bootcamp Course
- Bootcamp Completion Year

The study uses the employment information of the individual users' profiles to collect employment information:

- Internship Role (if applicable)
- Internship Company (if applicable)
- First Post-Undergraduate Job Role
- First Post-Undergraduate Company
- First Post-Bootcamp Job Role
- First Post-Bootcamp Company

Control Group

The control group was collected by using the LinkedIn Alumni feature and filtering for candidates with the same undergraduate school, major, and graduation year. The study tracked each individual user's career progression:

- Internship Role (if applicable)
- Internship Company (if applicable)
- First Post-Undergraduate Job Role
- First Post-Undergraduate Company
- Subsequent Job Role (or continuation of previous role)
- Subsequent Company (or continuation of previous company)
- Subsequent Job Role (or continuation of previous role)
- Subsequent Company (or continuation of previous company)

The third job role and company for the Control Group was matched to the "First Post-Bootcamp Job Role" and "First Post Bootcamp Company", implying that the treatment group went to a bootcamp instead of moving to a second job. The study then classifies the major, job titles, and companies as technical, as in related to technology, or non-technical. Furthermore, we added a third classification: a hybrid role, a non-technical position that requires high levels technical knowledge or previous technical experience, such as a Product Manager. Table 1 provides an illustrative example of technical and non-technical classifications.

Table 1. Illustrative Examples of (Non-) Technical Majors, Job-Titles, and Companies

	Undergraduate Major	Job-Title	Company
Technical	Computer Science, User Experience Design, Technology & Operations	UX Engineer, Data Scientist, (Technical) Founder, Product Manager	Technology Firms (i.e. Google), Bootcamps (i.e. General Assembly), Technology Startups
Non-Technical	International Relations, Business, Political Science	Marketing, Teacher, Client Growth, Business Analyst	Investment Banks, High Schools, Consulting Firms
Hybrid	UC Berkeley Management, Entrepreneurship & Technology; UPenn Jerome Fisher Program of Management & Technology	(Associate) Product Manager, Head of Business Analytics	N/A

Additional Data Collected

Furthermore, LinkedIn provides “top three endorsements” that the user chooses to showcase on their public LinkedIn Profile. This study will use endorsements to see if bootcamp graduates have similar endorsements. Finally, the study collects user’s geographic location to conduct preliminary research and share initial findings for geographic clustering, while taking into account the locations of both General Assembly and Flatiron School.

5.2 Regression Model Framework

Given the dichotomous nature of the outcome variable, whether or not the individual placed into a technical role, combined with the multiple categorical variables used to predict the outcome, the most appropriate statistical methodology to test the factors that affect placement into a technical role is a logistic regression (Chao-Yang, Lee, Ingersoll 2010). The logistic equation used in this study is described here:

$$\text{logit}(Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1(X_1) + \beta_2(X_2) + \beta_3(X_3) + \beta_4(X_4) + \beta_5(X_5) + \beta_6(X_2 * X_3) + \beta_7(X_3 * X_5)$$

where Y is the expected placement into a technical role after attending a bootcamp or completing their prior role (for non-bootcamp attendees). The *X*'s represent the following set of predictors:

- X_1: Undergraduate Graduation Year
- X_2: Bootcamp or Prior Role Completion Year
- X_3: Bootcamp Attendance (1 if individual attended a bootcamp, 0 if not)
- X_4: Undergraduate Technical Degree (1 if individual has a technical undergraduate degree, 0 if not)
- X_5: Post-Undergraduate Technical Role (1 if individual did not have an undergraduate technical role, 0 if they did)

The last component of the model consists of interactions between the completion year of those who attended a bootcamp as well as between attending a bootcamp and not having a technical undergraduate degree.

The packages "dplyr" and "stargazer" will be used in R to build the regression and output the summary of results, respectively.

5.3 Matched Pairs

While the logistic regression provides a model for predicting future placement given the multiple categorical variables, the existence of a control group that matches on undergraduate school, major, and graduation year allows for a more robust form of analysis: matching. Given the nature of the data-set, this study uses the Propensity Score Matching methodology outlined by Dehejia and Wahba (2002) which is based on the work of Rosenbaum and Rubin (1983).

Propensity Score-Matching

Dehejia and Wahba's methodology consists of matching the groups by similar observable characteristics. This matching method leads to an "unbiased estimate of the treatment impact" when the differences between the two groups can be captured by the covariates (2002). One of the methods to match is Rosenbaum and Rubin's "Propensity Score" matching (1983). The propensity score is "the conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum and Rubin 1983). Unlike randomized experiments which have directly comparable units, non-randomized experiments have units with systematic differences given the nature of the treatment. Propensity score-matching methods can correct for sample size biases driven by observable differences between the treatment and comparison groups through a functional weighting scheme of comparison units to calculate the estimated treatment effect (Rosenbaum and Rubin 1983; Dehejia and Wahba 2002).

The study uses the "MatchIt" package on R to estimate the propensity scores and find the distance between the matches. Furthermore, to avoid sensitivity to matching order (Rosenbaum 1995), the study matches with replacement which also allows to minimize propensity-score distance by finding the nearest match even if the unit has already been matched to another comparison unit. Similar to Dehejia and Wahba (2002), this study also uses single comparison unit matching to ensure the smallest propensity-score distance, trading off the precision of estimates to minimize the cost of biasing the sample.

First, the study looks at the comparison of variable means for the unmatched treatment and control groups respectively. Then, after observing the sample sizes and balances of the matched data, the study further looks at the comparison of means for the matched data. The respective *p-values* indicate whether the differences in means are statistically significant when the data is matched versus unmatched.

5.4 Classification and Regression Trees

The final method of analysis this study will use is recursive partitioning through classification and regression trees also known as “CART” or “decision trees” of Breiman, Friedman, Stone, and Olshen (1984) through the R package “rpart”. The “rpart” program consists of a two step-process to build the three: first, a single variable is found that splits the data into two groups by maximizing the decrease in risk or the cost of adding another variable. Once the data is separated, the process is re-applied to each of the sub-groups until no further improvement can be made. However, this tree is mostly too complex and needs to be pruned to minimize relative error without overfitting. This study will use the 1-SE rule during cross-validation, as established by Breiman, Friedman, Stone, and Olshen (1984) to determine the simplest model.

5.5 Limitations

The sample focuses on a small subset within limited geographic regions, notably New York and San Francisco. The dataset only shows participants who completed the course and then added it to their LinkedIn, implying a desire to professionally market the skill. This introduces a potential selection bias with the available data set and is expected to skew the data towards our initial hypothesis. Similarly, users can select which endorsements they wish to promote regardless of the actual number of endorsements they have. In addition, due to legal issues around scraping LinkedIn for data, the sample size selected was presented by LinkedIn’s algorithm based on the researcher’s geographic location, professional interests, and connections.

6. DESCRIPTIVE STATISTICS

6.1 Full Sample Summary Statistics

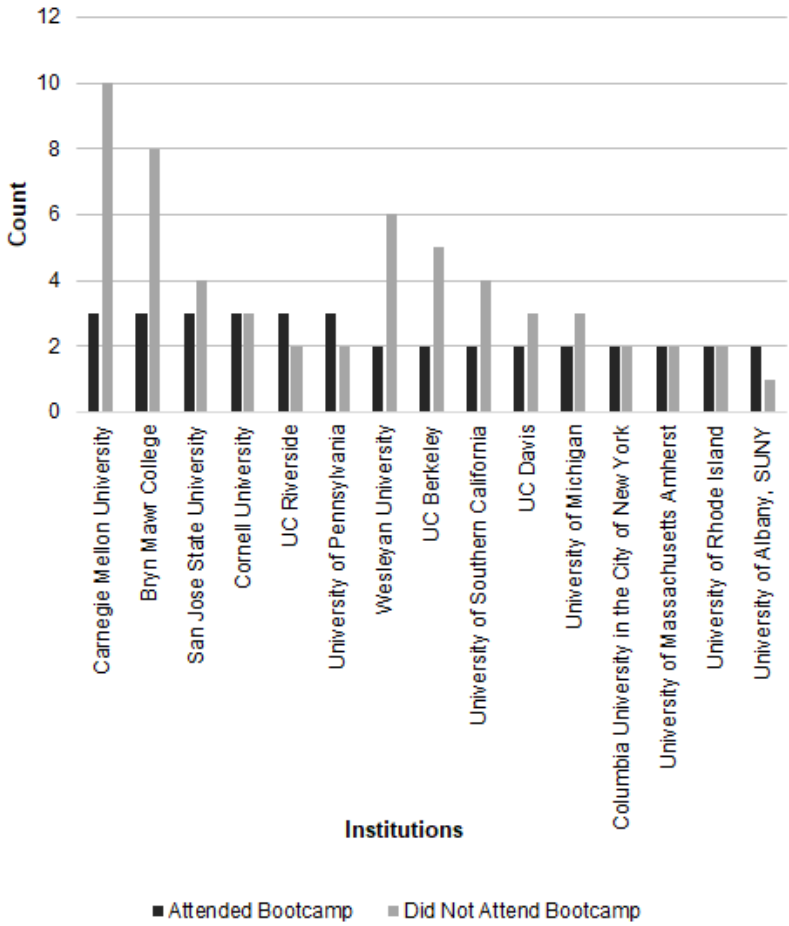
Table 2. Full Sample Summary Statistics for Independent and Dependent Variables

	N	Mean	St Dev.	Min	Pctl(25)	Pctl(75)	Max
Undergraduate Technical Degree	205	0.127	0.334	0	0	0	1
Undergraduate Graduation Year	203	2012	4.608	1992	2010	2015	2020
Internship	84	0.167	0.375	0	0	0	1
Internship Company	84	0.179	0.385	0	0	0	1
First Post-Undergraduate Job Role *(=0 if technical)*	203	0.862	0.346	0	1	1	1
First Post-Undergraduate Company *(=1 if technical)*	203	0.227	0.42	0	0	0	1
Year Joined	81	2014	3.592	1995	2013	2016	2018
Subsequent Job Role	81	0.136	0.345	0	0	0	1
Subsequent Company	81	0.21	0.41	0	0	0	1
Attended Bootcamp *(=1 if attended)*	209	0.612	0.488	0	0	1	1
Completion Year	205	2016	2.244	2000	2015	2018	2019
First Post-Bootcamp (or Subsequent) Job Role *(=0 if technical)*	197	0.548	0.499	0	0	1	1
First Post-Bootcamp (or Subsequent) Company *(=1 if technical)*	192	0.448	0.499	0	0	1	1

The sample consists of 205 observations, however, due to missing values from inconsistent or incomplete LinkedIn profiles, the regression discards 30 observations, resulting in 175 observations for the regression. Furthermore, internships were monitored to account for non-technical undergraduates who took technical roles immediately after completing their undergraduate degree. However, only three observations in each the treatment and control group (six total) had non-technical undergraduate degrees with a technical internship and roles upon graduation. Therefore, internship data was not used in building the regression analysis or as a matching determinant.

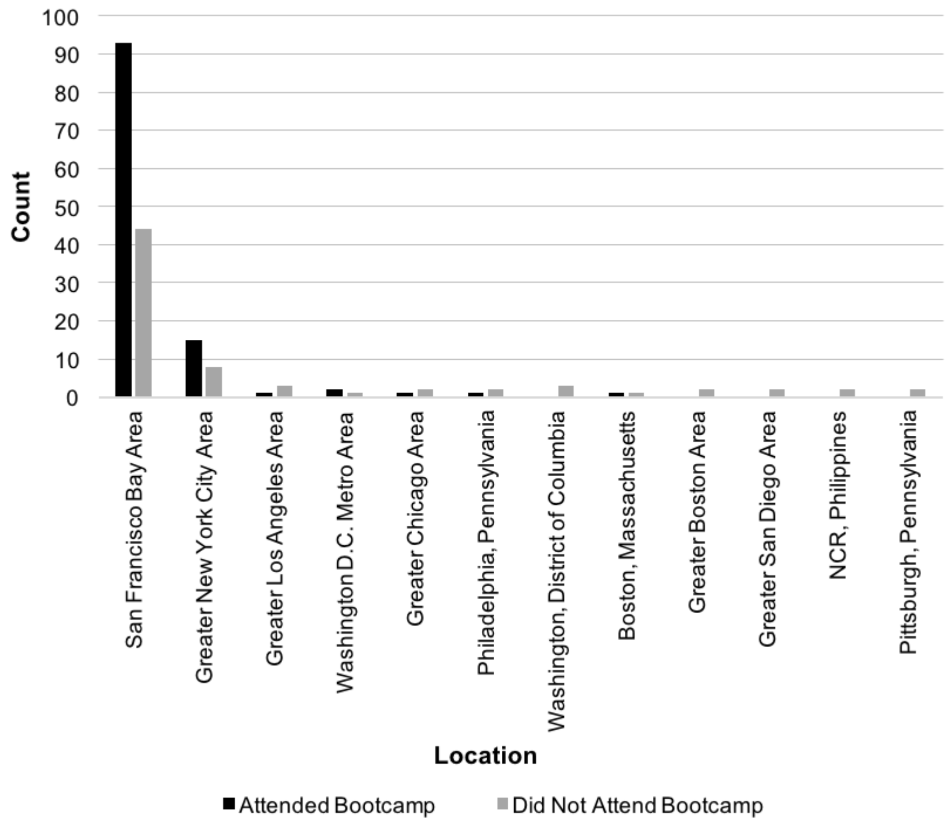
Prior to any analysis, the sample statistics also provide a visual representation of the difference in mean and distributions of first post-undergraduate job role and first post-bootcamp (or subsequent) job role. However, the study cannot make conclusions beyond speculation until further analysis has been completed.

Graph 1. Top institutions attended



Out of the 107 institutions in the sample size, the top 15 colleges for the sample size vary on multiple dimensions: location, size, type of school, public vs. private. While not represented in the top 15 institutions, the data also had community colleges such as De Anza College as well as technical schools such as the Aveda Institute. The large number of public California universities could be explained by a bias in LinkedIn's algorithm to the researcher's location. However, another explanation could be that larger schools have to spread resources amongst more students, and therefore students seek out other opportunities to advance their careers.

Graph 2. Geographic Distribution of Sample



A majority of the sample size is now currently located in San Francisco Bay Area and New York. As mentioned earlier, this could be a bias of LinkedIn's algorithm to the researcher's personal information. However, an alternate explanation can be provided as these locations provide the most job opportunity for the demographic studied.

Table 3. Graduation Years of Sample Size

	Control	Bootcamp Attendees	Total
1992	1		1
1996	1		1
1997	1		1
1999		*2*	2
2000		*2*	2
2002		2	2
2003	2	2	4
2004		2	2
2005		2	2
2006	2	6	8
2007	2	5	7
2008	2	1	3
2009	2	8	10
2010	10	10	20
2011	10	10	20
2012	8	7	15
2013	7	12	19
2014	9	14	23
2015	7	9	16
2016	9	11	20
2017	4	12	16
2018	4	3	7
2019		1	1
2020		1	1
Total	81	122	203

Most of the sample consists of more-recent graduates less than 10 years out of college, which matches the roles they enter as most of post-bootcamp roles are at entry-level engineering.

Table 4. Completion Years of Bootcamp Attendees and Year of Subsequent Job Role for Non-Bootcamp Attendees

	Control	Bootcamp Attendees	Total
2000	1	*n/a*	1
2007	1	*n/a*	1
2010	1	*n/a*	1
2011	1	*n/a*	1
2012	2	*n/a*	2
2013	7	4	11
2014	8	11	19
2015	7	9	16
2016	14	20	34
2017	18	22	40
2018	18	44	62
2019	3	14	17
Total	81	124	205

Most of the sample size recently completed their bootcamps or entered a new role. Given the time to recruit, the age of this cohort introduces further exploration on the sustainability of the success in their first roles. Most of the cohort were a couple months to a year into their first role post-bootcamp.

Table 5. Courses Taken by Bootcamp Attendees

	Number of Students
Adobe Indesign Bootcamp	1
Back End Web Development	1
Bootcamp Prep	4
Computer Programming	3
Computer Science	2
Computer Software Engineering	7
Data Science	2
Data Science	2
Full Stack Web Development	91
General Web Development	15
HTML	2
Intro to Front End Web Development	3
iOS Development	10
Mobile Development	2
Product Management	6
Ruby on Rails	1
Software Development	3
Software Engineering	9
UX Design	4
UX Design Part-Time	3
Total	171

The most popular courses are full stack and general web development, followed by iOS development, matching the growing labor demands of companies as mentioned earlier with regards to the "age of automation."

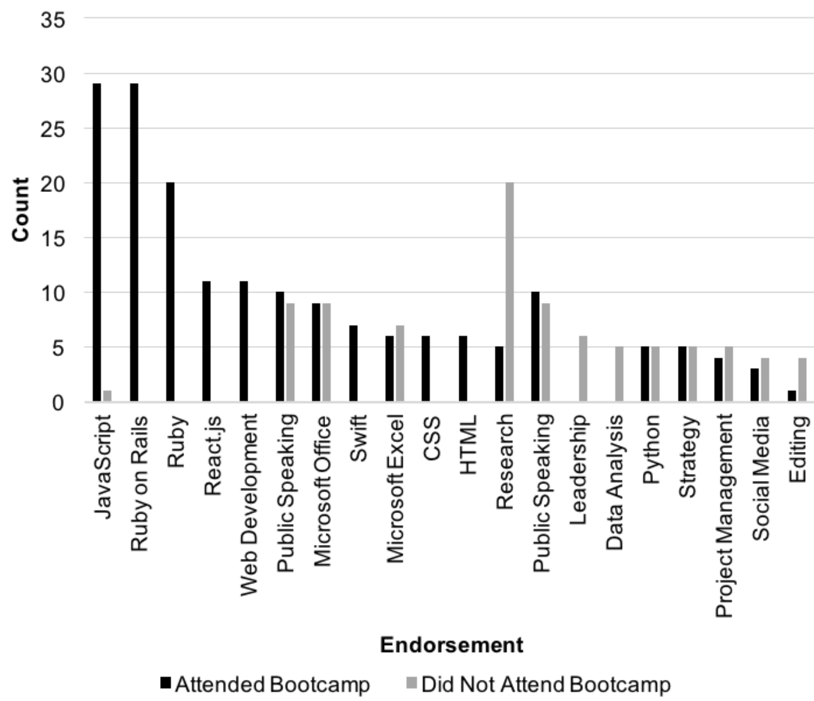
Table 6. Sample of Job Roles and Companies

Control			
Post-Undergraduate		Subsequent	
Sample Roles	Sample Companies	Sample Roles	Sample Companies
Account Representative and Leader	Active Mind Technology	Account Coordinator	#AllofUs
Americorps VISTA Volunteer Coordinator	American Institute for Economic Research	Account Representative	23andMe
Assistant Professor	Applied Materials	Assistant Professor	Boston University
Associate Account Executive	Argyle	Associate Consultant	California State Assembly
Associate Chemist	ARMGO Pharma	Associate Director of Financial Aid	Carnegie Mellon University
Associate Product Manager	Ateneo School of Medicine and Public Health	Business Development Manager	CBS Interactive
Field Organizer	Carnegie Mellon University	Chemistry Masters Student	Choate Rosemary Hall
Investment Banking Analyst	Cisco Systems	Client Relations Coordinator	Gilead
Linguistics PhD Student	JP Morgan	Co-Founder	UC Berkeley
Research Assistant	UC Berkeley	Linguistics PhD Candidate	UC San Diego

Bootcamp Attendees			
Post-Undergraduate		Post-Bootcamp	
Sample Roles	Sample Companies	Sample Roles	Sample Companies
Associate	Bank of America	Software Engineer	Affirm
Co-Founder	Carnegie Mellon University	Web Developer	Andreessen Horowitz
Project Manager	Cisco Systems	Full Stack Developer	Apple
Data Analyst	Goldman Sachs	Apprentice Software Engineer	EPAM Systems
Office Manager	Google	iOS Developer	Facebook
Sales Associate	24 Hour Fitness	Product Manager	Freelance
Field Organizer	Aclara Biosciences	Associate Product Marketing Manager	Google
Research Assistant	Allen & Company	Founder/CEO	LinkedIn
Lab Assistant	Amerifilm Casting	Junior Software Engineer	Self-Employed
Account Manager	AppNexus	Technical Coach	WeWork

The sample roles and companies post-undergraduate are similar for both groups. However, after the bootcamp there is an emergence of software engineers and web developers at technology firm unlike the attendee’s counterparts in the control group.

Graph 4. Top Ten Endorsements for Sample



JavaScript and Ruby on Rails/Ruby are the two highest endorsements for those who attended the bootcamp, whereas the control group had Research, Public Speaking, and Microsoft Office.

7. RESULTS AND ANALYSIS

7.1 Technical Role Placement Regression Results

As mentioned earlier, the primary regression in the study evaluates technical role placement based on factors related to undergraduate education and prior experience, with the treatment of attending an intensive coding bootcamp while factoring for any possible time variance based on undergraduate graduation year or bootcamp completion year. Time invariance arises due to the natural progression of the data which first requires an undergraduate degree and employment prior to enrollment in the coding bootcamp. Modelling for both time variant and time invariant helps understand both the factor time plays into technical role placement and how well the other factors predict for technical role placement.

Table 6. Technical Role Placement Testing for Time-Variance

	Dependent Variable
	Hired into Technical Role
Graduation Year: 1996-2006	-0.26
	(0.213)
Graduation Year: 2006-2013	-0.285
	(0.200)
Graduation Year: 2013-2020	-0.277
	(0.204)
Bootcamp/Second Role Completion Year: 2013-2015	0.010
	(0.145)
Bootcamp/Second Role Completion Year: 2015-2017	-0.126
	(0.128)
Bootcamp/Second Role Completion Year: 2017-2019	-0.111
	(0.139)
Attended Bootcamp	0.197
	(0.265)
Undergraduate Technical Degree	0.188*
	(0.097)
No Post-Undergraduate Technical Role	-0.694***
	(0.139)
Attended and Completed Bootcamp 2013-2015	-0.120
	(0.248)
Attended and Completed Bootcamp 2015-2017	0.092
	(0.232)
Attended and Completed Bootcamp 2017-2019	-0.101
	(0.236)
Attended Bootcamp without Post-Undergrad Technical Role	0.446***
	(0.169)
Constant	1.087***
	(0.227)
Observations	179
Log Likelihood	-64.427
Akaike Inf. Crit.	156.855
Note:	*p<0.1; **p<0.05; ***p<0.01

The first result of the regression addresses the role that time plays in predicting future technical job placement. Both undergraduate graduation year and completion year do not play a statistically significant role in job placement. The study attributes this lack of significance due to the significance of other factors in the model, such as prior experience as well as the existence of technical education either through an undergraduate degree or bootcamp. However, bootcamp completion year demonstrates preliminary trends that call for further exploration in future research. Older years having a positive effect on completion years can be explained by having more time to find a technical role. Based on observation, participants who had completed a bootcamp within 2013-2015 had already placed into a new job role and had recently progressed to more senior roles or different roles related to their post-bootcamp role. For non-bootcamp attendees, many of these roles were the continuation of school or senior positions at the same companies. However, the results for the cohort that attended a bootcamp and completed the course between 2017-2019 have a slight negative trend compared to their earlier counterparts that is not consistent with the trend in graduation years. While the results of the regression show no statistical significant, an interesting question for further exploration is whether coding bootcamp graduates have a longer time to hire than their counterparts from accredited and licensed universities. Because graduation year and bootcamp completion year are not statistically significant in this model, the study re-runs the regression excluding time factors (See Table 3).

The next results of the regression relate to education levels. According to the model, while an undergraduate technical degree only has a slight positive role in acquiring a technical role, the technical degree does not play as significant of a role as expected for this sample set. However, it is important to differentiate that this data does not suggest that technical role does not play a significant role in landing a technical role at all. For further context, in this data set, approximately 50% of individuals (*.48529 with statistical significance at* $p<0.01$*)* with an undergraduate technical degree will end up in a technical role after undergrad. Rather this data suggests that for an individual who is trying to enter the technical space will not be penalized for not having an undergraduate technical degree.

As hypothesized, the strongest predictor of a future technical role is a prior technical role. Furthermore, the results answer the question and support the original hypothesis that attending a bootcamp significantly helps non-technical graduates place into technical roles. Those who have a technical role and attend a bootcamp do not see as much of an impact explained for two reasons: first, their technical degree is more of a contributing factor to their placement. Second, someone who is enrolling in a coding bootcamp for “Full-Stack Development” or an “Engineering Immersive” who has a technical job may be trying to improve their coding or diversify their skills.

Table 7. Technical Role Placement Assuming Time-Invariance

	Dependent Variable
	Hired into Technical Role
Undergraduate Technical Degree	0.210**
	(0.095)
No Post-Undergraduate Technical Role	-0.648***
	(0.138)
Attended Bootcamp	0.174
	(0.159)
Attended Bootcamp without Post-Undergrad Technical Role	0.413**
	(0.168)
Constant	0.697***
	(0.132)
Observations	186
Log Likelihood	-75.544
Akaike Inf. Crit.	161.088
Note:	*p<0.1; **p<0.05; ***p<0.01

Assuming time-invariance highlights the importance of a post-undergraduate technical role into placement. The constant/intercept here represents the contribution of a post-undergraduate technical role assuming no bootcamp attendance or undergraduate technical degree. Furthermore, the statistical significance of the positive contribution of an undergraduate technical degree increases while the attending a bootcamp decreased. However, on an absolute scale, attending a bootcamp without a post-undergraduate technical role remains a statistically significant opportunity to increase the likelihood of landing a technical role. The combination of the time-variant and invariant results confirms and concludes the study's first and second hypothesis: graduates of coding bootcamps can place into technical roles, however, those with prior technical experience, especially previous technical employment are more likely to.

7.2 Propensity-Score Matched Pairs

As mentioned earlier, the study uses propensity-score matching to match the control and treatment group on factors related to their undergraduate factors of degree and graduation year as well as their first role post-undergraduate. The treatment here is the attendance and completion of a coding bootcamp prior to the individual's subsequent role.

Table 8. Comparison of unmatched samples

	Control	Treated	*p*
n	81	101	
Technical Undergraduate Degree *(mean (SD))*	0.05 (0.22)	0.18 (0.38)	*0.008*
Undergraduate Graduation Year *(mean (SD))*	2012 (4.69)	2011 (4.38)	*0.448*
Post-Undergraduate First Role *(mean (SD))*	0.10 (0.30)	0.18 (0.38)	*0.129*
Post-Bootcamp (Treatment) /Third Role (Control) *(mean (SD))*	0.12 (0.33)	0.72 (0.45)	<*.001*

Note: The sample size presented here is less than the total sample set as the matching estimator removes all data points with missing values.

At *p=.05,* the comparison of unmatched sample highlights a statistically significant difference in individuals with technical undergraduate degrees between the control and the treatment group. Therefore, although the treatment group shows a statistically significant increased likelihood of attaining a technical role, the study is unable to draw conclusions on the effect of the treatment prior to matching.

Table 9. Sample sizes

	Control	Treated
All	81	101
Matched	53	101
Unmatched	28	0
Discarded	0	0

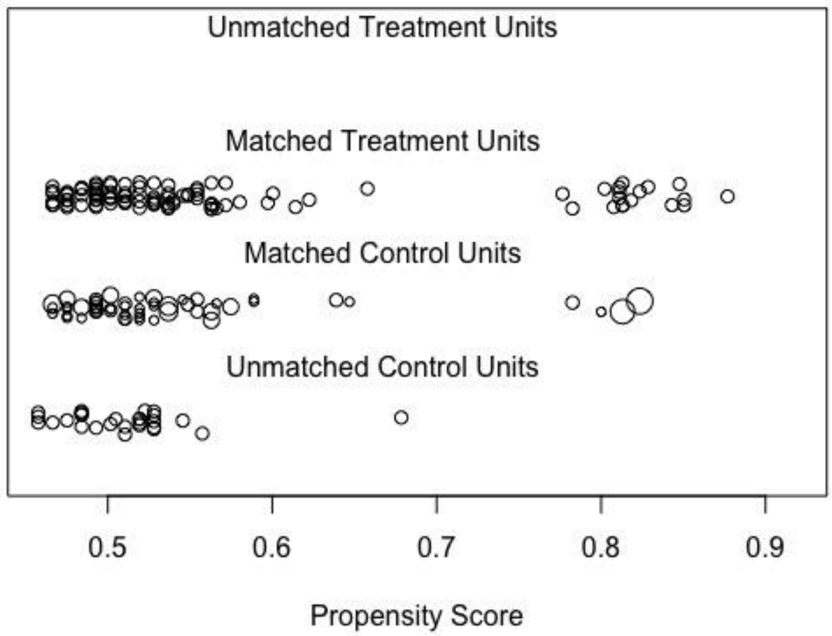
The table above shows the number of matched pairs (on average, each control unit was matched to approximately two treated units), leaving 28 control units unmatched. Furthermore, no units were discarded from the dataset.

Table 10. Summary of balance for matched data

	Means Control	Means Treated	Mean Diff
distance	0.57	0.57	0
Technical Undergraduate Degree	0.18	0.18	0
Undergraduate Graduation Year	2011	2011	-0.42
Post-Undergraduate First Role	0.21	0.18	-0.03

The summary of balance above shows the difference in means of the matched control and treatment group. The distance between the mean propensity score of the two groups is zero as well as for technical undergraduate degrees. The undergraduate graduation year of the control group is graduates on-average five months earlier and the control group has slightly more individuals in post-undergraduate technical roles than the treated group.

Graph 5. Distribution of Propensity Scores Across Unmatched and Matched Treatment and Control Data



The graph above provides a visual representation of the propensity-score matching between unmatched and matched treatment and control units.

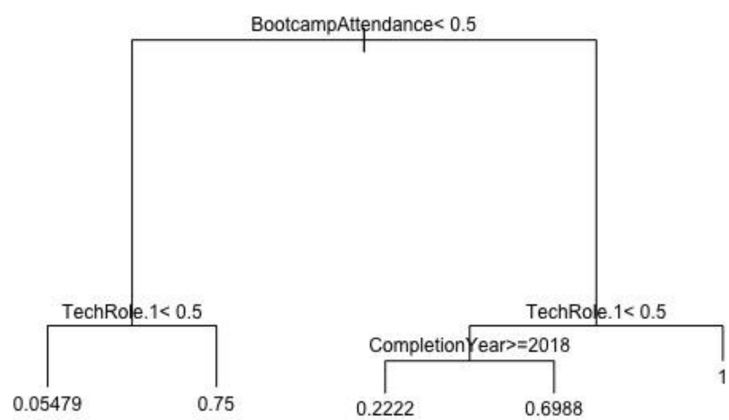
Table 11. Comparison of matched samples

	Control	Treated	*p*
n	53	101	
Technical Undergraduate Degree *(mean (SD))*	0.08 (0.27)	0.18 (0.38)	*0.084*
Undergraduate Graduation Year *(mean (SD))*	2012 (4.50)	2011 (4.38)	*0.859*
Post-Undergraduate First Role *(mean (SD))*	0.09 (0.30)	0.18 (0.38)	*0.167*
Post-Bootcamp (Treatment) /Third Role (Control) *(mean (SD))*	0.15 (0.36)	0.72 (0.45)	*<0.001*

Unlike the unmatched sample at *p=.05*, the matched samples show no statistically significant differences in background between the control and the treatment groups. However, there is a statistically significant difference in technical job placement between the control and treatment group. Using the matched pair method reconfirms the results of the regression that attending a bootcamp increases the likelihood of landing a technical role.

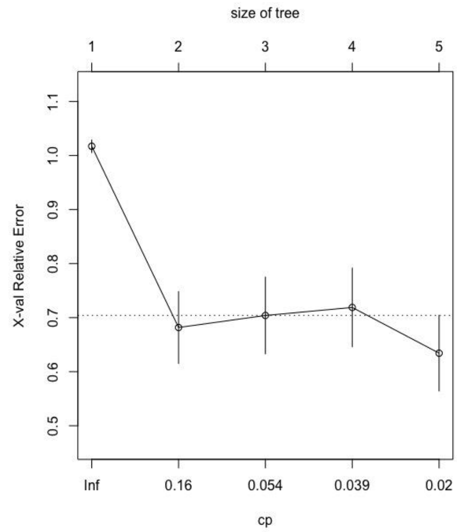
7.3 Classification and Regression Tree

Graph 6. Regression Tree for Future Technical Placement



The regression tree above indicates that bootcamp attendance is the cost minimizing factor to predict future technical job placement, followed by a previous experience a tech role as well as completion year. However, looking at the regression tree stand-alone does not provide the necessary insight to draw conclusions but rather the “least cost” path to accurate predict outcomes. The cross validation results below indicate the tree above is the result of overfitting.

Graph 7. Cross Validation Results



The increase in x-value relative error when the size of the tree increases from two to three indicates over-fitting has occurred. The plot of relative error against the complexity error shows that a cost and error minimization pruning would result in only the first split of whether the subject has or has not attended a bootcamp. The main takeaway is that there is insufficient data to accurately provide a classification tree that maps outcomes.

8. CONCLUSIONS AND SUMMARY

8.1 Summary

The objective of this study was to determine whether specialized, intensive bootcamps can successfully place non-technical college graduates into technical roles upon completion of the bootcamp. The findings of this study suggest that while the marketed placement rates are higher than actual rates, specialized, intensive coding bootcamps can place non-technical college graduates into technical roles. With regards to the strongest predictor, the study found that technical role is the strongest predictor of placement into a future technical role, however, attending a bootcamp without a technical role appeared to be a stronger predictor the technical undergraduate degree in this context. Furthermore, although completion year did not have a statistically significant impact on technical role placement, the study hints at higher rates of success from earlier graduates as opposed to more recent. While in line with general time for recruiting, these results provide a future opportunity for exploration as to whether time to placement is longer for bootcamp graduates compared to traditional technical graduates.

8.2 Further Exploration

To further understand the role of bootcamps for software developers and the computing industry, further studies around demographic analysis around geographic clustering within and beyond the US (i.e. companies such as Andela who train and place remote developers from Africa) are suggested. In addition, this research looks at immediate employment effects, however, the field can benefit from longitudinal research on the long-term sustainability of bootcamps compared to universities. While the completion year results are in line with general recruiting patterns, these results provide a future opportunity for exploration as to whether time to placement is longer for bootcamp graduates compared to traditional technical graduates. A further evaluation can be done by stratifying between different types of technical graduates, such as Associate's versus Bachelor's degrees for undergraduates as well as Master's and PhD programs on job placement. Finally, the rise of coding bootcamps has overshadowed the use of leadership and management bootcamps and workshops that have existed long before technical bootcamps. This initial exploration around the "hybrid role" suggests further exploration to whether having a business undergraduate degree supplemented by a technical bootcamp provides different outcomes in both short-term and long-term employment than a technical undergraduate degree followed by a business bootcamp.

REFERENCES

Acemoglu, D. and P. Restrepo. (2017). Robots and Jobs: Evidence from US Labor Markets. National Bureau of Economic Research, no. March 2017 https://www.nber.org/papers/w23285.

Al-Sakran, H. O. (2011). Development of Business Analytics Curricula to Close Skills Gap for Job Demand in Big Data. Information and Knowledge Management, vol. 5, no. 3 https://www.iiste.org/Journals/index.php/IKM/article/viewFile/20580/21001.

Attorney General's Press Office. (2017). A.G. Schneiderman Announces $375,000 Settlement with Flatiron Computer Coding School for Operating without A License and for its Employment and Salary Claims, https://ag.ny.gov/press-release/ag-schneiderman-announces-375000-settlement-flatiron-computer-coding-school-operating.

Bailey, T. R., and C. Belfield. (2018). The Impact of Occupational Licensing on Labor Market Outcomes of College-Educated Workers Community College Research Center, Teachers College, Columbia University

Bailey, Thomas R., and Clive Belfield. Stackable Credentials: Do they have Labor Market Value? Columbia University, 2017, http://www.dx.doi.org/10.7916/D8446038, doi:10.7916/D8446038.

Bajaj, R. H., and P. L. Ramteke. (2014). Big Data – the New Era of Data. *International Journal of Computer Science and Information Technologies*, vol. 5, no. 2: 1875-1885.

Bartels, A., N. Meneer, M. Guarini, M. Cecere, R. Valdovinos, I. McPherson. (2017). Debunking the US Tech Talent Shortage. Forrester Research Inc.

Beatteay, S.L. (2018). Let's Talk about Whiteboarding Interviews and the Possible Alternatives. Free Code Camp

Lighthouse Labs (2016). "Bootcamp Admissions.", https://lighthouselabs.ca/admissions.

British Academy of Media. (2013). Skills-Based Short Courses, Taught Online, are in Big Demand in 2013

Brown, J. and M. Kurzweil. (2017). The Complex Universe of Alternative Postsecondary Credentials and Pathways. American Academy of Arts & Sciences, Cambridge, MA.

Burke, Q., C. Bailey, L.A. Lyon, E. Green. (2018). Understanding the Software Development Industry's Perspective on Coding Boot Camps Versus Traditional 4-Year Colleges, ACM,

Cappelli, P. H. (2015). Skill Gaps, Skill Shortages, and Skill Mismatches. *ILR Review,* vol. 68, no. 2: 290.

Casimir, J. (2014). What Happened to Hungry Academy? Quora.

Chao-Ying, J., L.L. Kuk, and G.M. Ingersoll. (2002) An Introduction to Logistic Regression Analysis and Reporting." *The Journal of Educational Research* 96, no. 1

Christensen, G., A. Steinmetz, B. Alcorn, A. Bennett. (2013). The MOOC Phenomenon: Who Takes Massive Open Online Courses and Why? SSRN Electronic Journal. CrossRef, doi:10.2139/ssrn.2350964.

Council on Integrity in Results Reporting. "AUDITED JANUARY - JUNE 2016 GRADUATE OUTCOMES;", https://cirr.org/data.

Cross, P. K. (1976). An Introduction to Non-Traditional Education in the United States. US-USSR Seminar on Higher Education: 1-3

Dehejia, R.H. and S. Wahbha (2002): Propensity Score Matching Methods for Nonexperimental Causal Studies. *The Review of Economics and Statistics,* 84(1): 151–161.

Deloitte, Datawheel, and Collective Learning. (2014). Computer Science | Data USA.

Eggleston, L. (2017). 2017 Coding Bootcamp Market Size Study; Course Report

---. 2018 Coding Bootcamp Market Size Study; Course Report, 2018.

Enbar, A. (2018). What are Bootcamps Looking for in a Student?

Entangled Solutions. (2017). Assuring Quality Education Outcomes. https://www.educationqa.org/.

Hlavac, M. (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.2. https://CRAN.R-project.org/package=stargazer

Ho, A., I. Chuang, J. Reich, C. Coleman, J. Whitehill, C. Northcutt, J. Williams, J. Hansen, G. Lopez, and R. Petersen. (2015). HarvardX and MITx: Two Years of Open Online Courses Fall 2012-Summer 2014

Huard, P. and N. Joyaux. (2017). L'Oréal and General Assembly Launch "Digital Marketing Level 1". https://www.loreal.com/media/press-releases/2017/june/loreal-and-general-assembly-launch-digital-marketing-level-one.

Illanes, P., S. Lund, M. Mourshed, S. Rutherford, and M. Tyreman. (2018). Retraining and Reskilling Workers in the Age of Automation. McKinsey & Company. https://www.mckinsey.com/featured-insights/future-of-work/retraining-and-reskilling-workers-in-the-age-of-automation.

Indeed. (2017). What Do Employers Really Think About Coding Bootcamps? http://blog.indeed.com/2017/05/02/what-employers-think-about-coding-bootcamp/

Jong-Wha, L. (2018). This Is the Key to Surviving the Age of Automation. World Economic Forum. https://www.weforum.org/agenda/2018/09/education-in-the-age-of-automation.

Krishnan, A. (2018). The Race in Tech: Why Coding Bootcamps are a Hurdle.

Lientz, A. and Forbes Technology Council. (2018). Hiring Bias Starts at the Whiteboard https://www.forbes.com/sites/forbestechcouncil/2018/05/08/hiring-bias-starts-at-the-whiteboard/#d26cf0cb85f3.

McAfee, A. and E. Brynjolfsson. (2012). Big Data: The Management Revolution. *Harvard Business Review*, no. https://hbr.org/2012/10/big-data-the-management-revolution.

-- (2016). "Human Work in the Robotic Future: Policy for the Age of Automation," Foreign Affairs 95, no. 4 (July/August 2016): 139-150

McBride, S. (2016) Want a Job in Silicon Valley? Keep Away from Coding Schools. Bloomberg.

McKinsey Global Institute. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity.

National Academies of Sciences, Engineering, and Medicine. (2017). Information Technology and the U.S. Workforce: Where are we and Where do we go from here? The National Academies Press, Washington, DC.

Noda, A. (2017). Coding Bootcamp Hiring Stats are Still Misleading and Harmful.

Obama White House Archives. (2015). TechHire Initiative Available at: https://obamawhitehouse.archives.gov/issues/technology/techhire.

Petrone, P. (2018). The Skills Companies Need most in 2018 – and the Courses to Get Them.

Pew Research Center. (2016). The State of American Jobs. Pew Research Center.

Rosenbaum, P. and D. Rubin. (1983). The Central Role of the Propensity Score in Observational Studies For Causal Effects. *Biometrika*: 41-55.

Stewart, L. (2018). Changing the Face of the Tech Industry

Tambe, P. (2014) Big Data Investment, Skills, and Firm Value. *Management Science,* vol. 60, no. 6: 1452-1469.

U.S. Department of Education. Educational Quality through Innovative Partnerships (EQUIP) , https://tech.ed.gov/equip/.

Weaver, A. (2017). The Myth of the Skills Gap. *MIT Technology Review*, no.September/October https://www.technologyreview.com/s/608707/the-myth-of-the-skills-gap/.

Williams, A. (2015) Coding Bootcamp Vs. College. CourseReport.

Wixom, B., T. Ariyachandra, D. Douglas, M. Goul, B. Gupta, L. Iyer, U. Kulkarni, J. Mooney, G. Phillips-Wren, and O. Turetken. (2014). The Current State of Business Intelligence in Academia: The Arrival of Big Data. Communications of the Association for Information Systems, vol. 34. ABI/INFORM Collection China: 1-2.