Evaluation of Code Louisville Training Program

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Executive Summary

The Code Louisville (CL) program (administered by KentuckianaWorks) is designed to provide participants with training in modern computer software development (coding). The program was implemented in May 2015 and served over 1,400 participants between May 2015 and January 2018. The program is a departure from traditional Workforce Innovation and Opportunity Act (WIOA) training programs in that it uses online software to conduct the training, rather than the more common classroom style training, and combines a mentoring component in small groups. Typically, participants begin with the Front End Web Development track, and then may pursue up to seven additional tracks: PHP Development, Rails Development, iOS Development, Android Development, .Net Development, Python and Full Stack JavaScript.

Generally, the program has been oversubscribed and waiting lists for participation have, at times, been long. Bottlenecks include finding a sufficient number of volunteer mentors, finding space to accommodate mentor meetings, and administrative staffing levels.

The program serves a very different demographic group than other comparison programs. Code Louisville participants are more likely to have education beyond a High School degree, are younger, and more likely to be white.

Our evaluation of this program has three components: a qualitative study of the implementation of the program, a quantitative study of the outcomes, and a cost study. The qualitative study was performed by personnel at IQS research during the implementation to provide real time feedback to KentuckianaWorks.[1] The quantitative and cost study components are retrospective. All components are summarized in this report.

The qualitative findings include:

- Participants were initially frustrated with some components of the program, including changes during their sessions and misunderstandings of the role of the mentors.
- Later in the implementation of the program, participants were generally satisfied with the structure of the program.
- Employed participants are satisfied with their employment and with potential advancement. Participants who were not employed in software development roles generally considered the problem to be their lack of search effort.
- Mentors are excited and engaged in the program and are likely to continue to volunteer. Successful past graduates are now volunteering as mentors.
- Employers are generally satisfied with the skills of recent graduates, although some desire a stronger background in coding and more training.

The quantitative findings include:

- The overall completion rate of 58% is low compared to other programs such as Individual Training Accounts (ITA), Certified Production Technician (CPT) and Manufacturing and Employment Training Connection (M-TEC).
- Code Louisville participants have rising average earnings post program.
- Code Louisville participants used in a matched comparison to the ITA, CPT and M-TEC control groups experienced declining average earnings post program.

[1] The final implementation report is included in Appendix I.

- Code Louisville participants in the matched comparisons with more than a high school education have earnings changes that are more comparable to similar participants in other training programs.
- Code Louisville participants in the matched comparisons are less likely to be employed after enrolment than other training participants, although for some programs this gap closes over the first year.
- The employment rates during the first year for Code Louisville participants in the matched comparisons with more than a high school degree are comparable to similar participants in other programs.

Findings for the cost study include:

- The cost per participant is $1,095 which is significantly less than the cost per-participant in the ITA ($4,281) and CPT ($1,383) programs and is comparable to the per-person cost of the M-TEC ($1,117) program.
- The cost per participant is also less than the national average per-participant cost of the WIOA program of $1,765.
- If volunteer mentors were paid this would add $204 per participant to the cost. Even with the additional cost, the cost per-participants of the Code Louisville program would still be less than the ITA program, comparable to CPT program, and slightly more than M-TEC program.

Given the very different demographic group that participates in Code Louisville, the matched comparisons may not fully describe the overall experience of Code Louisville participants. Further investigation of both the short and long run earnings and employment profiles is warranted. While the comparison to other training programs is informative, the differences in type of participant may be affecting our results. It appears that Code Louisville participants who are more educated than the typical participant in the comparison programs performs much better relative to similarly educated participants in the comparison program. However, because they look different than participants in the comparison programs, these more successful participants receive less weight in the overall evaluation of the Code Louisville programs suggesting that the Code Louisville program is unique and may require additional investigation and different methodology to estimate the impact of the program on the typical participant.

Intervention

The Code Louisville (CL) program is designed to provide participants with training in modern computer software development (coding). The program is also motivated by an identified need for software development talent in the Louisville Metropolitan area. The program is open to adults in Jefferson, Bullitt, Henry, Oldham, Shelby, Spencer, and Trimble counties in Kentucky as well as Clark, Crawford, Floyd, Washington, Harrison, and Scott counties in Southern Indiana. The program is administered by KentuckianaWorks and is targeted towards individuals who would qualify for training through the Workforce Innovation and Opportunity Act (WIOA).

The program is a departure from traditional WIOA training programs in that it uses online software to conduct the training rather than the more common classroom training. The advantage of the online approach is believed to be lower cost and a more flexible time commitment: participants can work at their own pace at times convenient for them, rather than attending classes at times determined by the program that may conflict with other commitments.

The program uses the TreeHouse system to provide course content, including video lectures and reference material. The system also provides the ability to track participant progress and provide feedback on assignments. A second online element is SLACK, which provides participants an online interface between other participants in the mentoring group and their mentors. SLACK allows for online discussions and responses by mentors, other participants or program administrators to participant questions.

A second key difference is the mentoring program. Participants are assigned to small mentoring groups of approximately twelve participants, led by volunteer mentors who provide support during the program. The mentors are experienced software development workers in the Louisville Metropolitan area. Mentors typically met with the students as a group on a weekly or bi-weekly basis and responded to online discussions and emails throughout the week. The mentoring program is seen as bringing accountability, guidance, and support to the learning process.

The program also includes job placement services and assistance in a variety of forms. Job readiness workshops and one-on-one meetings are key components of the job placement services that are tailored to the tech industry. In focus groups, these were often cited as crucial in helping with job placement. Additionally, social mixers were conducted and designed to provide participants with networking opportunities. The job placement services worked with local employers to identify potential matches and assisted participants with resume and other job search support. The program's job placement services are typically more hands on than the typical job placement services offered through KentuckianaWorks.

Following the nomenclature used by Code Louisville, we use the term "cohort" to mean a group of participants who started a training subject in a particular month and year. The program groups individuals into cohorts and then, within cohorts, into mentor groups. Cohorts last 12 weeks. Participants were told to expect to spend 15 hours per week working on the courses. Again, following terms used by Code Louisville, we call the particular subject in which a participant is receiving training a "track." Within each cohort, different participants may be learning different material depending on the track in which they are enrolled.

Cohorts were formed in May, July, and September of 2015, and then in January, May and September of subsequent years (note, the dates are not exact and may have started slightly later). Every effort was made to accommodate all registrants in each cohort. In some cases, registrants who were contacted failed to follow up and start the program. This rate significantly increased when Code Louisville added prerequisites to the program. Participants were required to complete some basic computing modules on TreeHouse. Our focus in the analysis below will be on participants in the cohorts formed through January of 2018. As we will discuss below, this cut off was chosen based on the availability of post-participation earnings data.

The program allows participants to complete several tracks (topics) which provide training in different aspects of software development. Nearly all participants begin with the Front End Web Development track which teaches participants how to write and produce HTML, CSS and JavaScript for a website or Web Application. There were two exceptions to this typical starting path. Two cohorts (May and September of 2016) started with a track teaching Full Stack JavaScript which combines some of the front-end web development skills (HTML, CSS) with "back end" web development (e.g. management of underlying databases for a web page). The second exception was a small group of people who had already demonstrated some knowledge of the material from Front End Web Development and began the program with another available track.

In order to be considered a successful completion, participants must attend at least 9 of the 12 weekly meetings with the mentors and must complete all of the online curriculum assigned for that module within the twelve-week period. Additionally, they must attend at least two events (conferences for example) where technology is the main subject of the event and where they will meet new people in the technology field. Finally, each participant must submit a final project within the twelve-week window, which demonstrates the skills developed and would suitable as a "portfolio" element in their job search.

After completing the initial track, participants are able – but not required – to pursue training in up to seven additional tracks: PHP Development, Rails Development, iOS Development, Android Development, .Net Development, Python and Full Stack JavaScript (or Front End Web Development for those starting in May and September 2016). Different tracks were offered in different time periods depending on both student demand and feedback from industry. Each of these tracks allows participants to further develop software design skills.

After completion of at least one track, participants were eligible for job placement assistance through the Code Louisville program and its partnerships with local companies seeking software developers.

Target Populations

The broad target population for the study are individuals eligible for either WIOA displaced worker or disadvantaged worker training programs. Most of the participants are classified as a disadvantaged worker, however, some are classified as a displaced worker. Further refining this population, the Code Louisville programs focuses on job seekers who are interested in pursuing job training or educational programs and not simply programs designed to help them find a job. By focusing on job seekers who qualify and pursue WIOA programs we can compare Code Louisville participants who are similar to individuals in other WIOA job training programs. Our analysis is designed to assess whether this novel program provides the same or larger benefits than the other existing WIOA programs at a lower cost.

Code Louisville participants are recruited through advertisements in one-stop centers, on television, radio and in print media. Counselors at the one-stop centers may recommend this program to individuals seeking job training. Since this program is not designed to replace any large-scale program, it is likely that this type of recruiting will continue as the program expands.

Research Questions

The research questions outlined in the RFP for evaluators, the proposal and the ERD have guided our data collection and evaluation. The central question is whether the Code Louisville program is as effective at providing job training for job seekers and is more cost effective than other job training programs available as part of the WIOA Adult programs. Given that this is a new type of program, a related and important question is how to structure the program to maximize the benefit of the program while minimizing the costs The implementation study was conducted during the study period, with results reported to Code Louisville quickly, so that adjustments could be made. We group the research questions into three different components: those that are part of the implementation study (typically approached with a qualitative analysis), those that are part of the outcome study (typically approached with a quantitative analysis) and those that are part of the cost study. The research questions are:

Implementation Study:
(1) *What program aspects are identified by participants as having value or needing change or improvement?*
(2) *Can the initiative rely on the programming coaches or are salaried instructors necessary?*
(3) *Are employers satisfied with computer programming skill level of students?*
(4) *Can program participants identify specific changes to the program that will yield better outcomes for them?*
(5) *How satisfied are students with the employment they obtain after the program?*
(6) *What career advancement opportunities do students have in the employment they have obtained?*
(7) Did mentors provide mechanisms to support students in their completion of the program?
(8) Are mentors engaged and willing to participate in the program in the future?

Quantitative Outcomes Study:
(1) *Is the completion rate of the initial required module in the CL program higher than completion rates of comparable training in the comparison groups?*
(2) *How does the length of time to employment from initial entry into the program and from completion of the program compare between the CL participants and the comparison groups?*
(3) *How do earnings profiles differ between the CL participants and the comparison groups?*
(4) *How does the length of employment compare between the CL participants and the comparison groups?*
(5) *Do completion rates, length of time to employment, and earnings differ by pre-program education levels for participants?*
(6) *Do completion rates, length of time to employment, and earnings differ by age of participants?*

Cost Study
(1) *How does the marginal cost of the program compare to other programs?*
(2) How well does the program scale? As the program grows will the administrative costs grow in proportion, or only the marginal cost per student?
(3) What are the cost implications of the mentors? How will the cost change if these become paid positions?

The Implementation Study questions focused on a continuous improvement aspect of the Code Louisville program and fit into the logic model by working to align the activities and outputs.[2] The study was designed to address concerns which arose in a pilot program administered by KentuckianaWorks. The results were exploratory and descriptive in nature.

The quantitative questions are focused on the outcome study which is designed to evaluate the final outputs of the program and are confirmatory in nature. We focus on comparing the Code Louisville program to three similar programs offered by KentuckianaWorks: ITAs, M-TECH and CPT.

The goal of the cost study is to determine if the cost structure of the Code Louisville program is comparable to other training programs. In Cost Question One, we focus on the marginal costs of participant activities: those costs which increase in direct proportion to the number of participants. In Cost Question Two, we focus on administrative and other costs which can be thought of as "fixed in the short run." These costs are directly associated with the program but are not directly tied to the activities of particular job seekers, and may not increase, or may increase slowly, with increases in the program size. We will be comparing the costs to those of other WIOA training programs, in particular, the ITA program.

A key issue in the cost structure is the cost of volunteer mentors which we address in cost question three. We examine the possibility of having to hire mentors to sustain the program and estimate cost structure changes.

[2] The Implementation Report is contained in Appendix I.

Background Studies

Early efforts at evaluating the effectiveness of job training programs culminated in the seminal paper by Robert LaLonde (LaLonde, 1986) which described some techniques that could be used to produce a rigorous evaluation of training programs and led to a significant world-wide increase in program evaluation studies. One resulting study is Orr, *et al.*, (1996) which discusses the results from the evaluation of the Job Training Partnership Act program. The study was conducted as a random assignment study. They found small but statistically significant impacts of job training on earnings for adult disadvantaged workers.

In 1998, the Workforce Innovation Act (WIA) allocated federal money to create a comprehensive workforce investment program which would provide not only training but a system of centers which would coordinate a variety of employment services. The provider in this study, KentuckianaWorks is one such center, providing employment services throughout the greater Louisville Metropolitan area.

Since its implementation in 1998, there have been relatively few attempts to evaluate the effectiveness of the WIA program. One early attempt is Hollenbeck, *et al.*, (2005) which studies the impact that WIA programs have on supplemental employment and earnings for participants in seven states. Similarly, Andersson, *et al.*, (2013) evaluate training programs in two states. Both find modest impacts of training programs. Hollenbeck (2009) examines WIA programs specifically. While the findings are mixed, he supports the conclusions these programs have some impacts.

One of the more comprehensive evaluations of WIA is the study by Heinrich, *et al.*, (2011) which examines WIA support and training programs across 12 states by following participants for up to four years. They find that participants in the adult disadvantage worker program (designed for individuals with poor work histories) experience larger increases in earnings and the probability of being employed than participants in the dislocated worker program. They find that participants in the dislocated worker program have insignificant gains in earnings and employment. This finding is important in our study as the individuals participating in the Code Louisville program are more typically classified as disadvantaged workers. The results from the recently released random assignment study of WIOA (Fortson, *et al.*, 2017) largely mirror the results in Heinrich, *et al.* (2008)

Two meta-analyses provide an excellent overview of these and other job market training evaluations. Card, Kluve, and Weber (2009) provide an analysis of 97 studies of 199 active labor market policies from around the world. They find that job search assistance programs have the highest impact, but this impact is relatively short term and fades over time. Job training programs appear to have smaller impacts, but these impacts are more long-lasting. They find that conclusions are not particularly sensitive to whether a randomized design was used or whether the evaluation was conducted using quasi-experimental statistical approaches. This is important to the validity of our study. Heckman and Smith (1999) provide some guidance in this and note that it is crucial to control for pre-program status well in advance of the entry to the program.

The analysis by Greenberg, Michalopoulos, and Robins (2006) studies 31 evaluations of 15 programs in the U.S. between 1964 and 1998 and find that the strongest gains for job search programs while only longer-term gains for job training programs. They also conclude that randomized control and quasi-experimental designs find similar results. A survey by Decker (2011) examines ten years of WIA research, and also finds similar results.

Our evaluation is not designed to address the research question of whether training programs as a whole, or this training program specifically has an impact on employment and earnings. Rather, we seek to determine whether this program has a larger or smaller impact compared to other similar programs already in place, and whether this program can provide that impact more cost effectively. We take as a starting place the results from the previous literature that job training programs have modest impacts on earnings and employment.

Authors such as Heckman, LaLonde and Smith (1999), Bloom, Michalopoulos, and Hill (2005), Mueser, Troske and Gorislavsky (2007), Cook, Shadish and Wong (2008) and Pirog, *et al.*, (2009) provide guidance on applying non- experimental methods to evaluate job training programs. While they are somewhat critical of non-experimental methods, Smith and Todd (2005) and Heckman, LaLonde and Smith (1999) find similar results are typically found using careful quasi-experimental approaches. In general, the literature cautions that controlling for basic demographic characteristics and prior labor market activities are crucial in accurately identifying the impact of job training programs. They also highlight that it is important to compare the outcomes for individuals in the same labor market. Of course, quasi-experimental evaluation has drawbacks compared to randomized control trials that provide an internally consistent approach to evaluating training programs. The largest concern is selection into the programs based upon unobservable characteristics. In terms of the treatment effect this is particularly problematic if the Code Louisville program replaces other programs (such as the ITA grants). The literature above makes suggestions on how to address these issues.

A related strand of literature examines the importance of computer skills and computer training on employment and earnings. Krueger (1993) is often cited as the earliest evidence that workers who use computers tend to have higher earnings. Other authors such as Doms, Dunne, and Troske (1997), Autor, Katz, and Krueger (1997) and Green (1999) have also provided evidence showing that the use of more advanced technology is associated with higher wages. The paper by DiNardo and Pischke (1997) cautioned against drawing strong causal conclusions from the Krueger findings by showing that higher paid, more productive, workers tended to use computers along with other managerial tools such as calculators, telephones and pencils in their jobs. Similarly, Entorf and Kramarz (1996) and Doms, Dunne, and Troske (1997) present evidence showing that workers who use computers tend to be more highly paid prior to starting to use a computer. This informs our study in two dimensions. As is noted above, this highlights the need to control for pre-training employment and earnings history. Secondly, it highlights why the study focuses on comparing this to other approaches to obtaining job skills training, rather than focusing on gains to computer training as compared to no training.

Hamilton (1997) found that more direct measures of computing skills, such as use of specific software and knowledge of specific programming languages, was associated with higher wages. Borghans and Weel (2001) showed that while there is a premium for specific computer skills, the premium does not differ with the level. Similarly, Vakhitova (2006) finds that Microsoft certification only provides returns beyond basic proficiency. Some certifications are associated with higher returns, but in general, the level of certification is not important. Vakhitova (2006) does not establish a causal relationship. Vakhitova (2006) does note that it appears that the basic and lower level certificates may be substitutes for higher education in employment decisions, while higher level certifications appear as compliments to higher education.

While online learning settings have been growing rapidly, and literature examining these approaches in general has grown rapidly as well. The 2010 Meta-Analysis (Means, *et al.*, 2010) identified over a thousand papers written on the topic in the previous decade. In their analysis of 50 of these papers, Means, *et al.*, (2010) find that overall online courses appear to do slightly better for learning outcomes than traditional face-to-face instruction (it should be noted that of 50 studies only 11 showed statistically significant positive gains; in contrast only 3 showed that online was statistically worse). Perhaps most important for this study, they find that blended approaches, those where the online course is combined with some face-to-face instruction, had the largest gains compared to traditional classroom settings (of the 11 significant studies, 10 of them were the blended type approach).

When authors compared different types of online approaches, they find little difference between the purely online and the blended online approach. A similar study to the work here is Caldwell (2006) who examines the difference between an online computer course and a blended computer course with both online instruction and an instructor-led lab component. In this case, Caldwell (2006) finds no significant difference in learning outcomes. Figlio, *et al.*, (2013) provides more recent evidence about online learning compared to face-to-face. In contrast to the general findings in the review by Means, *et al.*, (2010), Figlio, *et al.*, (2013) finds that face-to-face instruction produces slightly better learning outcomes. He also finds that the advantage of face-to-face is larger for average or struggling students.

While the studies reviewed by Means, *et al.*, (2010) and the Figlio, *et al.*, (2013) study provide an excellent overview of the impact of online learning compared to face-face, the primary outcome measure was learning outcomes, and the vast majority of these programs were in a collegiate setting. Our study will be focused on completion rates, earnings, and employment outcomes for a job training program. Some of the studies do provide some information on completion rates, but this tends not to be the primary focus either of the studies themselves and is seldom tested.

Perhaps the closest study to ours is Streich (2014) who examines the difference in earnings between students enrolled in traditional face-to-face type classes in a community college, with those who take the online courses offered by the community college. Streich (2014) finds large earnings gains for online students. She also finds that completion rates are higher for the online students.

The literature on mentoring programs is sparse and little of it relates to the type of program designed by KentuckianaWorks. Denny, *et al.*, (2014) examines a comprehensive student mentoring program at a major university in Ireland. They use a natural experiment based on an expansion of the program. The program is far more comprehensive that simply mentoring. Similarly, Nuria (2012) examines a high school intervention which included mentoring, in addition to other services and financial rewards to improve graduation rates and college matriculation. A number of studies have examined mentoring as a human resources development tool. Allen, *et al.,* (2008) review the mentoring literature in mentoring as a human resource (within a company) tool. However, the approach in the program here is somewhat different. The mentors serve a role as both advisors and tutors and motivators, similar to a teacher. To our knowledge, no program like this has been implemented or evaluated.

The above studies inform our approach to evaluating the Code Louisville program in a number of different ways. The Code Louisville program is most closely related to the adult disadvantaged worker WIOA program. Current information suggests that it is attracting younger workers with relatively short spells of employment and little total labor market experience. While the Code Louisville program is not part of WIOA, participants in the WIOA disadvantaged worker program are an important comparison group. The studies above highlight that controlling for detailed demographic and labor market information is critical. We have worked with KentuckianaWorks to obtain past employment history as well as detailed demographics characteristics from participants. In addition, based on the results from the literature on computer skills and wage premiums we keep track of the specific types of IT skills obtained through training. Our study informs the literature on the efficacy of blended online learning as compared to traditional face-to-face learning styles for labor market outcomes, however, our study is not designed to assess learning outcomes.

Data Sources and Data Collection

Data for the three analysis areas were obtained from multiple sources. For the qualitative (implementation) analysis, performed by personnel at IQS Research, focus groups and directed interviews were conducted. Three broad types of individuals participated in the focus groups and interviews. A summary of these groups is presented in Table 1 below.

The largest group was focused on participants in the program. Over the course of 2016 through 2018 a total of five sets of participants in the Code Louisville program were included in interviews or in focus groups. Different sub-populations were targeted including program participants having recently completed the first track, those completing a second more advanced track, those who had completed at least one track but were not employed in the coding industry, and those who had completed at least one track who were employed in the industry. A total of 98 Code Louisville participants were included in one of the student focus groups or interviews.

The second largest group were mentors. Between 2017 and 2018 two sets of mentors were included in focus groups designed to understand their motivation and availability continuing forward. In all cases, any individual who had served a mentoring role between 2015 and the time of the interviews were eligible, but generally more recent mentors made themselves available for participation. A total of 33 mentors participated in one of the focus groups.

Finally, a total of 19 employers were interviewed. These interviews occurred in the spring of 2017, two years into the Code Louisville trial. These 19 individuals represent 17 companies with wide variation in the number of coders employed. The individuals were typically supervisors of workers who produce code and thus supervisors of recent Code Louisville graduates. As such, they had direct knowledge of the graduates and typically were employers who were aware of the Code Louisville program.

Table 1: Subjects in Qualitative Study (Implementation Study)

Subject Category	**Sub-Category**	**Dates**	**Number of Subjects**
Code Louisville Participants	Current Participants with one completed track	April 2016	9
Code Louisville Participants	Current Participants with one completed track	August 2016	19
Code Louisville Participants	Current Participants with two completed tracks	December 2016	16
Code Louisville Participants	Participants completing a track not employed in SDLC	June 2017	28
Code Louisville Participants	Participants with a completed track employed in SDLC	April 2018	26
Mentors		August 2016	21
Mentors		August 2017	12
Employers		May 2017	19

Note: Implementation Reports included in Appendix.

Recruitment of Code Louisville participants as subjects for the focus groups or interviews typically followed a two-stage progression. First, the focus groups (or interviews) were announced through the online platform (ASANA) used by Code Louisville to communicate general announcements to program participants. Second, an email list of Code Louisville participants was provided to IQS Research personnel who then directly emailed Code Louisville Participants with a request to be subjects in the study. The participant list consisted of names and emails of all potential subjects (for example, those in the January 2016 Cohort who completed the Front End Web Design track). Initially, recruitment for focus groups and interviews did not use incentives. However, based on smaller than desired response, incentives were offered (typically a $50 gift card) to all later subjects. Participants in the student focus groups were diverse with respect to race and gender and in terms of their activities outside of the Code Louisville program. Some were currently working full-time while others had family obligations.

Recruitment of mentors followed a similar pattern. An email list of potential subjects was provided by Code Louisville to IQS. An email was sent directly from IQS personnel and a gift card incentive was offered. While nearly all the mentors participating in the focus groups were white males, they had varied experiences volunteering for Code Louisville. Mentors have been volunteering for Code Louisville anywhere from one to five years, with some mentors having completed Code Louisville courses themselves. All of the mentors were currently employed as software developers at the time of their participation in the focus groups.

Recruitment of employers was initiated with an email from IQS based on a list of firms that had participated in employment activities coordinated by Code Louisville. No incentives were offered for employer interviews.

Data for the quantitative outcomes analysis was obtained from two sources. The first, and primary source of the data, were individuals registered for the Code Louisville program. Code Louisville initially tracked participants through a pair of systems. First an online web site that fed the information into the "Client Track" system when participants began their first track. The Client Track system works with WIOA and state unemployment agencies to track participants served by agencies like KentuckianaWorks. After 2016, KentuckianaWorks began tracking all registrants through Client Track. The Client Track system provides basic data on their progress through the program as well as demographic, education and some basic employment information. Similar data were obtained for participants in the three comparison programs: Individual Training Account recipients, Manufacturing and Employment Training Connection (M-TEC) and Certified Production Technician (CPT).

These data were also provided to the Kentucky Center for Statistics (KYStats). The center houses administrative data from the state of Kentucky, including employer quarterly earnings reports for unemployment insurance purposes, known as UI earnings records data. KYStats then matched the participants in the programs to quarterly earnings data from the UI records. This provided data on earnings and employment both prior to entry to the training program and for a year post training.

Implementation

KentuckianaWorks was able to initiate the program under the name Code Louisville in early 2015. The first cohort was formed and began training in May of 2015. While Code Louisville has done some limited advertising for the program, a speech by then President Obama while visiting Louisville in the spring of 2015, and word of mouth seems to have generated substantial interest in the program during the last four years.

Typically, the program has been oversubscribed, with Code Louisville maintaining a wait list of up to 1,000 individuals. The constraint on the program has been finding volunteer mentors, suggesting that mentors' opportunity cost could be substantial and should be included in the costs. Given the difficulty of finding mentors to meet the demand, scaling up the program may require hiring permanent mentors, or changing the program's current mentorship component

A total of 1,421 individuals have started through January of 2018. An additional 1,066 individuals were registered (prior to January 2018) in the online system but failed to start any track. The vast majority of these individuals were "wait listed" and represent potential participants after January of 2018. Our analysis below will focus on those who started a track. Of the 1,421 individuals who started a track, 822 (or 58%) completed at least one track.

Table 2 provides counts of participants by cohort. The columns labelled “All Starts” includes all individuals who started a track during that cohort. This includes not only people starting the first track, but also individuals who failed to complete that track in a previous cohort and are attempting it again, as well as individuals who completed their first track and are now pursuing an additional track. The columns labelled “First Time Starters” are those who were enrolled in a track for the very first time. The first cohort, May 2015, consisted entirely of individuals in their first attempt at any track. By September of 2016, roughly half of participants were either retaking the first track or a starting an additional track. It is interesting to note that, of those who completed at least one track, 91% completed it on their first attempt. There are 71 individuals who retook their first track and completed it. Individuals may enroll in additional tracks in any future cohort. They are not required to take tracks at any particular time or order.

Table 2: Participation and Completion by Cohort

Cohort	All Start	First Time Start	All Completers	First Time Completers	Percent Any Complete	Percent First Time Complete
May 2015	265	265	125	125	47.2	47.2
July 2015	179	167	69	66	38.6	39.5
September 2015	212	102	90	43	42.5	42.2
January 2016	244	106	134	66	54.9	62.0
May 2016	177	111	75	39	42.4	35.7
September 2016	246	130	79	35	32.1	26.9
January 2017	269	129	170	90	63.2	69.8
May 2017	254	120	122	75	48.0	62.5
September 2017	258	138	152	107	58.9	77.5
January 2018	322	153	185	104	57.5	68.0
Total	2426	1421	1201	750	49.5	52.8

Note: Data provided by KentuckianaWorks include all individuals who started a track in the Code Louisville program.

Table 3 presents basic descriptive statistics on the 1,421 participants who started at least one track. These data derive from those collected at registration by Code Louisville and missing values are not uncommon. The typical participant was 33 years old when they started the program. Fifty percent of the participants were between 27 and 39 years old. Women comprised 32% of the participants, while 74.8% reported a primary race of white. This percentage of whites is identical to that reported for the Louisville-Jefferson County Metropolitan Area in 2017 U.S. Census data. Twelve percent of participants reported their race as Black (or African American), which is less than the 22% reported in 2017 U.S. Census Quick Facts. However, if all those who refused to respond to the race question were Black then the percent Black would match Census statistics. Asian participants were 4% of the total, much higher than the less than 1% reported in Census data as living in the Louisville MSA. Hispanics were 5% of the participants and Veterans were 5.7%. We coded all non-response to the veteran status question as non-veteran since there is substantial incentive in the WIOA system to claim veteran status since they are a priority group. Very few individuals responded to the disability question, of those who did 4.6% report being disabled. If we assume non-response as no disability the rate falls to 1.7%.

Finally, we note that 73% of participants reported Kentucky residency, while 10% reported living in Indiana. The remaining 17% did not provide any address information. Jefferson County includes the city of Louisville and nearby suburbs and accounts for at least 66% of participants. Bullitt and Oldham counties account for the next largest percentage of participants at 2.2% and 2.7% respectively. These two counties contain many of the nearest suburbs to Louisville.

Table 3: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.
Age	1,192	33.5	9.7
Percent Female	1,194	31.9	46.6
Percent White	1,249	74.8	43.4
Percent Black	1,249	12.3	32.9
Percent Asian	1,249	4.2	20.0
Percent Native American	1,249	1.6	12.6
Percent Pacific Islander	1,249	0.4	6.32
Percent Hispanic	1,164	5.33	22.5
Percent Veteran	1,421	5.70	23.2
Percent Ever Finish the Program	1,421	57.8	49.4
Percent in Jefferson County	1,421	66.2	47.3
Percent in Kentucky	1,421	73.4	44.2
Percent in Indiana	1,421	9.99	30.0
Percent Disabled	528	4.55	20.8

Note: Data provided by KentuckianaWorks include all 1,421 individuals who started a Code Louisville track between May 2015 and January 2018.

Table 4 presents the distribution of education levels for the participants. As we will discuss below, this group is more educated than the typical WIOA participant. Nearly 10% of participants claim a GED or High School diploma, while over 50% claim a Bachelor's degree or higher education, including 13% reporting having a Master's degree and 1.3% reporting having a Ph.D.

Table 4: Educational Attainment

Education	Freq.	Percent
Other	2	0.2
GED	10	0.9
High School	104	9.2
Voc. Training	7	0.6
Some College	308	27.1
Assoc. Deg.	90	7.9
Bachelor's	449	39.5
Master's	151	13.3
Ph.D.	15	1.3
Total	1,136	

Note: Data provided by KentuckianaWorks. include all 1,136 individuals who started a Code Louisville track between May 2015 and January 2018 and provided valid educational attainment.

While the Department of Labor guidelines for demonstration grants require participants to be enrolled in WIOA, due to a misunderstanding of the requirements and the large number of applicants to the program in 2015 and 2016, Code Louisville personnel did not enroll many early participants in WIOA. The program was designed to provide this training opportunity to those eligible for the Adult Worker or Displaced Worker WIOA programs. To be eligible for these programs, workers had to either have been displaced from a previous job, economically disadvantaged or facing a significant barrier to employment, such as being a single parent of a young child. Once DOL auditors pointed out to the Code Louisville administrators that they were not following the guidelines, they began documenting eligibility and registering all participants in one of the two WIOA program.

Table 5 provides the number of participants enrolled in WIOA by cohort. Table 6 presents similar summary statistics as Table 2, limited to those participants who were enrolled in WIOA. Similarly, Table 7 presents the educational tabulations only for those participants enrolled in WIOA.

Table 5: WIOA Enrollment by Cohort

Cohort	Not Enrolled	Enrolled	Total
May 2015	234	31	265
July 2015	148	19	167
September 2015	82	20	102
January 2016	71	35	106
May 2016	72	39	111
September 2016	54	76	130
January 2017	0	129	129
May 2017	0	120	120
September 2017	0	138	138
January 2018	0	153	153
Total	661	760	1,421

Note: Data provided by KentuckianaWorks and include all 1,421 individuals who started a Code Louisville track between May 2015 and January 2018.

Table 6: Summary Statistics for WIOA Enrolled

Variable	Obs.	Mean	Std. Dev.
Age	759	34.0	9.6
Percent Female	759	32.1	46.7
Percent White	759	76.7	42.3
Percent Black	759	13.3	34.0
Percent Asian	759	5.3	22.4
Percent Native American	759	2.0	13.9
Percent Pacific Islander	759	0.6	8.1
Percent Hispanic	746	5.8	23.3
Percent Veteran	760	9.0	28.6
Percent Ever Finish Program	760	71.8	45.0
Percent Jefferson	760	79.5	40.4
Percent KY	760	87.6	32.9
Percent IN	760	12.1	32.6
Percent Disabled	121	15.7	36.5

Note: Data provided by KentuckianaWorks. Derived from 1,421 individuals who started a Code Louisville track between May 2015 and January 2018 and include only those who were enrolled in WIOA.

We note that a total 760 individuals were enrolled in WIOA and generally data are more complete for those individuals. The WIOA enrolment process itself provides some of these data. Comparing Tables 2 and 5 shows that for many of the demographic characteristics the two groups are quite similar. Those enrolled in WIOA are more likely to report their address, so we observe higher percentages of participants from Kentucky and Indiana, but the relative frequency is quite similar. One of the main differences between the WIOA group and the full sample is that we are more likely to have an address for the WIOA group. The other major difference between the two groups is that the WIOA group are significantly more likely to have finished at least one track. Overall, 58% of participants finished at least one track, while among the WIOA group, 71.8% completed at least one track. However, since the WIOA eligible are concentrated in the last five cohorts, which generally had higher completion rates, this may have little to do with WIOA enrolment.

Comparing Table 4 to Table 7, we see remarkably similar educational attainment between the WIOA group and the full sample suggesting that enrolling potentially non-WIOA eligible participants early in the program did not lead to the higher than typical levels of education among Code Louisville participants. One explanation for the rather high education levels (compared to other training programs) of the Code Louisville program could be the lack of attention to WIOA enrolment. This does not appear to be the case. Indeed, the two groups are remarkably similar: over 50% of the participants who are WIOA enrolled have a Bachelor's degree or higher education, with a full 15% having a Master's degree.

Table 7: Educational Attainment for WIOA Enrolled Participants

Education	Freq.	Percent
GED	3	0.6
High School	48	8.9
Voc. Training	3	0.6
Some College	144	26.7
Assoc. Deg.	44	8.2
Bachelor's	209	38.7
Master's	83	15.4
Ph.D.	6	1.1
Total	540	

Note: Data provided by KentuckianaWorks. and include the 540 individuals who started a Code Louisville track between May 2015 and January 2018, were enrolled in WIOA and provided valid education data.

We next turn to examining the tracks participants took and completed. As noted above, of the 1,421 individuals that started a track by January 2018, 1,110 (78%) of them began with Front End Web Development, while 236 began with Full Stack JavaScript. The remaining few individuals began with a variety of other tracks.

A total of 617 individuals started a second cohort, 469 of whom completed their first track on their first attempt. Of the 148 individuals who started a second cohort but had not successfully completed their first track, 135 had initially taken either the Front-End Web Development or the Full Stack JavaScript (the typical first tracks). Of those 135, 133 retook one or the other of the typical first tracks and 62 (or 46%) were able to finish it on their second attempt.

Table 8 presents the tracks and completion rates for those who participated in a second cohort and successfully completed their first track. We note that 88 participants attempted the other typical first track (Full Stack Java Script or Frond End Web Development), with Full Stack Java being the more common of the two. The most common second track was the .Net Development track followed by the PHP Development track (171 and 97 participants respectively). Overall completion rates were similar to those in first time cohorts, with 49.5%

completing their second track. This low rate of completion is somewhat surprising since this group all completed the first track, so one might expect higher completion rates of additional tracks. It appears that Python and .Net were the most challenging second tracks.

Table 8: Second Cohort Tracks for those Completing First Track

Track	Participants	Percent	Percent Completed
Full Stack Java Script	82	17.5	58.5
Front End Web Dev.	6	1.3	66.7
.Net Development	171	36.5	40.9
PHP Development	97	20.7	55.6
Rails Development	19	4.0	52.6
iOS Development	17	3.6	52.9
Android Development	28	6.0	53.6
Python	47	10.0	8.6
Group Project	2	0.4	100
Total	469		49.5

Note: Data provided by KentuckianaWorks. Individuals who have completed one track and enrolled in a second track.

Overall, 57% of the 1,421 individuals attempted only one track while 25% attempted two tracks and 18% attempted three or more tracks. Similarly, 42% completed no tracks, 38% completed one track, 14% completed two tracks and 6% completed three or more tracks. The vast majority of students were involved in only one cohort and completed only one track, while the plurality of students failed to complete any tracks, although the data in Table 2 shows that the rate of completing at least one track is higher in the more recent periods

An innovative component of the Code Louisville program is the use of volunteer mentors. Mentors were recruited from the Louisville metropolitan area and are individuals with experience in computer sciences broadly and coding in particular. The mentors were assigned small groups of approximately 12 participants each for a twelve-week period. The mentors met with participants for two hours per week and monitor an online discussion platform which typically takes 1 to 3 hours per week. Including preparation time, mentors contribute approximately five to six hours a week. Over the course of the last three years, the program has engaged over 150 volunteer mentors. Mentors cycle in and out depending on their time and interest.

Typically, the program has been oversubscribed, with wait lists reaching over 1,000 individuals at times. While detailed data on the wait list was not kept (especially prior to fall of 2016), and detailed information on wait listed individuals was not collected, the existence of waitlists, and patterns in later data, indicate there were many more people interested in participating in the program than there were slots available.

There appear to be three key bottlenecks in the process. First, and perhaps most important, is the availability of volunteer mentors. Since the size of mentor groups was limited to 12 participants, a typical cohort of 120 participants would require 10 mentors. In order not to overwhelm volunteer mentors, each mentor was assigned only one group during each cohort. Recruiting volunteer mentors was a significant and time-consuming aspect of the administration of the program, although recently there has been an increase in mentor participation. In particular, past graduates who obtained employment appear to be returning as mentors for the program, increasing capacity.

A second bottleneck in the process was finding space for mentor groups to meet. Again, with a typical cohort having roughly 10 groups, meeting at least once a week, securing an appropriate venue (with necessary internet access) was difficult for the Code Louisville staff.

The third bottleneck was administrative staff time. This time necessary for the three staff administrator to collect data for WIOA requirements, orient both mentors and participants, coordinate space, job placement limited the number of participants they staff could serve.

Logic Model

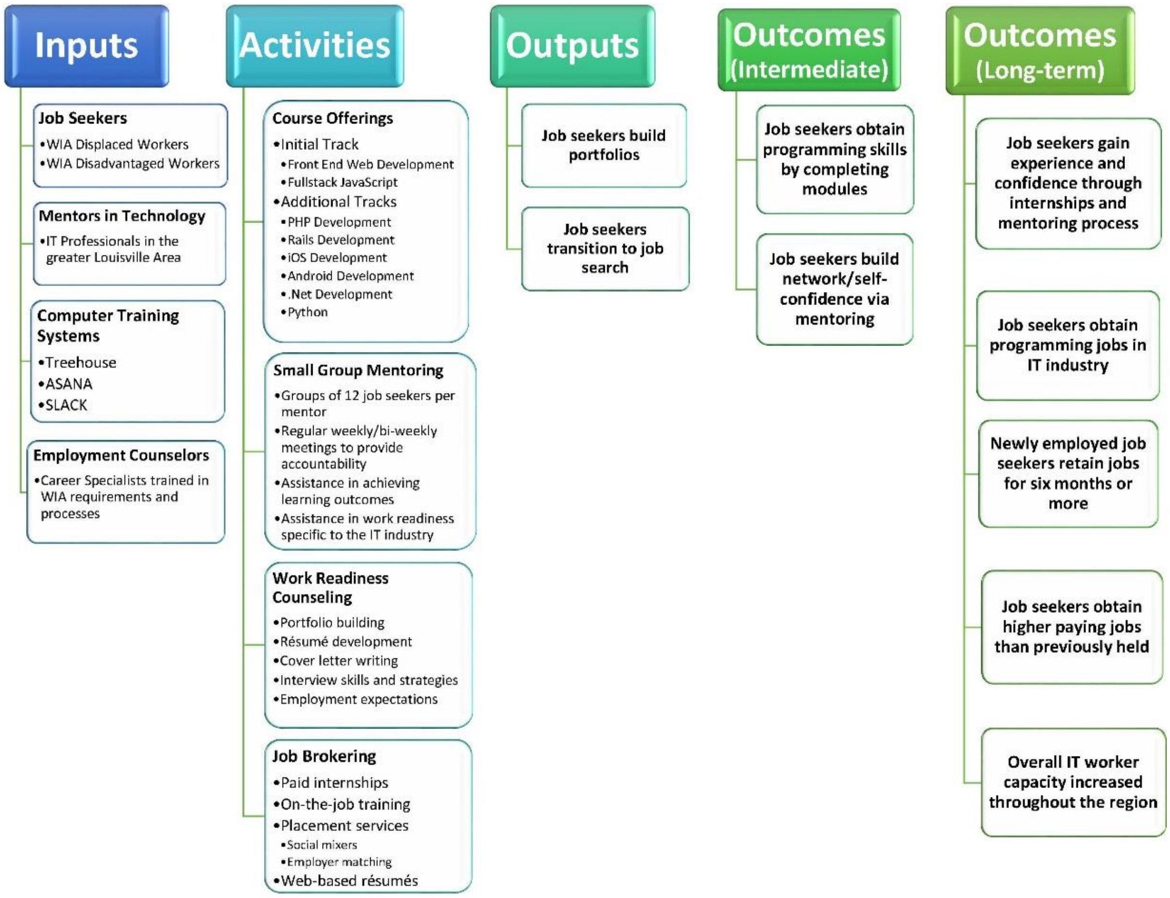
Our logic model, Figure 1, focuses upon the process of participants moving through the program, and the outcomes we will evaluate. Our main inputs are the participants in the program called Job Seekers, the mentors in the program, the computer training systems, and the employment counselors. Nearly all WIOA programs (such as those used below as comparison groups) utilize employment counselors and include participants who are Job Seekers. This program is unique in the inputs of mentors and online training systems.

The main activities are the course offerings through the online systems, the mentoring program, work readiness counseling and job brokering. The online course offerings include Full Stack Java Script, Front End Web Development, .Net Development, PHP Development, Rails Development, iOS Development, Android Development, and Python. The mentoring includes activities designed to help participants complete the program, both by providing an accountability mechanism as the mentors meet regularly with participants to monitor progress, and by providing additional tutoring to help participants who may struggle with certain aspects of the training. Additionally, the mentoring activities provide assistance in work readiness through informal advice and role modeling. Work readiness activities are supported by the WIOA counselors. Job brokering is supported through the relationships established by KentuckianaWorks with local IT employers.

The main outputs of the courses are the portfolios the job seekers complete during the modules. The portfolios along with the training itself provide the basis for the ability of job seekers to transition to active labor market search. Intermediate outcomes include programming skills which are marketable in the Louisville IT industry and the soft skills to successfully search for employment in the IT industry.

The desired outcomes of the program are to obtain employment, at wages higher than those they were able to obtain previously, and to maintain that employment for at least six months. Additionally, employment is specifically targeted in the IT industry to expand the number of workers with IT skills in the Louisville region. Our evaluation focuses on three of these outcomes: obtaining employment, earnings, and maintaining employment.

Figure 1: Logic Model



Note: Generated by authors.

Qualitative Analysis of Implementation

An important aspect of this project was the qualitative assessments performed through the course of the implementation of the Code Louisville Program. Personnel at IQS Research performed the analysis and provided timely reports to the Code Louisville program which allowed adjustments through ongoing assessment of the program. The qualitative assessment was designed to provide information about three main aspects of the program: the participants' overall satisfaction with the structure of the program, the participants' experience obtaining employment from the program, and the mentors interactions and commitments to the program. See the Research Questions section for the specific questions we address.

It should also be noted that the qualitative analysis was designed to be responsive to Code Louisville program administrators' concerns and questions about the program that arose during its development, and to follow up on issues discovered in earlier analysis. The implementation analysis took two major forms: focus groups and directed interviews.

Focus groups were conducted using in-person sessions which were comprised of up to twelve participants and which lasted approximately 90 minutes per session. A standard protocol of coordinating the sessions using discussion guides was followed so that groups feedback addressed a set of broad, pre-determined topics broached in a particular sequence, with the set of discussion guides fixed in each wave of research for each group of stakeholders.[3] In addition to covering the subjects addressed in the guides, the focus group moderator posed follow-up questions to explore unanticipated responses and encouraged discussion among focus group participants.

The facilitators' adherence to each session's discussion guide allowed the analyst—who attended each focus group along with the facilitator—to record live field notes matching the structure of the guide. The focus groups were recorded with a microphone, which allowed the analyst to review sections of the discussions and retrieve verbatim quotes for focused analysis and for inclusion in the presentation of findings. The analysis used a qualitative approach which is formally referred to as constant comparison analysis. In this process, thematic summaries of program participants' experiences were identified on the basis of the consensus or disagreements that emerged in the focus groups, rather than on the basis of a priori hypotheses formed before conducting the focus groups. In determining how best to articulate each theme, an inductive process of iteratively broadening and refining themes was used.

In depth interviews with graduates and employers of graduates were conducted using pre-written interview guides which standardized respondents' feedback while allowing interviewers the flexibility to adaptively pose questions responding to the unique feedback of each interviewee. In contrast to the focus groups, the in-depth interviews included not only open-ended questions but standard survey items using fixed wordings and rigid response formats (e.g. Likert response scales) which enabled the use of some quantitative techniques to summarize responses (primarily tallying responses and providing measures of central tendency). The feedback shared in responses to open-ended questions was analyzed using constant comparison analysis as well as classical content analysis wherein participants' comments were grouped into categories determined a-priori in the research design, whose prevalence in the total set of respondents' comments was then tabulated.

Recordings of the session were transcribed and analyzed for common responses and to focus on answering the major research questions above. Analysis of the transcribed focus groups and interviews was performed by personnel at IQS (who also conducted them). Major themes in the discussions and responses to directed questions were summarized and highlighted. These results were reported to Code Louisville throughout the process and used by staff there to adjust and improve the program.

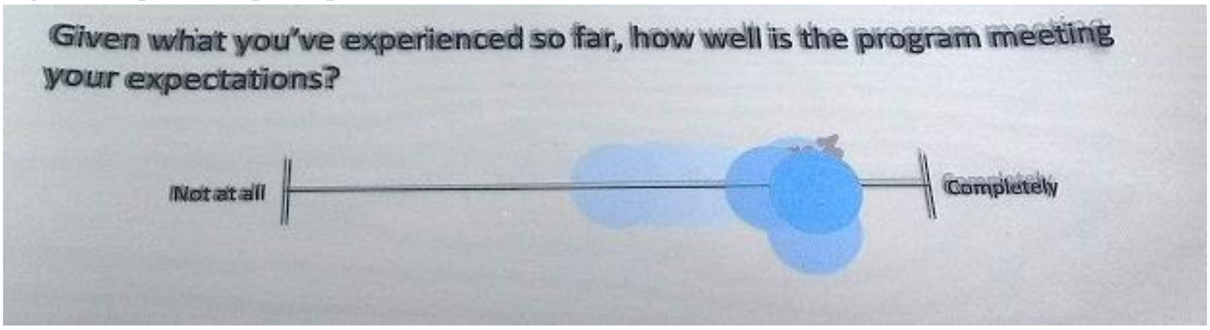
We begin by summarizing the participant focus groups and interviews. Questions 1,4 and 7 above focus on program participants satisfaction with the structure of the program with some emphasis on the role of the mentors. Three sets of two focus groups conducted in April of 2016, August of 2016 and December of 2016 engaged participants primarily from cohorts formed in January, May and September of 2016, respectively. The primary questions in these focus groups were overall satisfaction with the program and identifying specific aspects of the program that were either highly valuable or needed substantial improvement.

[3] e.g. A single guide was used for the two focus group sessions conducted with mentors in August 2016, and another guide was used for the two focus group sessions conducted with mentors in August 2017.

In each focus group, participants were asked to provide an evaluation of how well the program met their expectations by placing a blue sticker on a line labelled with "not at all" on the left and "completely" on the right (similar to a Likert scale). Figure 2 displays the April 2016 results, while Figures 3 and 4 display the August 2016 and December 2016 results of the same exercise. The three figures can be difficult to read as they are overlays of photographs of the actual responses by participants.

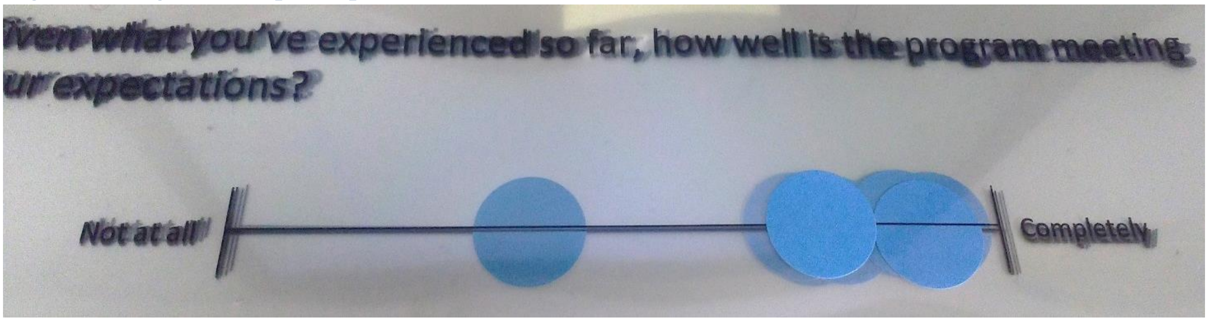
Overall, students' responses were strongly concentrated near the right of the line, representing strong overall satisfaction with the program. The satisfaction appears to have improved over the course of 2016 as well. In Figure 2, the darker blue areas about 80% of the way to "completely meeting expectations" although there is a distribution of responses in the middle of the line indicating that some participants found the program did not as completely meet their expectations. None of the lower responses were above the modal response. In Figure 3, the heaviest concentration of responses is again at about 80%, but the majority of the remaining responses are even closer to the "completely meets expectations" end of the line. However, there is still a small concentration towards the middle of the line. Finally, in Figure 4, all of the responses are concentrated is at about 90% satisfied level. However, the December 2016 focus groups were a selected sample of participants who had completed two tracks so we would expect these participants to be strongly satisfied with the program.

Figure 2: April 2016 participant satisfaction



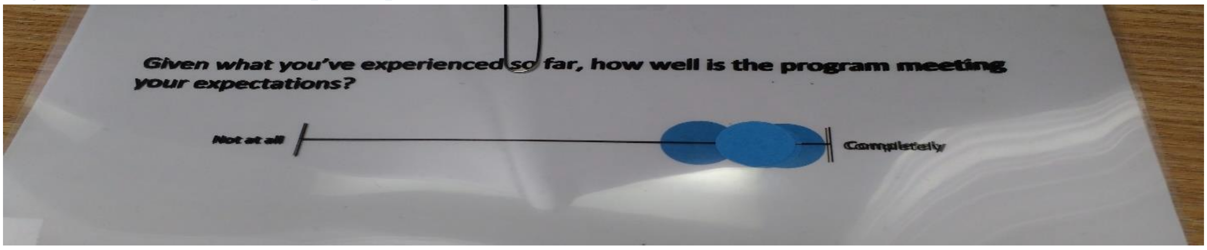
Source: See IQS May 2016 report in appendix.

Figure 3: August 2016 participant satisfaction.



Source: See IQS August 2016 report in appendix

Figure 4: December 2016 participant satisfaction.



Source: See December 2016 IQS report in Appendix.

Throughout the focus groups participants cited the fact that the program was free of charge to them as an important factor, allowing them to obtain valuable job training without incurring debt. Participants also expressed high satisfaction with the mentors and with the networking and social aspects of the program, allowing them a feeling of entry into the field. Participants were generally satisfied with both the online assignment software (ASANA) and the online communication software (SLACK).

The initial focus group in April 2016, with participants primarily drawn from the January 2016 cohort, exhibited some frustration with the program. Three key elements of frustration were expressed. First, participants were frustrated with the changes in the delivery of the program that occurred during their twelve-week session, which led to issues with organization and understanding expectations. A second frustration was that it was not clear what the purpose of the in-person group meetings with the mentors were. Finally, students expressed that the lectures and course content did not make them feel like they had mastered the material. They expressed frustration at course content that seemed to assume too much of the student and went too fast. Many were concerned that they did not have the skills necessary to work in the industry, even though they had successfully completed one track. The main take away from the early focus group is that the structure of the course should not change during the course.

It appears that most of these issues were resolved by the August focus groups as participants were generally more positive and did not express similar frustration. The one frustration that appeared to continue was concern that TreeHouse lectures did not provide participants with a sufficient level of detail about the subject. However, some concern about changes in course structure – typically now focused on TreeHouse – continued as well.

The December 2016 focus groups were comprised of participants who were completing their second track, typically the ".net" track (which was combined with C#). As such, these participants expressed that they were more prepared for the workload and understood how to make better use of the resources both in TreeHouse and ASANA, as well as interactions with the mentors. These two groups were generally highly positive about the program.

While not a focus of the final two groups of participant interviews (conducted in June of 2017 and April of 2018), some feedback on the structure and role of the program was a natural part of these interviews' focus on job placement. In general, the participants who engaged in these later two sets of interviews were quite positive about the structure of the Code Louisville program. It should be noted that the June 2017 interviews were conducted with participants who had not yet obtained employment. The main concern was that the Code Louisville program may not have provided them with enough training to obtain positions within the industry. However, participants in the April 2018 interviews –who had obtained positions – seemed to disagree with this assessment.

Mentors play a key role in this program and throughout the first three sets of focus groups were an important topic of conversation. Overall participants were very positive about the mentors and the role they play in the program. They expressed repeatedly and across all groups that the mentors were responsive and helpful both in the meet up sessions and through email and ASANA.

The main concern about the mentors was that the purpose of the meet up sessions (the regular mentor group meetings) was unclear. It appears that mentors used them differently as well. Some used them as time to answer specific questions of participants, often one on one or in even smaller groups. Some used them as additional lectures on specific content. At other times they appeared to be tech support meetings, helping participants with problems with their computers and the online systems. While participants expressed some frustration with this, it may be that this is the nature of this type system. With volunteer mentors, it may difficult to achieve uniformity. With participants from varied backgrounds, it may be that different approaches are necessary. It may also be that participant expectations of what the mentor system is designed to do was not well managed, though it may be difficult to manage these expectations (it should be noted that students in secondary education often have different expectations about the role of faculty and teaching assistants).

Overall, the participants generally expressed that the structure of the program was well suited to providing them the materials and the support they needed to be successful. It appears that as the Code Louisville staff became more experienced with administering the program, some of the early concerns were addressed. In summary, the program has value in providing training that participants desire (note also our observation in the introduction that the program is typically over-subscribed with a long waiting list), the mentors are a valuable component, the structure of the program, and particularly the online, self-paced structure, meets the needs of the participants (Question 1 above).

Aspects of the program needing change tended to be less structural and more incidental. As noted above, issues with changing the program mid-session and miscommunications about the role of the mentors appear to be largely addressed during the program without requiring major change in the program itself (Question 4 above).

Finally, the mentors appear to be a crucial part of the program. They provide a space for answering questions and support of a variety of kinds, including “cheerleading,” helping with networking and providing and clarifying content (Question 7 above).

We turn next to addressing questions five and six above, concerning participant satisfaction with employment obtained after completion of the program and opportunities for advancement within their new employment. To a lesser degree, this also answers question three, satisfaction of employers with participant skills.

Two sets of structured interviews were conducted with participants who had completed at least one track. The first set were conducted in the summer of 2017 with participants who had completed at least one track but had not obtained employment in a Software Development Life Cycle (SDLC) role. In order to obtain the sample to be interviewed, approximately 240 graduates who Code Louisville staff believed to not have obtained SDLC employment were contacted via email (in two waves) and asked to participate. As with the focus groups, a $25 gift card was offered as an incentive. The process of signing up for an interview included a screening question to ensure program participants were not employed. A total of 56 individuals provided responses to the screening question. Thirty-two responded that they were searching still, while seven had already obtained a job, eight were still completing tracks, and nine responded that they were not interested in obtaining an SDLC position. Ultimately, 28 individuals agreed to be interviewed.

The second set of structured interviews, conducted in April 2018, included participants who had completed at least one track and were employed in an SDLC position. A similar approach of contacting recent participants who had completed a track and were believed to be employed in an SDLC position was followed. A total of 26 respondents was identified and obtained. Again a $25 gift card incentive was offered.

In the first set of interviews, the primary objectives were to ascertain the participants' current employment status and then explore barriers and problems encountered in obtaining employment in an SDLC position. Of the 28 interviewed, 56% of the respondents were working full time and 15% were working part time (but not in a Software Development position). Twenty-five percent were unemployed. Nearly 70% of the interviewed participants had completed only one track, and 63% had completed that track within the last 6 months (during 2017, interviews took place in June of 2017). We note that the 26 respondents to the second set of interviews differed from the first group, in that the average participant had completed two tracks.

The typical respondent in the interviews with those not employed in SDLC spent a few hours each week in job search activities, was in regular contact with Code Louisville to assist with job search activities and expected a $50,000 a year position as a software developer. In assessing their barriers to employment, the interview asked about what activities they had completed to aid their search and the overwhelming majority had completed GitHub and LinkedIn Profiles as well as prepared a technical resume (common in the development industry). Similarly, the majority had participated in job readiness workshops and a one-on-one counselling session (through Code Louisville). They were heavily engaged in using online search platforms for positions in the Louisville area as well as attending networking meetings at tech events.

In general, the graduates who had not found employment in Software development cited two major issues. The first was their commitment in seeking such employment: 46% responded that they were not spending enough time while 32% responded that they were not trying hard enough. Overwhelmingly, however, the group was quite positive about Code Louisville, generally taking responsibility for their own search outcomes. Two factors however appear to be related to Code Louisville that could be improved. First, only 41% disagreed with the statement that they lacked the technical skills necessary to obtain employment. This, coupled with the observation that those who are happily engaged with SDLC employment, were more likely to have completed two tracks suggests that this is an important consideration. Additionally, many of those without SDLC positions would like more opportunities to network with potential employers.

Turning to the graduates of the program, a key difference, as already noted, appears to be the completion of more than one track in the program. Also, a key difference appears to be that these participants completed some of their work a year or two prior to the interviews (which occurred in April of 2018): many had completed at least one class at least as early as 2016 yet over half had found employment in the SDLC area within the last year (2017 or 2018). The majority (54%) had been hired into their current SDLC position from outside the company using their own search efforts (as opposed to a third-party placement company or temporary agency) while 15% had been promoted from within the company. Almost 27% of those cited placement through Code Louisville as an “other” and so it is possible that some of the 54% may have also found there employment through the Code Louisville placement or with some aid (Code Louisville was not a specific option, those selecting “other” provided that as an explanation).

The group of employed Code Louisville graduates was overwhelmingly positive about the role of Code Louisville in their employment: 96% agreed that they learned valuable information through Code Louisville training and 77% agreed that they could not have obtained the job without Code Louisville.

Overall, participants with SDLC jobs were very satisfied with their position: 69% of respondents reported being satisfied (or highly satisfied) with their current employment. In contrast, of the group without SDLC jobs, only 25% reported being satisfied with their current employment. Those with SDLC positions also find the position matches their expectations well (61%), 92% report being good at their job and 85% feel that they fit in with their company. Over 70% feel that they are well compensated and 61% like what their company does. These factors, in particular, feeling successful at their position, being satisfied with the mission of the organization and fitting in with the organization, were cited as major reasons for overall job satisfaction.

In looking to the future, 92% believe that they will continue in a software development role during the next two years and 57% believe they have opportunities to advance within their current organization.

Research question four above asks how satisfied participants are with their employment after the training. For those who obtain a position the evidence points to them being highly satisfied. However, it appears a relatively large group may not be obtaining positions. These individuals are not highly satisfied. Similarly, with research question five, those with SDLC positions see ample opportunities for advancement, those without positions may not.

Some of the results from the two interview groups address research question four – aspects of the program which could be improved - in the specific context of obtaining employment. The group who were not employed in an SDLC position did not see substantial problems with the Code Louisville Program. However, it appears that completing at least two tracks and participation in networking events may improve those outcomes.

We next turn to the interviews with representatives from employers who had hired Code Louisville graduates. These interviews address research question three, whether employers are satisfied with Code Louisville graduates as employees. Code Louisville staff provided contact information for 45 individuals (representing 34 unique employers) with supervisory and hiring roles who they believed had recently hired at least one Code Louisville graduate. Of the 45, 19 qualified individuals responded and participated in at least partial interviews. The respondents were a diverse group of employers with different experiences and backgrounds in the field. Respondents employed a varied number of developers at their organizations, ranging from four developers to 200. Eight companies had between one to 10 developers, and eleven companies employed between 11 to 200 developers. Experience employing developers ranged from six months to 21 years.

In general, employers found Code Louisville graduates ready to enter into entry level software development positions. However, only 56% of employers responded that Code Louisville graduates were qualified for the roles those employers most needed to fill. Comments suggested that those 44% who did not see Code Louisville graduates as qualified for the roles most needed fill are looking for programmers with broader and more experience and a deeper knowledge base.

In general, these employers were satisfied with their Code Louisville graduates: 59% thought they were performing well or extremely well, while none thought they were performing poorly. For a more detailed examination, employers were asked to rate their Code Louisville employees on cultural fit, interpersonal skills, work ethic, critical thinking skills, technical skill set/coding ability, and business acumen. Looking at the scores for these characteristics, employers were most satisfied with the cultural fit (88%) and their interpersonal skills (82%). Work ethic and critical thinking skills also receive high satisfaction marks of 81% and 75% respectively. Scores fall further when assessing an employee's technical set/coding ability at 67% and degree of business acumen at 50%. These indicate satisfaction across a broad range of attributes. Similarly, 53% of Code Louisville employers feel these graduates are performing better than developers in similar roles.

There does seem to be some concern about Code Louisville providing the necessary training to prepare graduates for the Software Developer market with only 47% satisfied with Code Louisville's ability to do so. Further only 6% were extremely satisfied. However, examining this leads to a similar conclusion as noted above: employers are seeking individuals with more experience and broader knowledge base. One might question whether this is something Code Louisville can or even should attempt to accomplish given the typical participant (with little prior coding experience) and the relatively limited time span for most participants.

Interestingly 57% of respondents indicated that they will likely hire more Code Louisville graduates.

Overall, the answer to research question three is guardedly positive: employers in general are satisfied with Code Louisville graduates, typically at least as satisfied as with other recruits into similar positions. Employers appear to desire to find a pool of workers with stronger skills and more experience. It should be noted that the Code Louisville program is designed to provide initial training in software development.

Finally, we turn to questions two and eight regarding whether the program can rely on the mentors and whether the mentors are engaged and satisfied. Two sets of mentor focus groups were conducted, the first in August of 2016 the second in August of 2017. Topics were similar, asking about their interest in the role, their impression of participants and their view of the program as a whole.

In 2016, a total of 66 mentors were contacted and 21 ultimately participated in one of two focus groups and were offered a $50 gift card incentive. Mentors were generally very positive and very excited about the Code Louisville program, with altruistic motives for their participation. The phrase, "give back to the community" was highly prevalent. Mentors are motivated by student success and by a feeling of making a difference. Mentors also simply enjoy interacting with students.

In 2017, out of 40 invited mentors a total of 12 agreed to participate. Similar to 2016, a $50 gift card was offered as an incentive. Again, mentors were very positive about the program and expressed strong altruistic motives for participation. Many indicated too that the engagement with students and the ability to give back to the community provided positive benefits of being mentors. In this group mentors were asked if they were likely to continue to serve in this role and whether they would recommend this service to friends and colleagues. Overwhelmingly there was strong sentiment for continued service.

In the 2016 focus groups, mentors expressed concern that there was little structure for their role, echoing statements from similarly timed participant focus groups. Mentors in both groups expressed concern that participants have little background in computing and this hampers participant success. However, these concerns were far less strong by 2017, indicating response by Code Louisville to address the concerns raised in 2016.

In the 2017 focus groups, the concept of paid mentors was discussed. Overwhelmingly, the volunteer mentors expressed a negative reaction to this idea. Mentors feel strongly that Code Louisville is a purpose-driven volunteer opportunity where being financially rewarded would feel disingenuous. It should be noted that the purpose-driven element for the mentors is largely derived from the fact that a wide variety of students are able to participate in what can be a life-changing program, for free. If the diversity of the student body changed- making it more exclusive for example or weeding out those exceptional, albeit unlikely, underdog students that mentors so appreciate – mentors would feel less inclined to volunteer for this program. Similarly, if a cost were imposed, they say that they might question their involvement as well. Both are important items to keep in mind as the Code Louisville staff considers partnerships beyond the current grant-funded, independent-operating arrangement.

These focus groups indicate that there is a strong volunteerism spirit among mentors and that this is sufficiently motivating. In answering research questions two and eight, mentors are engaged and can be relied upon. However, this response may need to be weighed against the need for more mentors to scale the program to meet demand.

Quantitative Outcome Analysis

Research Design and Methodology

We have implemented a quasi-experimental design in our quantitative analysis of Code Louisville. In order to estimate the impact of the Code Louisville program on participants we will compare earnings and employment outcomes for participants with a sample of statistically similar individuals who do not participate in the program. To choose our sample of statistically similar individuals we use a technique call propensity score matching (See Heinrich, *et al.*, 2013 and Mueser, Troske, Gorislavsky, 2007 for more details on this methodology). For our sample of similar individuals, we chose from individuals who participated in three other Code Louisville programs—the Manufacturing and Employment Training Connection (M-TEC) program, the Certified Production Technician (CPT) program and individuals who have an Individual Training Account (ITA) through WIOA. M-TEC is a training program in which individuals can earn certificates that are valued by manufacturing employers. CPT is a training program that was developed by the Manufacturing Skills Standard Council and provides training in safety, quality practice and measurement, manufacturing production and process, maintenance awareness and green production. Participants who complete the CPT training again receive a certificate that is valued by manufacturing employers. Individuals with an ITA receive training from an approved training provider (often a local community or technical college) in an area of their choosing that is paid for by WIOA. Participants in all three of these programs are enrolled in WIOA.

One important difference between the Code Louisville program and the CPT and M-TECH programs is the amount of time it takes to complete the programs. Completing the CPT program requires 125 contact hours, or a little over three weeks if attending for 40 hours in a week, while completing the M-TECH program requires 112 contact hours, which again would be about three weeks if attend for 40 hours in a week. In contrast, the Code Louisville program takes a minimum of twelve weeks to complete a track in combination of some other requirements. The Code Louisville program requires a much greater commitment in order to complete the program.

Since these programs are somewhat different, with participants who potentially have different characteristics, we estimate separate impacts of the program by performing our propensity score matching technique separately for each of the three comparison groups. For each comparison group we start by pooling participants in one of the three comparison group with participants in the Code Louisville program and then estimate the probability that an individual participates in the Code Louisville program using a logit model and controlling for the demographic characteristics of the participants. The characteristics included in the estimation are, age, gender, race (black, white, other), education (some college, four-year degree or more, other), average earnings in the four quarters prior to starting the program, quarter and year of enrollment, and employment status in the one quarter and sixteen quarters prior to participation. We then keep the estimated probability that someone participates in the Code Louisville program and match participants in the Code Louisville programs with all participants in the comparison program who have a probability within 0.1 of the probability of the Code Louisville participant—what is referred to as many-to-one radius caliper matching with replacement. We chose the caliper of 0.1 because it allows the most matches but is sufficiently small to ensure that matched individuals are similar.[4] We refer to participants in the Code Louisville program as our treated group and the participants in the comparison program as our comparison group.

Because we are concerned men and women have different labor market experiences for reasons that are not captured in in our data, we perform the matching separately for men and women. This ensure that male participants in the Code Louisville program are only matched with male participants in the comparison programs, and female participants in Code Louisville are only matched with female participants in the comparison program. We then pool the data for men and women when estimating the effect of the program.

Once we complete the matching, we check the quality of the matches using a balancing test. This involves comparing the difference in the mean value of the control variables between the treatment and comparison zip codes. We use a t-test to determine if no more than five percent of the variables are statistically significantly different at the 99% level. If there are more variables that are different then we adjust the specification and size of the caliper. The process described above passes the balancing test.

The effectiveness of the propensity score procedure to produce an appropriate sample of comparison individuals rests on the assumption that the probability that an individual receives the treatment is independent conditional on the observable controls—what is known as the conditional independence assumption. While it is impossible to formally test this assumption, the balancing test does help assure that we are matching similar individuals. We also believe we have a reasonable set of control variables that help determine whether an individual receives the treatment.

If we have successfully constructed a comparison groups of individuals who are similar to the individuals in the treatment group, then the estimate of the effect of the program for a given outcome variable can be calculated as the difference in the mean of the outcome variable between the treatment and control samples. However, we can improve the efficiency of our estimates by estimating a regression model of the form:

[4] One reason for using many-to-one caliper matching is that it produces more precise impact estimates by using all available data and not throwing out similar matches (Mueser, *et al.*, 2007). The downside to multiple matches is that it can produce a bias estimate resulting from using poor matches (Heinrich, *et al.*, 2013). However, our caliper is small enough to limit poor matches, so we believe the multiple matches helps improve the efficiency of our resulting estimates more than any bias that is introduced.

$$Y_i = \beta_0 + \beta_1 CL_i + \beta_2 \boldsymbol{X_i} + \varepsilon$$

where Y_i is one of our outcome measures, CL is a dummy variable that equals one if the person is a Code Louisville participant and zero otherwise, and $\boldsymbol{X}$ is a matrix of the same observable characteristics used in the matching procedure.

Our outcome measures are used to answer the four quantitative questions. One outcome measure is whether someone successfully completed the program. We also estimate the impact of the Code Louisville program on wages in each of the four quarters starting one quarter after the participant enters the program. Finally, we estimate the impact of the program on whether someone is employed in each of the four quarters starting one quarter after the participant enters the program, along with several other combinations of employment designed to estimate the program impact on duration of employment.

Description of Comparison Groups

We first turn to descriptive statistics of the three comparison groups: the ITA participants, the M-TEC participants, and the CPT participants. Comparing the statistics in Tables 9 and 10 for ITA participants with the statistics in Tables 3 and 4 for Code Louisville participants we see that participants in the two programs have a similar average age, but that there is more variation in age among the ITA participants. In addition, ITA participants are nearly twice as likely to be women and over four times as likely to be African American as Code Louisville participants. We also note that ITA participants are much more likely to complete the program-- 78.9% of ITA participants complete their training compared to 57.8% of the Code Louisville participants. Sixty one percent of ITA participants have a high school degree or a GED while only 10% of the Code Louisville participants fall into this category. The Code Louisville participants are more likely to have some college and significantly more likely to have a Bachelor's degree or higher.

Table 9: Descriptive Statistics, ITA

Variable	Obs.	Mean	Std. Dev.
Age	370	33.5	9.7
Percent Female	370	61.9	48.6
Percent White	255	54.1	49.9
Percent Black	255	42.7	49.6
Percent Asian	255	0.4	6.3
Percent Native American	255	0.8	8.8
Percent Hispanic	370	4.3	20.3
Percent Veteran	262	8.0	27.2
Percent Ever Finish Program	370	78.9	40.8

Note: Data provided by KentuckianaWorks on participants in the Individual Training Account program during 2015 through 2017

Table 10: Educational Attainment, ITA

Education	Freq.	Percent
Other	2	1.0
GED	23	11.0
High School	105	50.0
Voc. Training	20	9.5
Some College	33	15.7
Assoc. Deg.	14	6.7
Bachelor's	13	6.2

Total	210

Note: Data provided by KentuckianaWorks. on participants in the Individual Training Account program during 2015 through 2017 who provided valid education data.

Comparing the numbers in Tables 11 and 12 for CPT participants with the numbers in the corresponding tables for Code Louisville participants we see that CPT program participants are slightly older and have a wider variation in ages compared to Code Louisville participants. Like Code Louisville participants, only 30% of the CPT participants are women (Code Louisville has 32% female participants). However, as with the ITA participants, the CPT participants are nearly five times more likely to be African American than the Code Louisville participants—60% compared to 12%. The CPT program has a very high completion rate of 92.7%. Similar to the ITA participants, 53% of the CPT participants have a high school degree or GED. Indeed, those with a GED comprise 18.6% of the CPT participants, higher than both the ITA and CPT programs, and much higher than the Code Louisville program (1%). While the percentage of CPT participants with some kind of higher education is slightly larger than the ITA participants, it is still well below the levels of the Code Louisville program where 27% have some college, and 54% have a Bachelor's or higher.

Table 11: Descriptive Statistics, CPT

Variable	Obs.	Mean	Std. Dev.
Age	414	37.1	12.0
Percent Female	293	30.4	46.1
Percent White	216	36.1	48.1
Percent Black	216	60.6	49.0
Percent Asian	216	0.5	6.8
Percent Pacific Islander	216	0.9	9.6
Percent Hispanic	405	7.2	25.8
Percent Veteran	202	8.9	28.6
Percent Ever Finish Program	383	92.7	26.1

Note: Data provided by KentuckianaWorks. Participants in the Certified Production Technician Program between 2015 and 2018.

Table 12: Educational Attainment, CPT

Education	Freq.	Percent
Other	2	1.8
GED	21	18.6
High School	39	34.5
Voc. Training	14	12.4
Some College	19	16.8
Assoc. Deg.	8	7.1
Bachelor's	10	8.8
Total	113	

Note: Data provided by KentuckianaWorks. Participants in the Certified Production Technician Program between 2015 and 2018 providing valid education data.

Comparing statistics for M-TEC participants in Tables 13 and 14 with the comparable statistics for Code Louisville participants we see that the average age for CPT participants is 37 years and the spread is about 13 years which is again slightly older than the Code Louisville group. Even fewer women, 21%, are participating in the CPT program and African Americans comprise 65% of the participants, higher than any of the four training programs, and over five times the rate of the Code Louisville program. As with the CPT program, the completion rate is quite high at 92%. This group also has a high percentage of participants with a high school degree or GED. The percentage with any education beyond high school (37%) is the lowest of the four programs, although nearly the same as the ITA participants (38%).

Table 13: Descriptive Statistics, M-TEC

Variable	Obs.	Mean	Std. Dev.
Age	285	37.4	12.8
Percent Female	237	21.1	40.9
Percent White	83	30.1	46.2
Percent Black	83	65.1	48.0
Percent Asian	83	3.6	18.8
Percent Pacific Islander	83	1.2	11.0
Percent Hispanic	285	3.5	18.4
Percent Veteran	226	8.4	27.8
Percent Ever Finish Program	157	91.7	27.6

Note: Data provided by KentuckianaWorks Participants in the Manufacturing and Employment Training Connection Program between 2015 and 2018.

Table 14: Educational Attainment, M-TEC

Education	Freq.	Percent
Other	7	5.8
GED	14	11.7
High School	54	45.0
Voc. Training	5	4.2
Some College	24	20.0
Assoc. Deg.	6	5.0
Bachelor's	10	8.3
Total	120	

Note: Data provided by KentuckianaWorks. Participants in the Manufacturing and Employment Training Connection Program between 2015 and 2018.

These tables make clear that, relative to the Code Louisville participants, the participants in the comparison program are slightly older, are much more likely to be female and African American and much less educated. The differences in these groups informs our methodology as discussed above. We use propensity score matching where the first stage calculates the probability of obtaining Code Louisville training as compared to each of the other groups (in turn) conditional on these characteristics. Then we match individuals who have similar propensities across the programs. This helps ameliorate the differences in characteristics between the groups when we compare outcomes.

Estimation Results

Our estimation is focused on obtaining average treatment on the treated (ATT) estimates comparing the Code Louisville participants to participants in the three training programs--

ITA, CPT and M-TEC. We focus our outcomes in order to answer the six research questions posed above.

Our first outcome is completion of the program (answering question one), our second outcome is earnings for four quarters following entry into the program (answer question three), our third outcome is quarterly employment for four quarters following entry into the program (answering question two and four).

Our basic specification is simply the average difference, weighted by propensity score, between the Code Louisville and comparison group, controlling for age, gender, race, education, quarter and year of enrollment, pre-enrollment employment and four quarters of past earnings (both in the regression and in the propensity score). We summarize the results of these regressions for all nine outcome variables in Table 15.

Table 15: Baseline Estimates

Comparison Group	Outcome (Dependent) Variable								
	Completion	Q1 Wage	Q2 Wage	Q3 Wage	Q4 Wage	Q1 Employment	Q2 Employment	Q3 Employment	Q4 Employment
ITA	-.07* (.03)	1312.6* (288.0)	645.3 (352.9)	-1282.1* (335.0)	-865.9* (357.4)	-.08* (.03)	-.14* (.02)	-.12* (.03)	-.17* (.02)
M-TEC	-.41* (.02)	1226.9* (243.8)	225.0 (238.2)	-863.0* (249.5)	-484.5* (244.3)	-.17* (.02)	-.11* (.02)	-.17* (.02)	-.11* (.02)
CPT	-.47* (.02)	108.8 (219.0)	-846.2* (249.9)	-1090.1* (240.4)	-1034.4* (255.6)	-.30* (.02)	-.18* (.02)	-.16* (.02)	-.14* (.02)

* indicates statistically significant at the 5% alpha level.

Note: Data from KentuckianaWorks and KYStats. For completion, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing completion status, in addition to a Code Louisville treatment variable. For wage regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly wage, in addition to a Code Louisville treatment variable. For employment regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly employment, in addition to a Code Louisville treatment variable.

We consider the first column titled completion. The outcome variable is an indicator for whether the individual completed the program (completion = 1). As we noted in the descriptive statistics, the completion rate for the Code Louisville program is lower than the three other programs. The regression results further demonstrate that these differences are not due to demographic characteristics nor are they explained by past employment patterns among participants. The results indicate that the completion rate is 7% lower for Code Louisville participants than for ITA participants, 41% lower for Code Louisville participants than for M-TEC participants and 47% lower for Code Louisville participants than for CPT participants. We do note that the Code Louisville program is longer and more involved than either the CPT or M-TEC programs, which may explain the lower completion rates.

The second through fifth columns measure earnings by quarter after enrolment in the program. Quarters are measured from the UI Earnings data, and hence correspond to calendar quarters (January through March, April through June, July through September and October through December). The quarters are measured from entrance into the program, so Quarter 1 is the first calendar quarter after the individual enters the training program. Quarter 4 is the fourth calendar quarter after the individual enters the training program. We use calendar quarter adjustments in the regression to account for any seasonal variation in when individuals start a program. The sample is those who have started the program which includes individuals who failed to complete the program. We are measuring the effect of an intent to treat. In the regressions, we condition on past earnings. We note that in all cases, Code Louisville participants earned more, on average prior to the program than participants in the other training programs. The coefficients we report are best viewed as showing the difference in earnings gain for the typical Code Louisville participant relative to the typical participant in the comparison program.

Our estimates show that in the first quarter after enrolment the Code Louisville program participants experience earnings gains that were at least equal to the gain experienced by participants in the comparison programs. Indeed, their growth in quarterly earnings was $1,200 to $1,300 greater in the first quarter after entering than either ITA or M-TEC participants and nearly identical ($108) to those in the CPT program. However, by the second quarter, the difference in earnings growth was smaller. Code Louisville participants have a statistically significant growth advantage of $645 over the ITA participants in the second quarter and have a small and insignificant difference of $225 compared to the M-TEC participants in the second quarter. By the second quarter the CPT participants experience statistically significantly stronger growth in earnings relative to the Code Louisville participants ($846). By the fourth quarter the typical participant in all three of the comparison programs experience larger gains in earnings than the typical participant in the Code Louisville program. In all three cases, the difference is statistically significant and ranges from $863 for M-TEC participants to $1,282 for ITA participants. This does not imply that Code Louisville graduates are earning less than these groups, nor that they did not experience and increase in earnings. It simply indicates that the growth in earnings for participants in the comparison programs is higher by the fourth quarter than for Code Louisville participants.

We turn next to the last four columns. The outcome variable is an indicator for whether the individual had any positive earnings in the quarter. In all cases, employment rates are lower at every quarter for the Code Louisville participants.

The smallest difference in employment we see is between the Code Louisville and ITA participants. This difference ranges from 8% lower employment in the first quarter after the program to 17% lower employment after four quarters, so it appears that the differences in the employment rate is increasing over time. This growing difference in employment rates between Code Louisville participants and ITA participants stands in contrast to the declining employment rates between Code Louisville participants and participants in both the M-TEC and CPT programs. The CPT program in particular had an employment rate that was 30% higher than the Code Louisville employment rate in the first quarter after the program, but this drops to 18% in the second quarter and continues to decline to 14% by the fourth quarter. The change in the differential employment rate between M-TEC and Code Louisville participants is less pronounced. The initial difference in the first quarter is 17%, but this falls to 11% by the fourth quarter. Although we should point out that the differential was 17% in the third quarter.

We find that participants in the Code Louisville program are significantly less likely to complete the program than participants in the three comparable programs-- the completions rates are dramatically lower than the completion rates for the CPT and M-TEC programs and modestly lower than the ITA program (this answers question one). Examining employment rates and trends, we find that the comparison group matters. In all cases employment rates are lower for Code Louisville participants compared with participants in the comparison programs leading us to conclude that Code Louisville participants are less likely to obtain employment initially after completing the program. When compared to ITA participants the employment differential rises over time suggesting ITA participants are keeping jobs longer than Code Louisville participants. In contrast, the employment differentials fall over time when compared to both the M-TEC and CPT participants suggesting that participants in these other programs may be losing their jobs at a faster rate. (this answers question two and question four). Finally, we note that while Code Louisville participants initially have an earnings advantage over ITA and M-TEC participants, and have earnings that are comparable to CPT participants, participants in all three comparison programs experience earnings growth that catches up and then exceeds the earnings growth of Code Louisville by four quarters after entering training (this answers question 3).

We turn next to how these differentials differ by education group. We use three education groups: some college (including vocational training and Associate's degrees), college (Bachelor's and above) and other/less than college (including high school and GED). In many cases, the comparisons between Code Louisville and the other training programs are quite similar by education group to the overall results. This is particularly true for those with less than college. This is expected since, over all the training programs, this is the largest of the three categories. We note first that for those with some college, the completion rate for Code Louisville is similar to the ITA program. Perhaps more importantly, for those with at least a college degree, Code Louisville participants show statistically significant faster earnings growth. While this differential declines over time, even four quarters after enrolment the differential is still $1500. For college graduates the Code Louisville employment differential is nearly zero, while at four quarters post enrollment college educated Code Louisville participants have an 8% lower probability of employment. This is the first quarter in which the differential is statistically significant different.

Similarly, compared to the M-TEC program, Code Louisville participants with a college degree have approximately the same earnings growth. In addition, while employment for Code Louisville participants with college degrees is lower than their M-TEC counterparts in the first quarter, this differential is statistically insignificant and economically small in the remaining three quarters.

Interestingly it is the some college participants in Code Louisville that compare favorably to the some college participants in the CPT program. Among the Code Louisville participants with some college earnings growth is faster that the CPT participants with similar education for all four quarters after enrollment with statistical significance in the fourth quarter. And while the employment differential between these groups is initially negative, it becomes positive and statistically insignificant for the remaining three quarters.

These differences by education provide one explanation for the somewhat negative findings seen in Table 15. As we have already documented, Code Louisville participants are much more educated than participants in the comparison programs. However, our matching procedures are designed to make the typical Code Louisville participant similar to a participant in the comparison program. This is accomplished by failing to match (or giving less weight to) more educated Code Louisville participants. If the matching is successful, the results in Table 15 will reflect the results for less educated Code Louisville participants. In contrast, the results in Table 16 may be a better indicator of the results for Code Louisville participants with Some College and a College degree, which are the characteristics of the typical Code Louisville participant. Regardless, The Code Louisville program appears to serve participants with a college degree, or with some college relatively well compared to the other three programs (addressing question five).

Table 16: Estimates by Education Status

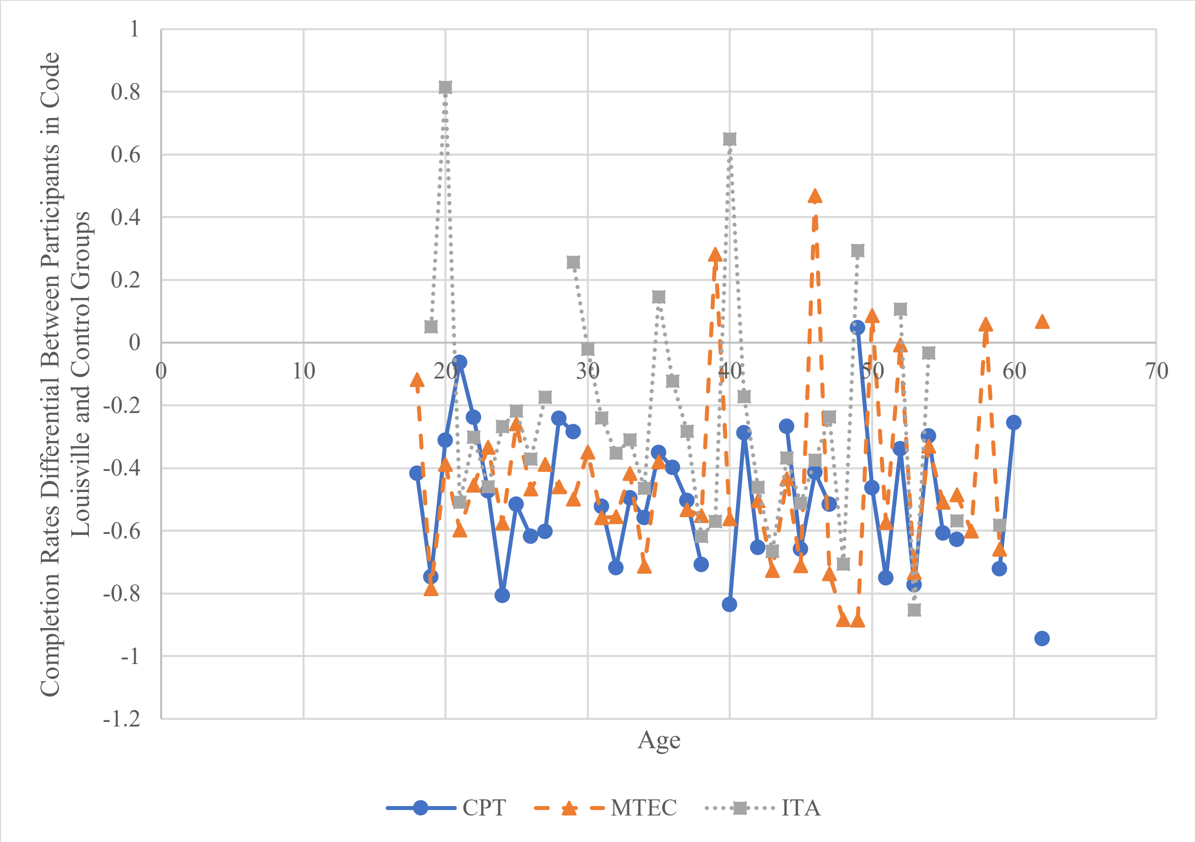
Comparison Group	Outcome (Dependent) Variable								
	Completion	Q1 Wage	Q2 Wage	Q3 Wage	Q4 Wage	Q1 Employment	Q2 Employment	Q3 Employment	Q4 Employment
ITA									
Treatment, High School	-.08* (.04)	806.1* (373.8)	-51.9 (457.4)	-1741.5* (432.5)	-1467.7* (462.2)	-.12* (.03)	-.16* (.03)	-.14* (.03)	-.16* (.03)
Treatment, Some College	-.04 (.04)	1451.3* (414.6)	624.7 (507.2)	-1992.4* (479.7)	-1366.5* (512.5)	-.07 (.04)	-0.14* (.04)	-0.13* (.04)	-.22* (.04)
Treatment, College	-.11* (.05)	2176.2* (473.7)	2276.8* (579.6)	1252.7* (548.1)	1554.1* (585.6)	-.01 (.04)	-0.07 (.04)	-0.03 (.04)	-.08* (.04)
M-TEC									
Treatment, High School	-.41* (.03)	1796.7* (331.6)	-360.8 (324.0)	-1303.3* (339.5)	-753.7* (332.6)	-.22* (.03)	-.16* (.03)	-.21* (.03)	-.19* (.03)
Treatment, Some College	-.44* (.03)	554.9 (401.5)	815.8* (392.2)	-170.7 (411.0)	-479.1 (402.7)	-0.13* (.03)	-.08* (0.04)	-.17* (.03)	-0.05 (0.03)
Treatment, College	-.35* (.05)	1025.2 (596.2)	858.3 (582.5)	-1443.5* (610.3)	938.0 (598.0)	-0.12* (0.05)	0.01 (0.05)	-0.01 (.05)	0.03 (0.05)
CPT									
Treatment, High School	-.48* (.03)	357.5 (289.9)	-1548.0* (329.6)	-1962.5* (317.9)	-2369.1* (336.8)	-.38* (.02)	-.29* (.03)	-.25* (.02)	-.26* (.02)
Treatment, Some College	-.45* (.03)	456.5 (348.4)	639.5 (396.2)	322.8 (382.2)	810.9* (404.9)	-0.13* (0.03)	0.04 (.03)	-0.01 (0.03)	0.04 (0.03)
Treatment, College	-.52* (.04)	-2852.4* (461.5)	-3600.9* (524.9)	-2560.3* (506.3)	-1858.7* (536.3)	-0.66* (.04)	-0.55* (0.04)	-0.38* (0.04)	-0.32* (0.04)

* Indicates statistically significant at the 5% level.

Note: Data from KentuckianaWorks and KYStats. For completion, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing completion status, in addition to a Code Louisville treatment variable. For wage regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly wage, in addition to a Code Louisville treatment variable. For employment regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly employment, in addition to a Code Louisville treatment variable.

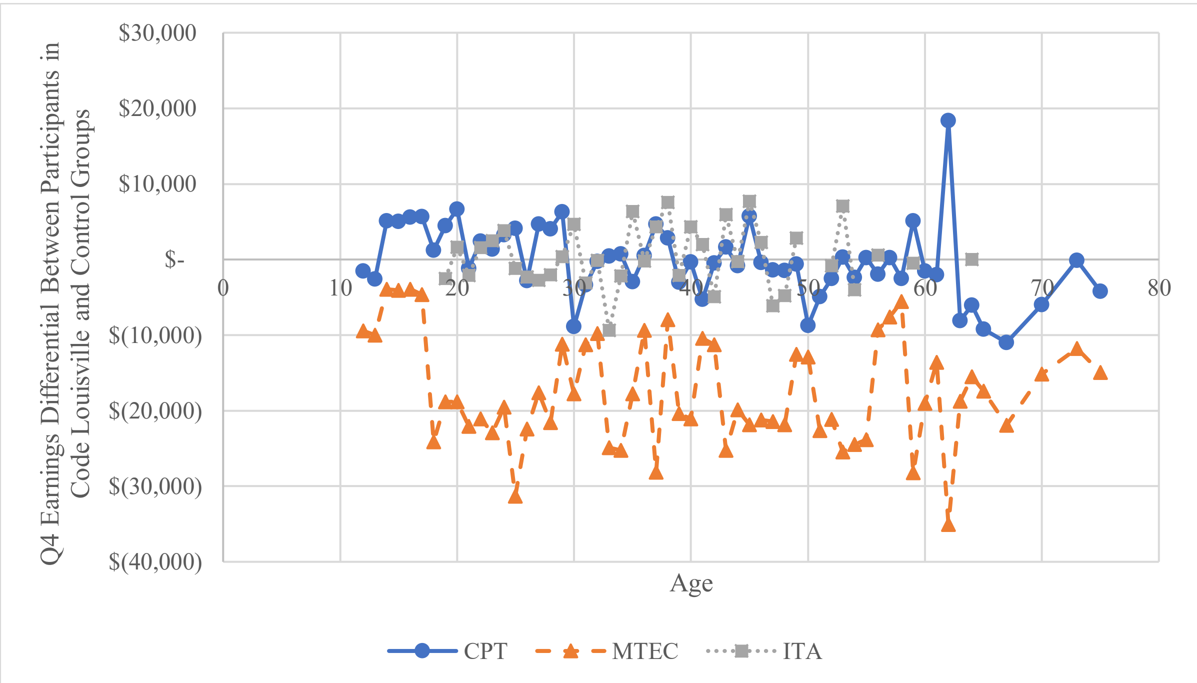
Finally, we turn to how the differentials are affected by age. We used a semi-parametric specification, with dummy variables by age to create a full age profile. We present these as Figures 5 through 7. We note, in particular, that there is little if any pattern. While the particular estimates vary across age, the standard errors are large (and available upon request) and thus no strong conclusions should be drawn about how the program differs across age profiles. This itself is an interesting conclusion. As shown earlier, the Code Louisville program does seem to attract a slightly younger group than the comparison programs (see discussion above). However, this does not appear to either improve nor hinder success in the program (as measured by completion) or either employment or earnings post program.

Figure 5: Completion Rates by Age



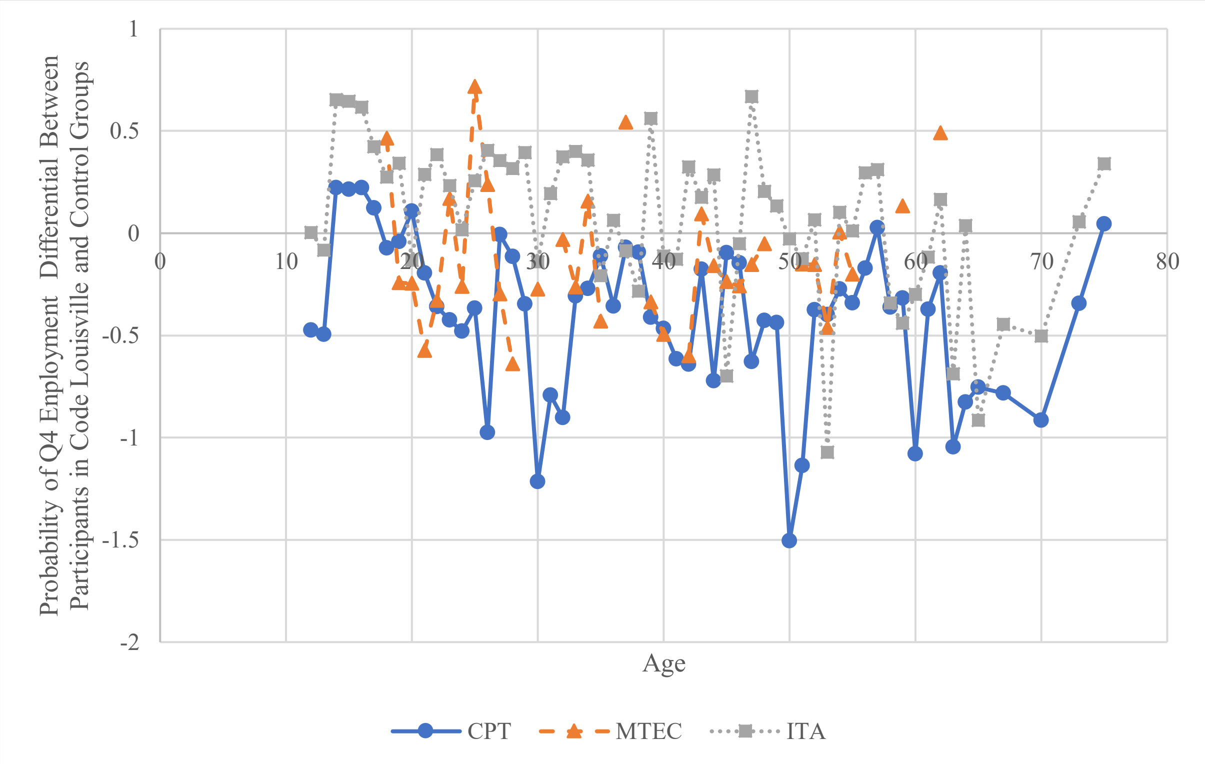
Note: Data from KentuckianaWorks and KYStats. These are the estimated coefficients the age variable in completion regressions. For completion, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing completion status, in addition to a Code Louisville treatment variable.

Figure 6: Earnings by Age



Note: Data from KentuckianaWorks and KYStats. These are the estimated coefficients the age variable in Q4 wage regressions. For wage regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly wage, in addition to a Code Louisville treatment variable.

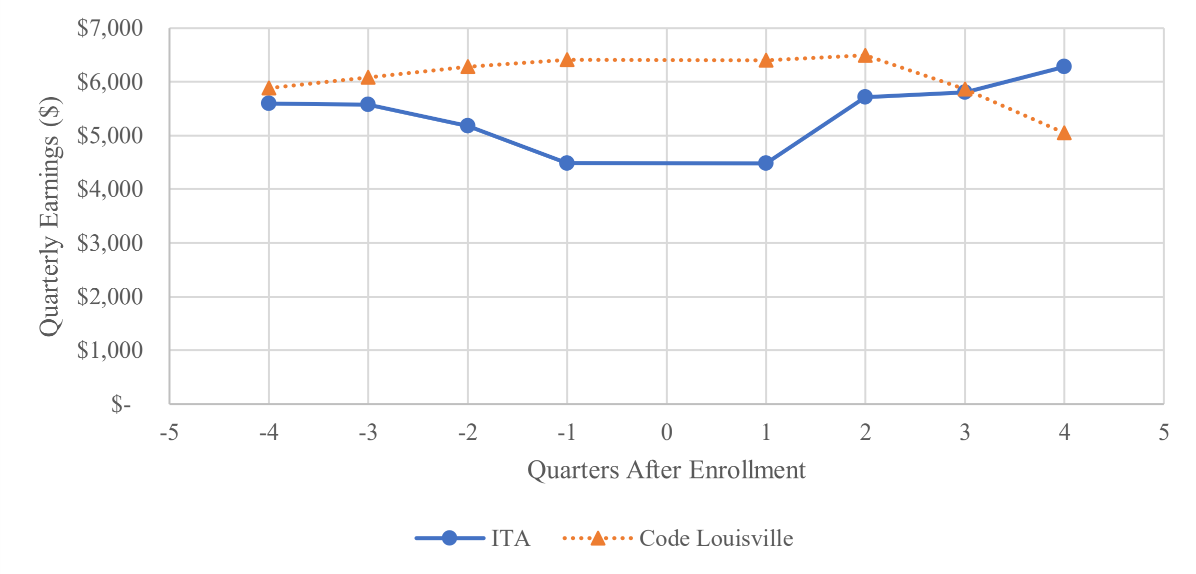
Figure 7: Employment by Age



Note: Data from KentuckianaWorks and KYStats. These are the estimated coefficients the age variable in Q4 employment regressions. For employment regressions, individuals in control and treatment samples are matched on age, gender, race, education, quarter of enrollment, pre-enrollment employment patterns and pre-enrollment wage, these are also the independent variables used when regressing quarterly employment, in addition to a Code Louisville treatment variable.

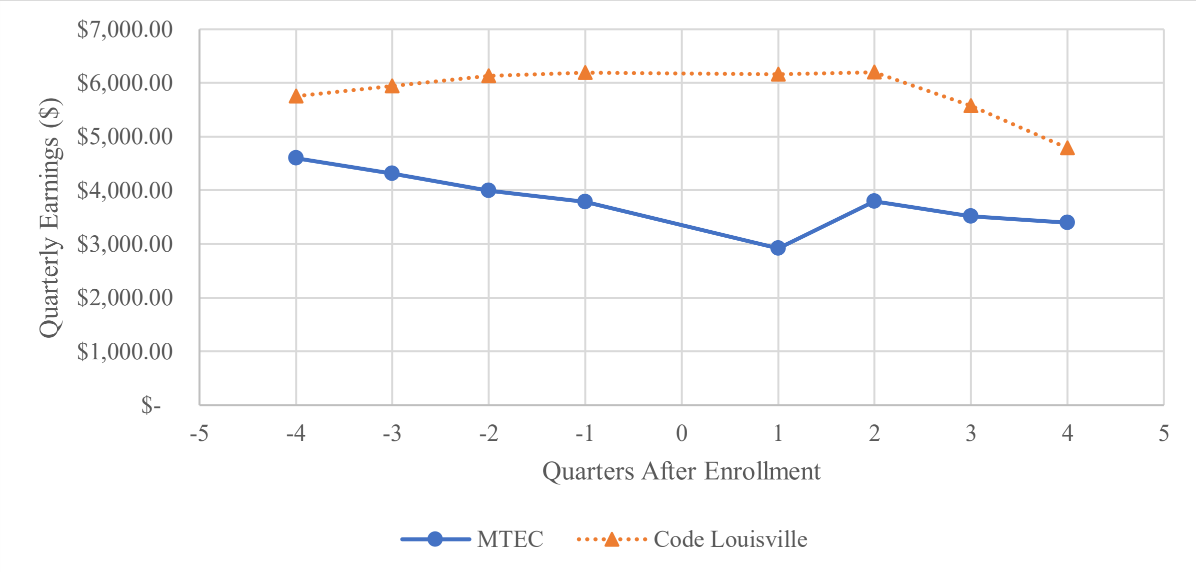
In order to further examine these differentials, we have plotted average earnings by quarter relative to program entry for those in each matched sample. We present these in Figures 8 through 10. Differences in the Code Louisville profile between graphs are due to differences in who specifically was matched in each comparison but are minor. We highlight two interesting facts about these earnings averages. For all three comparison programs, the so called “Ashenfelter dip” is readily apparent: individuals experience a decline in earnings just prior to entering the program. This is markedly absent for those in the Code Louisville program. Secondly, the Code Louisville participants have higher earnings (on average) than their comparison group (we condition on past earnings in both the propensity match and the estimated differential). Thus, while Code Louisville participants do seem to have declining earnings post program, they are still above (on average) participants in other programs. At this date, we do not have sufficient information to draw conclusions about the decline in earnings. One potential explanation may be that Code Louisville participants may be leaving positions to begin new careers in coding and thus sacrificing current earnings for higher growth in the future, suggesting that a longer study is needed to completely evaluate the relative impact of the Code Louisville program on participants.

Figure 8: Earnings profile for ITA-Code Louisville Matched samples



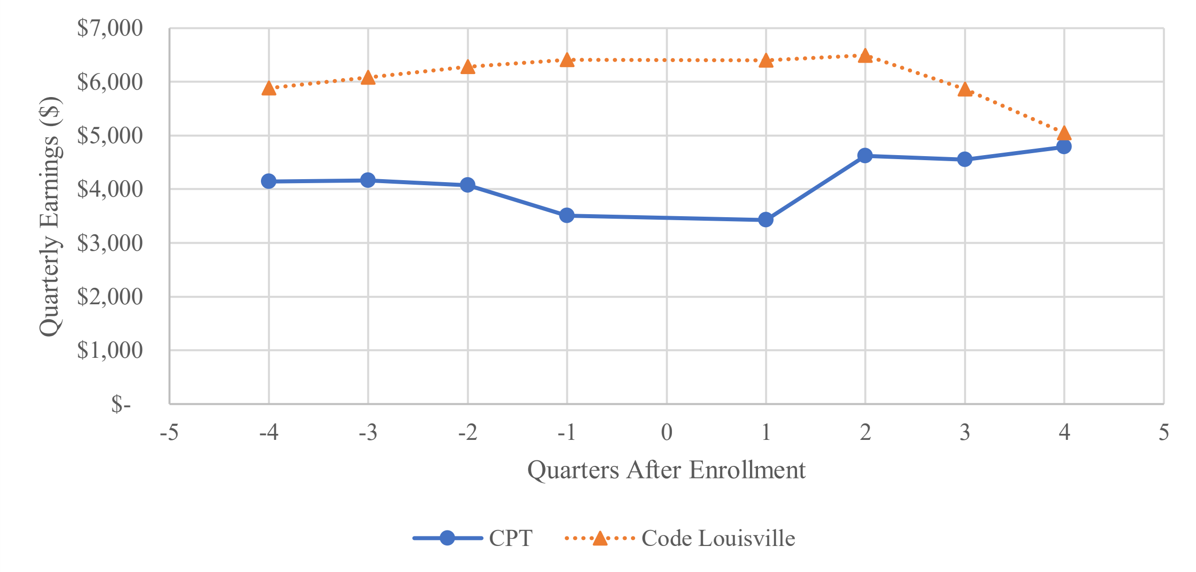
Note: Data from KentuckianaWorks and KYStats. Averages quarterly earnings before and after enrollment for the matched sample of participants in ITA and Code Louisville.

Figure 9: Earnings profile for M-TEC-Code Louisville Matched Samples



Note: Data from KentuckianaWorks and KYStats. Averages quarterly earnings before and after enrollment for the matched sample of participants in MTEC and Code Louisville.

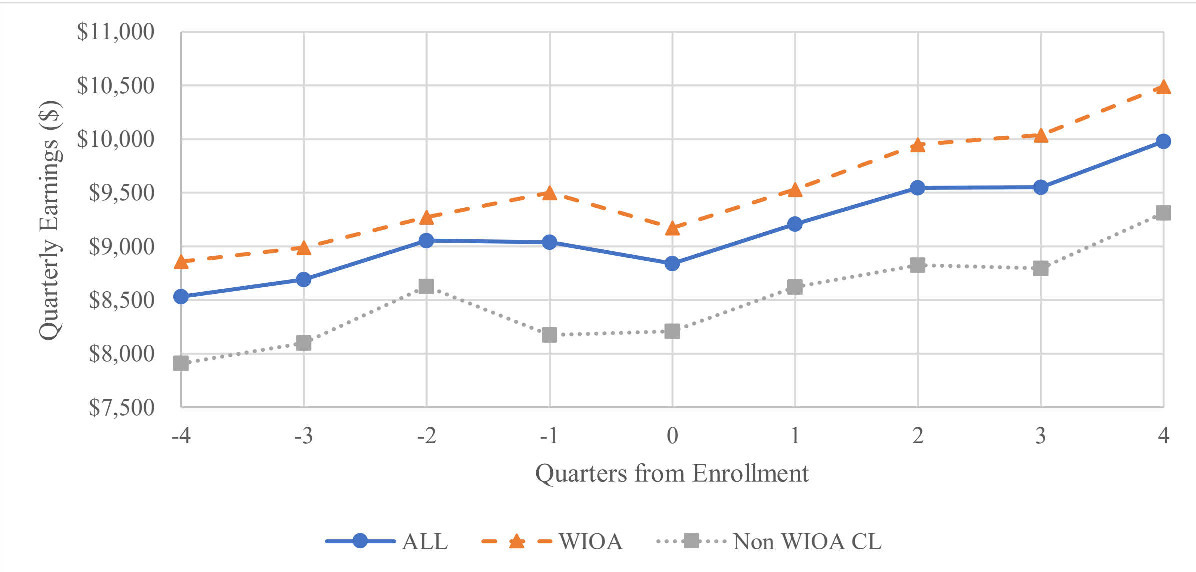
Figure 10: Earnings Profiles of CPT-Code Louisville Matched Samples



Note: Data from KentuckianaWorks and KYStats. Averages quarterly earnings before and after enrollment for the matched sample of participants in CPT and Code Louisville.

The figures and results paint a relatively negative view of the impact of the program on participants. In order to further address the concern that our matching is disproportionality affecting the more successful Code Louisville participants, we examine earnings for all Code Louisville Participants. Figure 11 presents these average earnings by quarter. We note two important things First, although not as early or as clear as the other programs, we find some evidence for the typical Ashenfelter Dip prior to the program participation among all participants. More importantly, we find that the average Code Louisville Participant has rising earnings after starting the program.

Figure 11: Earnings Profile of all Code Louisville Participants



Note: Data from KentuckianaWorks and KYStats. Average quarterly earnings of Code Louisville participants by WIOA status.

This suggests that further evaluation needs be conducted to consider the impact of the Code Louisville program on the entire participant group. While Figure 11 does show that Code Louisville participants do experience a growth in earnings after entering the program, without using a control group we do not know whether this growth in earnings would have occurred in absence of the program. Thus, while Figure 11 is suggestive, it cannot be taken as evidence of a gain from the program.

Cost Study

One important point of comparison between the Code Louisville program and the other job training programs is differences in the costs of providing the training. In order to estimate cost differentials, we focus on the three cost questions previously discussed in the Research section. Using the program expenditures reported for Code Louisville, we focus on the period starting in April of 2015 through September of 2018. While the initial grant began in October of 2014, the first cohort was formed in May of 2015 and began work that summer. Total expenses prior to April of 2015 were $15,892 (less than 10% of the total expenditures during the October 2014 to September 2015 planning period). We end in September of 2018 rather than September of 2019 for two important reasons. The final expenditures for FY 2019 are not yet completed, and our participant data and quantitative evaluation end with participants who began prior to October 2018 (indeed, our quantitative evaluation focuses on participants who began no later than January of 2018, however data were obtained on participants through September of 2018).

The total expenditure and fiscal year expenditures on the program are summarized in Table 17. We adjusted expenditures for inflation on a monthly basis using the CPI, to reflect real, September 2018 dollars. We note that in assessing costs, differentiating between fixed and marginal costs is crucial. Also removing costs which are not directly associated with the program – specifically the evaluation cost – is important. In Table 17, we highlight some of these different costs.

Table 17: Measures of Code Louisville Total and Average Program Cost (in real September 2018 dollars) for the period April 2015 through September 2018

Cost	Total	Per Participant (n = 1,752)	Per Completion (n = 881)	Per participant module (n = 3,154)	Per completed participant module (n = 1,406)
Total Expenditures	$2,364,940	$1,350	$2,684	$750	$1,682
Total Expenditures less Evaluation Costs	$1,917,590	$1,095	$2,176	$607	$1,363
Total Expenditures less Evaluation and administration costs	$1,391,572	$794	$1,579	$441	$990
Expenditures on TreeHouse, Space Rental, other software	$709,182	$405	$805	$224	$504

(Note: Data from KentuckianaWorks accounting system. We use a different number of participants that in Table 2 of Section 1 because we span a longer time period).

The number in parenthesis in the heading column is the denominator in the calculations: For example, there were a total of 1,752 participants. The first row is the total of all expenditures of the Code Louisville program from April 2015 through September 2018. In the first column we report the total cost of the program. In the second column, we divide the total cost by the total number of individuals who participated in the program during that period. While it may be possible that some fluctuation in total spending is associated with fluctuations in participant numbers participation was relatively constant across the years. Attempting to assign expenditures to particular cohorts is difficult as some costs (such as the cost of TreeHouse) are paid on quarterly or even annual basis while others are paid monthly. Further, some costs, such as administrative and personnel costs, may reflect important recruiting or organizational tasks, as well as tasks serving participants who have completed the track they desired, but are still utilizing resources (placement services for example). The third column reports the total cost of the program divided by the number of individuals who complete at least one module. These two columns fail to reflect individuals who may choose to attempt or even complete multiple modules, typically over multiple cohorts. We address this in columns four and five where we consider total cost per person-tracks and total cost per person-tracks completed.

The first row is the total expenditures for the program. The second row subtracts the expenditures associated with the evaluation of the program from the total expenditures. We highlight this row as being the most comparable when comparing the costs of the Code Louisville program to the costs of other WIOA programs. However, this may over-state the costs of expanding the program (the marginal cost) because some administrative and organizational expenses may not increase as rapidly because of gains from scale. In the third row, we attempt to capture this by subtracting administrative costs of the program. These include staff salaries of personnel associated with administration of the program, outreach and conference fee expenditures, auditing expenditures, travel expenditures and administrative overhead. Finally, in the last row we attempt to capture the cost of the course work alone. Here we include only the cost of the TreeHouse Platform, the cost of rental space for meetings with mentors, and the cost of other software which includes ASANA for example. We argue that this row most closely compares to the outlay costs we consider for the ITA program, which are primarily tuition expenditures. While tuition expenditures include certain overhead and administrative costs incurred by the educational unit, they do not include the costs incurred by KentuckianaWorks in administering the program. The cost of TreeHouse, for example, presumably includes similar administrative costs and is comparable to the administrative costs covered by tuition.

Our comparison begins with the ITA program. In many ways this is perhaps the most comparable program in that participants are receiving educational content (indeed, at least one ITA recipient in 2016 was studying computer security systems). Other courses of study include Transportation and Logistics (primarily CDL training), medical training (primarily nursing), and skilled trades (primarily welding). We focus on the actual grant provided to the participants in this program. Assessing the associated administrative costs for the ITA program is complicate. By ignoring these costs, we are producing a conservative estimate of the relative difference between the costs of the Code Louisville program and the cost of ITAs. One argument for ignoring administrative costs in our comparison is that all programs will have some administrative costs.

The ITA program has an average expenditure on grants of $4,281 per participants (using September 2018 dollars). This includes individuals who failed to complete the program. Considering only those who complete the program the average cost is $5,045. Both of these numbers are significantly higher than the per capita costs of the Code Louisville Program, regardless of how we account for overhead and administrative costs. As we argue above, the best comparison row for Code Louisville is the fourth row of Table 17 (counting only the direct costs of the educational program). In this case the ITA program is nearly 10 times more expensive than the Code Louisville program. Even including the full cost of the program (including the evaluation), the ITA program is still nearly 4 times more expensive.

An interesting and important point is that while the Code Louisville program has a markedly lower completion rate than the ITA program, even comparing the cost per completed participant costs are still lower for the Code Louisville Program. The ITA program has a $5,045 cost per participant who completes their training. Even using the full cost of the program in the first line of Table 1, the Code Louisville costs per completed participant of $2,684 are just slightly more than half the costs of the ITA program. When we compare the direct program costs in the fourth row, the ITA program is more than five times more expensive per completion. Given the differential in completion rates, this is an important comparison.

The second program we consider is the CPT Training program. This program is significantly shorter in duration than the Code Louisville program. Based on data provided by KentuckianaWorks, the cost per participant is $1,383. This cost includes Instructors and other direct costs (e.g. assessments, forklifts, drug screening), and does not include the administrative costs, so the comparison here should be to costs reported in line 3 of Table 17, which shows Code Louisville costs of $794 per student. The Code Louisville program has a lower completion rate (92.7% of CPT participants complete the training), so it is worth comparing costs of the CPT program to the $1,579 cost per completer of the Code Louisville program. The per-completer cost of the CPT is $1,492, which is slightly lower than per-completer cost of Code Louisville. We again need to note that the duration of the Code Louisville program (12 weeks for a single track) is significantly longer than the duration of the CPT program.

The third program is the M-TEC training. Like the CPT program, this program is shorter in duration and has a higher completion rate (91.7%) than Code Louisville. The costs provided by KentuckianaWorks show that the cost per participant of the M-TEC program is $1,117. Like the CPT training above, the M-TEC training costs include the cost of instructors and other direct costs but does not include costs such as KentuckianaWorks administration and coordination so the most direct comparison with the costs of the Code Louisville program is line 3 of Table 17 so the per-participant cost of Code Louisville is lower. The per-completion costs of Code Louisville are $1,579, while the per-completion cost for M-TEC is $1,218.

Finally, we compare the cost of the Code Louisville program to the published costs of the overall WIOA program (see https://www.doleta.gov/Performance/Results/AnnualReports/PY2019/WIOA-PY-2017-National-Summary-ETA-9169v4-REVISED-4_24_19.pdf). The estimates for 2017 (the latest available) have average per participant costs of WIOA training programs of $1,765 per participant. The Code Louisville program is less expensive than the WIOA program even using the highest estimate per participant of $1,350.

One important issue when thinking about the cost of the Code Louisville program is the value of mentors' time. The value of mentor's time is a part of the resources of the program but is not explicitly accounted for in the costs of the program because all mentors volunteer. In focus groups mentors expressed that they would be less interested in participating if they were paid. They were motivated by a sense of "giving back" and keeping the program free to participants.

However, we also note that a serious constraint on the size of the program was the availability of mentors. An approach to alleviating this would be to hire mentors. We examine two scenarios to estimate the cost of this. The first scenario is to contract with many individuals on an hourly basis. Essentially extrapolating the volunteer approach currently used where over 200 individuals supply the mentoring service irregularly as a side job or contract job. The second scenario would be to hire a small number of mentors who are full time employees of Code Louisville. The second scenario may have spillover effects (lowering costs) that we cannot capture: this may reduce burden on the current Code Louisville staff (not needing to spend time recruiting mentors each period) allowing for lower costs than we calculate in expanding the program, or possibly allowing the program to operate at the current level of participants with fewer staff, or allow staff to provide additional services.

Using a five-year panel of the American Community Survey, we estimated average hourly earnings for individuals who have occupation codes in the broad category of computer and mathematical occupations, excluding actuaries, operations research analysists and miscellaneous mathematical science occupations. We limited the sample to workers working for salary or wages, more than 34 hours a week, and working at least 50 weeks (full time, full year workers). Table 18 presents estimates by geography for both hourly wage and annual earnings. The comparison states are the seven contiguous states to Kentucky and the five states in the same census region as Kentucky but are not contiguous[5].

For the purposes of estimating the costs of the Code Louisville program, the Louisville Metro area estimates are the most applicable. The program costs already discussed derive from the Louisville Area (including both labor costs and the costs of meeting space). The comparison programs are similarly from the Louisville Area. However, the remainder of the table

[5] Alabama, Georgia, Illinois, Indiana, Mississippi, Missouri, North Carolina, Ohio, South Carolina, Tennessee, Virginia, and West Virginia.

provides information likely to be of use for organizations who may choose to initiate a similar program elsewhere.

Table 18: Earnings and Labor Force Share of Computer Occupations

Region	Hourly Wage	Annual Earnings	Percent of Labor Force
Louisville Metro Area	$34	$75,691	3.7%
National Metro Areas	$42	$93,718	4.2%
National	$41	$91,471	3.6%
Kentucky	$32	$72,102	2.4%
Comparison States	$38	$85,050	3.6%
Comparison State Metro Areas	$39	$87,281	4.2%
Rest of Kentucky	$31	$69,242	1.9%

Note: Data from the five-year 2018 panel of the American Community Survey, U.S. Census Bureau and authors calculations.

We note that Kentucky and Louisville have a small percentage of workers in computer occupations--a key motivation for the Code Louisville program. While the 3.7% of workers in Louisville's in computer occupations is comparable with the national average of 3.6%, the average rate in U.S. Metro Areas is 4.2%, roughly 0.5% higher than the rate in Louisville. Our twelve comparison states have levels which match the national levels, and establish that Louisville, and Kentucky in general, have developed or attracted fewer of these workers. However, we also note that the earnings for IT workers in Louisville are 13%-20% less than the national or comparison state metro area earnings. This may suggest that demand for computer occupations is lower in Louisville than the rest of the country.

A typical mentor spends 5 to 6 hours a week on the project, for a total of twelve weeks for each cohort they serve. A typical mentoring group is 12 participants. Thus, for a typical cohort, the per participant cost for mentoring is $204 ($34 per hour, 6 hours per week, 12 weeks spread over 12 participants). Given that the typical participant enrolls in 1.8 cohort tracks, the cost per participant for mentoring would be $367. Adding this to the totals in Table 1 above implies our full estimate of the per-participant costs ranges from $772 (using only the Treehouse software and space costs) to $1,717 using the all expenditures. Our best estimate uses the expenditures less the evaluation costs is $1,462 per participant. This still is less than half the costs of the ITA program, slightly higher than the CPT program and about $300 more per participant than the M-TEC program.

We next consider the costs of having full-time mentors. A typical cohort had an average of 243 participants grouped into roughly 20 cohorts. This would require 100 hours per week for mentors, which would require two full-time mentors. Similarly, even if work was spread out over a year, it would still require a total of 3,600 hours of mentoring for a given year of three cohorts of approximately 243 participants and 5 hours per week commitment. This would be an annual hourly commitment of 3,600 hours, which is close to the 4,000 hours for two full time workers. Given an estimated $75,000 annual salary, we would expect mentors to cost $150,000 per year. This adds $499,500 in additional costs to the 3 years and four-month costs considered above. This is similar to our estimate of the per-participant costs of hiring part-time mentors on an hourly basis combined with the other costs of the program. This still is less expensive than the national average cost of training programs at $1,765.

Findings and Conclusions

In this section we summarize the results of the three portions of the evaluation. First, the qualitative analysis of the implementation of the program:

(1) *What program aspects are identified by participants as having value or needing change or improvement?*
The program has value in providing training that participants desire (note: also, our observation in the introduction that the program is typically over-subscribed with a long waiting list). The mentors are a valuable component, the structure of the program, and particularly the online, self-paced structure, and meets the needs of the participants.

(2) *Can the initiative rely on the programming coaches or are salaried instructors necessary?*
Mentors are an important component of the program and the sentiment of the mentors was that it should be a volunteer position. Finding mentors does, however, appear to be an aspect of the limitation related to access to the program. This should be tempered by noting that the program has served much higher numbers of participants over the study period than any of the other three programs.

(3) *Are employers satisfied with computer programming skill level of students?*
Overall, employers are satisfied with the skills developed. Some employers express a need for more experienced software programmers, but this finding should be tempered by noting that the program is designed to only provide entry level workers.

(4) *Can program participants identify specific changes to the program that will yield better outcomes for them?*
Aspects of the program needing change tended to be less structural and more incidental. The largest issue early in implementation were changes implemented mid-session, which confused participants and caused miscommunication about the role of the mentors. Both issues were addressed during the study period without requiring major changes in the program itself.

(5) *How satisfied are students with the employment they obtain after the program?*
Participants in the program who were employed in software development positions were extremely satisfied with the program. Those who had not obtained those types of positions still expressed satisfaction and expressed that responsibility for lack of employment was largely theirs.

(6) *What career advancement opportunities do students have in the employment they have obtained?*
Participants who had obtained employment in software development positions expressed optimism at potential for advancement and growth in these positions.

(7) Did mentors provide mechanisms to support students in their completion of the program?
Participants generally considered mentors to be a key portion of the program. There was some initial confusion as to the role mentors should play. This role appears to have been clarified but should be communicated regularly both to mentors and participants.

(8) Are mentors engaged and willing to participate in the program in the future?
Mentors are engaged and willing to participate. Over 200 different individuals have participated as mentors, with additional mentors volunteering – often from the pool of Code Louisville graduates – in every year.

Quantitative Outcomes Study:
(1) *Is the completion rate of the initial required module in the CL program higher than completion rates of comparable training in the comparison groups?*
The completion rate for Code Louisville participants is significantly lower than for all comparison programs. Overall, the completion rate is 58%.

(2) *How does the length of time to employment from initial entry into the program and from completion of the program compare between the CL participants and the comparison groups?*
Code Louisville participants typically have lower employment rates than the comparison groups during the year post program entry. For two programs (M-TEC and CPT), the difference declines over time, while for the ITA program, the difference rises over time. This indicates that compared to M-TEC and CPT, the Code Louisville participants are gaining or keeping employment at a higher rate over time but begin with lower rates of employment.

(3) *How do earnings profiles differ between the CL participants and the comparison groups?*
Code Louisville participants initially have higher earnings post program, however this difference declines and even becomes negative (conditional on individual characteristics) over the first-year post-enrolment. Comparison of simple levels reveals that Code Louisville participants earned more both pre-program and post program than the comparison groups, but these earnings declined over time, while earnings for other groups rose.

(4) *How does the length of employment compare between the CL participants and the comparison groups?*
Code Louisville participants initially had lower employment rates than other programs. This gap widened compared to the ITA group but narrowed compared to both the CPT and M-TEC programs. However, overall, employment rates were lower for Code Louisville participants post-program.

(5) *Do completion rates, length of time to employment, and earnings differ by pre-program education levels for participants?*
Earnings and employment rate differentials were affected by education level. In particular, individuals with higher education have similar or higher employment and earnings than ITA, CPT or M-TEC participants. This suggests that the program is particularly beneficial to those with more than a high school degree.

(6) *Do completion rates, length of time to employment, and earnings differ by age of participants?*
We found no strong effects of age on completion, employment rates or earnings by age.

Cost Study

(1) *How does the marginal cost of the program compare to other programs?*
The Code Louisville program is substantially less expensive than the ITA program and comparable in expense to the CPT and M-TEC programs.

(2) How well does the program scale? As the program grows will the administrative costs grow in proportion, or only the marginal cost per student?
The program will scale well and is already operating at a higher level than all three other programs.

(3) What are the cost implications of the mentors? How will the cost change if these become paid positions?
Even if mentors' opportunity cost is included, the program is still less expensive than the ITA program and only slightly more expensive than the M-TEC or CPT program. Mentors appear to consider this an important program and are likely to continue to volunteer.

Additional Conclusions

An important aspect we note is that this program serves a very different population than ITA, CPT or M-TEC. The propensity score matching estimation performed (as promised in the EDR) seeks to find an average treatment effect over the entire population of participants. Given that the largest overlap is among those with only a high school degree, this group receives a large weight in the overall average. However, as noted in the estimates by education group, Code Louisville participants with higher education than a high school degree benefit most from the program.

We also note that this program prepares individuals for entry level positions in a career which may have high employment and earnings growth. The one-year time horizon is limited in examining this phenomenon and warrants further research.

The low completion rates are a concern. Further investigation into why participants fail to complete the program appears warranted. However, it may be inappropriate to compare this program to the CPT or M-TEC program on this dimension, given the differences in structure and length. The ITA program completion rates, while still higher, are not dramatically higher.

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