Evaluation of a New Job Training Program: Code Louisville

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Abstract:

In this paper we estimate the returns to a new and novel job training program, called Code Louisville, designed to provide participants with training in modern computer software development (coding). The program is open to adults in the Metropolitan Louisville area seeking job training in the sector. Since Code Louisville is administered through the Louisville, KY Workforce Development Board (WDB)—KentuckianaWorks, this evaluation provides evidence on whether sectoral programs continue to provide higher returns when they are part of the workforce job training system. In addition, since the primary training in Code Louisville is offered online, we provide evidence of the success of less expensive online training programs. A final feature of our analysis is we use a new, but fairly widely available, source of data to construct comparison samples for our matching. We find that the Code Louisville program produces positive impacts on labor market outcomes for participants that are somewhat larger than traditional federal training programs. However, the size and timing of benefits differs by gender and educational attainment prior to entering the program. While the returns are smaller than those seen in sectoral programs, administering the online Code Louisville appears substantially less costly than other programs.

INTRODUCTION

Estimates of the returns to participating in a federal job training program such as the Workforce Innovation and Opportunity Act (WIOA) program, or its predecessor the Workforce Innovation Act (WIA) program, or the Trade Adjustment Act (TAA) program suggest that these programs provide positive but modest increased earnings and employment (see Andersson et al., 2022; Heinrich, et al, 2013; Hyman, 2018; and Schochet et al., 2012). In contrast, recent research examining training programs that focus on training workers to work in a specific sector or occupation and that are often financed by private or nongovernmental organizations—commonly referred to as sectoral training programs—tend to show much larger returns (see Baird, et al., 2022 and Katz, et al., 2022).[1] Obvious questions arising from these later studies are whether differences between federal training programs and sectoral training programs might account for the estimated differences in returns, and whether it is possible to increase the scale of private sector sectoral training programs such that participants continue to experience these higher returns.

In this paper we begin to address these questions by estimating the returns to a job training program called Code Louisville, which has many of the characteristics of a sectoral training program but was originally funded through the Department of Labor's Workforce Innovation Fund (WIF) and is administered through the Louisville, KY local Workforce Development Board (WDB) —KentuckianaWorks. Code Louisville, which is open to all adults in the Metropolitan Louisville area, is designed to provide participants with training in modern computer software development (coding). The program is also motivated by a perceived need for software development talent in the Louisville Metropolitan area.

[1] Baird et al. (2022) estimate the returns to the Career Pathways program which is part of WIOA.

Launched in 2015, Code Louisville is a departure from traditional federal and sectoral training programs in that it uses online software to conduct training rather than the more common classroom experience. The advantages of the online approach are lower costs (see Troske & Bollinger, 2019) 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. A second key difference is the inclusion of a mentoring program in which participants are assigned to small mentoring groups of approximately twelve participants that are led by volunteer mentors who are experienced software development workers in the Louisville Metropolitan area. The program also includes job placement services that are more hands-on than the traditional job placement services and more closely resemble the job placement services available through sectoral training programs (see Katz et al., 2022).

Another unique aspect of our study is that we evaluate the Code Louisville programs by matching data on Code Louisville participants to records that are part of Kentucky Center for Statistics' (KYSTAT) Kentucky Longitudinal Data System (KLDS). These data contain demographic, earnings and residential information for most people who live in Kentucky by combining data from a variety of state administrative databases, including data from all public schools in Kentucky, the state Unemployment Insurance system, and driver's license information. Given the large population we must draw from, we are able to create comparison samples that are nearly identical to our treatment samples on observable characteristics. The KYSTAT's administrative data system is similar to administrative data created in numerous other states (Bloom-Weltman, 2019). We believe we are among the first researchers to use these data to conduct this type of analysis, so one contribution of our paper is demonstrating whether and how these data can be used in evaluating government training programs.

Our main findings are that the Code Louisville program impacts labor market outcomes for both men and women but in different ways. Initially after enrolling in the program men show very little gains in earnings, but, by the end of the data—three years post enrollment—men experience quarterly earnings gains of between 5-10% relative to individuals in the comparison sample. However, men experience significant gains in employment of approximately 5 percentage points within one year of enrolling in the program that persist through the end of the data. In contrast, women in the program experience a 5% gain in quarterly earnings relative to the comparison groups within one year of enrolling in the program, which grows to approximately a 15% by three years after enrollment. However, women experience a 3-percentage point increase in employment by three years after enrollment. These benefits primarily accrue to people who complete at least one module in the program. We also find that the gains tend to primarily accrue to individuals with the most education—a bachelor's degree or higher. We find a smaller and often statistically insignificant estimated impacts for individuals with less education. Individuals for whom we do not know their education level show very little increase in earnings as a result of participating in the program, but males in this group do experience approximately a 5-percentage point increase in employment. These estimated effects are comparable, or slightly better than previous evaluations of federal job training program (Andersson et al., 2022; Card et al., 2018; Heinrich et al., 2013) but below estimates from previous evaluations of sectoral training programs (Baird, et al., 2022 and Katz, et al., 2022). One factor accounting for the smaller impacts may be that the training in the Code Louisville program is delivered in an online format while training in the other programs is primarily in-person. However, the fact that the cost of the Code Louisville program is substantially below the cost of other federal programs (see Bollinger & Troske, 2019) suggests that the Code Louisville program may be a more efficient way to provide this type of training to interested participants. We believe this evidence is strong enough to suggest that federal officials consider expanding the Code Louisville program to other locations. We also believe that our success in creating matched comparison groups using data on the population of people living in an area suggests that other researchers should consider using similar data when available.

The rest of our paper is as follows. In the next section we provide a brief review of the recent literature examining the returns to federal job training programs and sectoral job training programs. In section III we provide a brief history of and more details about the Code Louisville program. In section IV we discuss the data used in our analysis in more detail and in section V we discuss our empirical methodology. We discuss our results in section VI and present our conclusions in section VII.

LITERATURE REVIEW

Evaluating the effectiveness of job training programs has a long history. We divide this literature into four relevant groups in Table 1. General evaluations, panel A, were the first approaches and Card et al (2018) provide an excellent Meta-Analysis of 97 evaluations of workforce development programs. They find that while job assistance programs have the largest initial impact, the impact fades over time. While generally training programs have smaller initial impacts, they have more persistent effects.

Table 1. Program Evaluation Literature Review

Paper	Analysis	Findings
	Panel A - Evaluation of Various Training Programs	
LaLonde, 1986	Assesment of early evaluations of job training programs	Need to use experimental methods to rigorously evaluate job training programs
Or, et al., 1996	Randomized control trial evalution of Job Training Partnership (JTPA) program	Small, statistically significant impacts of job training on earnings for adult disadvantaged workers of a 10% increase in earnings for women and a 5.6% increase in earnings for men.
Card, Kluve, and Weber (2018)	Meta-analysis of 97 studies of 199 active labor market policies from around the world.	Job search assistance programs have the highest initial impact, but this impact is relatively short term and fades over time. Job training programs appear to have smaller initial impacts, but these impacts are more long-lasting.
	Panel B - Evaluation of Workforce Investment Act (WIA) program	
Fortson, et al. (2017)	Randomized control trial evalution of WIA	Training programs produce no statistically significant increase in earnings above that received through core and intensive services.
Heinrich, et al. (2008, 2013)	Quasi-experimental evaluation of WIA in 12 states	Training programs provide incremental returns of approximately 25% for women and 15% for men who are part of the WIA adult worker program, but no impact on eanrings for workers in the dislocated worker program.
Andersson, et al. (2022)	Quasi-experimental evaluation of WIA in 1 state	Training programs provide largely similary long-run incremental increases in earnings for men and women in the WIA adult worker program and a decline in earnings for particpants in the dislocated worker program.
	Panel C - Trade Adjustment Act (TAA) training program	
Schochet, et al. (2012)	Quasi-experimental evaluation of TAA	Program participation has no significant impact on future earnings.
Hyman (2018)	Exploits random case-worker variation in application approval rate	Workers who receive training experience approximately a $10,000 increase in annual earnings ten years after participation
	Panel D - Sectoral training programs	
Katz, et al. (2022)	Summarizes resuclt from RCT evaluations of four sectoral training programs	The programs produce large earnings gains of 12%-34% that persist over time. Most of the earnings gains appear to come from providing skills that allow participants to move into occupations that pay above-average wages.
Baird, et al. (2022)	Evaluation of the New Orleans career pathways training program	Participants in this program experienced an average increase in earnings of about 12%. A large part of the gain comes from workers who are unemployed at the start of the training obtaining employment after training, but also from workers moving into the targeted sectors.
Bollinger and Troske (2019)	Evaluation of Code Louisville training program	Results suggest small impacts of the training program

Three programs, the Workforce Innovation Act (WIA) program, its successor the Workforce Innovation and Opportunity Act (WIOA) program and the Trade Adjustment Act (TAA) program, have dominated much of the job training literature. Panel B summarizes the WIA literature and Panel C summarizes the TAA literature. The WIA programs show 15% to 25% gains, while the TAA programs show more mixed and modest gains.

Finally, panel D summarizes the literature on sectoral training programs, including Bollinger & Troske (2019), the initial Department of Labor-mandated evaluation of the Code Louisville program. Katz et al. (2022) summarizes and compares the results from four RCT evaluations of sectoral training programs across three different sectors: advanced manufacturing, health care, and information technology (IT). These programs produce large earnings gains of

12%-34% that persist over time. Baird, et al., (2022) evaluate a training program in the IT sector and find that participants experience a 12% increase in earnings.

Bollinger & Troske (2019) provide an initial evaluation of the Code Louisville program produced for the Department of Labor. In this evaluation we compare the outcomes of Code Louisville participants with the outcomes of other WIOA programs conducted by KentuckianaWorks, —Certified Production Technician (CPT), Manufacturing and Employment Training Connection (M-TEC), and Individual Training Accounts (ITA).[2] There are two shortcomings with this report. First, we had at most four quarters of earnings and employment information after entry for participants in the Code Louisville program, which previous research suggests is too short a period to see impacts of these programs (i.e., Card et al., 2018; Heinrich et al., 2013). Second, participants in the Code Louisville program tend to be much more advantaged and more educated than participants in WIOA programs, making it difficult to find comparable individuals in these other programs. We address both shortcomings in the present study, using a longer follow-up period and a much larger potential comparison sample (see below for details).

More details on our research questions about the Code Louisville program can be found in our initial Evaluation Design Report (EDR) for the Department of Labor (Bollinger & Troske, 2016). Based on the EDR as well as the previous research, our hypothesis is that the returns to Code Louisville will exceed the returns to other federally funded training programs, such as WIOA, but will be less than the returns or non-governmental sectoral training programs. We also

[2] The ITA program was suspended in 2017. It overlaps our study period by two years. While some participants could use the training accounts to take computer classes, our data indicate that over this period ITA's were primarily used for training in medical, transportation or skilled trades.

hypothesize that the return will be higher for more educated workers, consistent with findings in the extensive literature on human capital investment.

Research on the importance of computer literacy and usage is also relevant to this analysis. Krueger (1993) is often cited as the earliest evidence that workers who use computers tend to have higher earnings. Other authors such as Autor, et al. (1998), Doms et al. (1997), and Green (1999) provide evidence showing that the use of more advanced technology is associated with higher wages. Hamilton (1997) finds that more direct measures of computing skills, such as use of specific software and knowledge of specific programming languages, are associated with higher wages.

Our current paper contributes to the existing literature in several ways. First, we evaluate a unique, new sectoral training program that is partially financed with federal dollars. Our study also informs the literature on the efficacy of blended online training compared to traditional federal face-to-face learning of most training programs. However, we emphasize that our study is not designed to assess learning outcomes. Finally, we use novel data to form our matched comparison samples used in our estimation.

THE CODE-LOUISVILLE PROGRAM

The Code Louisville (CL) program is designed to provide participants with training in modern computer software development (programming or coding). The program is also motivated by a perceived need for software development talent in the Louisville Metropolitan area. The program is open to individuals 18 years old or older who have at least a high school diploma or GED and who live 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, the Workforce Development Board for Louisville, Kentucky.

Code Louisville is a departure from traditional federal 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 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.

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 meet in person in the evening with the students in groups of approximately 12 on a weekly or bi-weekly basis.[3] Mentors interact with participants both to answer questions on projects and coding as well as providing advice on career management and interviewing. Mentors also respond to online discussions and emails throughout the week. The mentoring program is seen as bringing accountability, guidance, and support to the learning process. Mentors often become an important part of the participants' professional network and facilitate contacts within industry.

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, participants often cited these two

[3] The meetings are held at a variety of locations in downtown Louisville, including at the Code Louisville offices and the local community college. Mentoring meetings moved online during COVID but have returned to being in-person.

services as crucial in helping with job placement. Additionally, social mixers are conducted and designed to provide participants with networking opportunities. The job placement services work with local employers to identify potential matches and assist participants with resume writing and other job search support. The program's job placement services are more hands-on than the typical job placement services KentuckianaWorks offers.

The program does not provide a formal certification from any external source but does provide a certificate of completion. Administrators of the program note that building a portfolio of work more effectively demonstrates participants' skills to employers. KentuckianaWorks personnel developed this approach in conjunction with the mentors and potential employers. Some KentuckianaWorks job training programs do result in external certification, but similar to M-TEC (see Bollinger and Troske, 2019), the certification is through KentuckianaWorks.

The program uses the TreeHouse system for the online course content, including video lectures and reference material.[4] 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 to questions by mentors, other participants, and program administrators.

Following the nomenclature used by Code Louisville, we use the term "cohort" to mean a group of participants who start a training subject in a particular month and year. The program groups individuals into cohorts and then, within cohorts, into mentor groups. Each training module lasts 12 weeks. Participants are told to expect to spend 15 hours per week on

[4] In late 2020 KentuckianaWorks switched to the PluralSight system to provide course content.

coursework. Again, following terms used by Code Louisville, we call the 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 through 2019. In 2019 August and October cohorts were formed, and in 2020 January and March cohorts were formed. Our data end with the March 2020 cohort. As we discuss below, this cutoff was chosen based on the availability of post-participation earnings data.

Every effort is made to accommodate all registrants in each cohort. In some cases, registrants who are contacted fail to follow up and start the program. This loss rate significantly increased in 2016 when Code Louisville added prerequisites to the program. Participants are required to complete some basic computing modules that are designed to test participants' ability to learn in an online environment and their ability to devote sufficient time to the program. In addition, KentuckianaWorks gives some priority to people who receive public assistance, who are low-income, or who are deficient in basic skills. However, applicants are generally taken on a first come, first served basis.[5]

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 are two exceptions to this typical starting

[5] Originally, when the program was funded through DOL's Workforce Innovation Fund the broad target population for the study were individuals eligible for either WIOA Dislocated Worker or Adult training programs. In practice the Code Louisville programs focus on job seekers who are interested in pursuing job training or educational programs.

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.

To be considered a successful completion, participants must attend at least 9 of the 12 weekly meetings with the mentors and complete all 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 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 be 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 are offered in different time periods depending on both student demand and feedback from industry. Each of these tracks allows participants develop additional software design skills. During the period of our data, 55% of participants successfully complete one track. Of those who complete one track, 25% complete two or more tracks. Among all participants the average number of tracks finished is 0.82, while among people who successfully complete one track the average number of tracks completed is 1.5. After completion of at least one track, participants are eligible for job placement assistance through the Code Louisville program and its partnerships with local companies seeking software developers.

While participants are given the option of completing multiple tracks, overall, 35% of participants in our data completed more than one track. Given our sample size of completers (635, see Table 1 below) the sample who would have completed multiple tracks is approximately 220 individuals (our 35% calculation is based on our data in Bollinger & Troske, 2019). Given the complexity of the model, this sample size will lead to very imprecise estimates. Moreover, individuals may have, upon completion of the first track, obtained a new job reflecting their completion, and continued with subsequent modules. Our data do not enable us to distinguish when individuals move into a new position post-training. Since placement services are not available to participants until the first complete module, using this as our indicator of completion is the cleanest definition.

KentuckianaWorks started the Code Louisville program in early 2015. The first cohort was formed and began training in May of 2015.[6] Participants are recruited through advertisements in American Job-Centers, on television, radio and in print media. Counselors at the job centers may also recommend this program to individuals seeking job training. Typically, the program has been oversubscribed, with Code Louisville maintaining a wait list of up to 1,000 individuals. An initial constraint on the program was the number of volunteer mentors. However, as the program has continued, more mentors have been drawn from previous participants in the program, allowing the program to grow over time. The recruitment strategy adopted by Code Louisville is one reason why we have chosen to estimate the effect of treatment on the treated as

[6] While Code Louisville did some limited advertising for the program initially, a speech by then-President Obama while visiting Louisville in the spring of 2015 in which he mentioned the program, and word of mouth, seem to have generated substantial interest in the program since then.

these estimates reflect the impact of the program on people who choose to participate in the program.

DATA

The Code Louisville program collects basic information on participants including name, address, and social security number. Code Louisville also tracks start dates (the date the module was started), all modules started, and whether a participant completes a module. For our analysis KentuckianaWorks provided the participant data to KYSTATS, which maintains the Kentucky Longitudinal Data System (KLDS).[7] The KLDS includes administrative data from a variety of sources. For our purposes KLDS contains individual records from all K-12 public schools, all non-proprietary post-secondary institutions in Kentucky, employer, wage and claims data from the unemployment insurance (UI) system, birth and death records from Vital Statistics, and driver's license data.[8] KYSTATS linked the Code Louisville data to the KLDS data using social security number and person name. It is from the KLDS data that we obtain data on a participant's age, gender, race (White, Black, Asian, Other, Two or more, unknown), education (high school degree or GED, attend some college, associate degree or certificate, bachelor's degree, master's degree or more, unknown education), quarterly employment status and earnings, and county of residence.[9, 10]

[7] Due to data restrictions, employees with KYSTATS did the actual matching and ran all the regressions following instructions that we provided.
[8] KYSTATS has education data starting in 2008, so education information will be missing for anyone who completed schooling or left school prior to this date or attended school in another state or country.
[9] Race categories also include Hawaiian and other Pacific Islander, and Alaskan native or American Indian. However, since there were so few Code Louisville participants in these race categories, we had to drop them from the analysis for disclosure reasons. We also do not include people of these races in the potential comparison sample.
[10] While KentuckianaWorks collects much of this demographic data for participants, we limit ourselves to information available from the KLDS to ensure that we have comparable data for participants and people in our comparison group.

The initial data set provided by Code Louisville contains 2005 individuals who enrolled in the program. We restrict analysis to individuals who were between age 20 and 63 at the time of enrollment (start date of their first module), who live in the Kentucky counties in the Metropolitan Louisville area and who had at least one quarter of nonzero earnings in the year prior to enrollment.[11] This reduces the sample of participants to 1222 individuals, which is 60.9% of the original sample.[12]

The sample of potential comparison individuals consists of people whose most recent residence, as of 2021, was Jefferson, Bullitt, Oldham and Shelby counties (see footnote 12) who were between 20 and 64 years old between 2013 and 2020. Participants in the Code Louisville program are excluded from the sample of potential comparison individuals.[13]

Matching occurs in two steps. First, treated individuals are exactly matched to individuals in the comparison sample based on gender, race and education.[14] This results in 1,212 treated individuals matched to approximately 4 million individuals in the comparison sample. Once this match is done, the quarter/year the treated individual starts the program is set as the zero quarter for both the treated and matched individuals. We calculate the earnings in the year prior to treatment as the sum of total quarterly UI earnings in the four quarters prior to the zero quarter.

[11] This study included Jefferson, Bullitt, Henry, Oldham, Shelby, Spencer, and Trimble counties. However, actual participants were from only Jefferson, Bullitt, Oldham and Shelby counties. We speculate that individuals in other counties may not have known about the program, may not have thought they were eligible, or did not want to drive to participate in the mentoring meetings. Spencer, Trimble and Henry County are much further from the Louisville Central Business District, where KentuckianaWorks is located.

[12] We drop 327 individuals because their age was missing or not between 20 and 64 or who have no UI wage information. We drop an additional 456 individuals because they either have missing residency information or do not live in the Kentucky portion of the Louisville MSA.

[13] In order to improve the speed of the matching algorithm we also drop anyone in the potential comparison sample with quarterly earnings above $200,000. This number is the maximum value of quarterly earnings across all the participants, plus one standard deviation of the distribution of quarterly earnings across all participants rounded up to the nearest $25,000 increment.

[14] Matching is done with replacement so the same comparison individual could be matched to multiple treatment individuals.

Next, the initially matched sample is refined by matching treated individuals to the comparison individuals based on a match on age and also matching to all individuals whose average earnings over the four quarters prior to the participants' quarter of entry was within 2% of the prior earnings of a treated individual.[15] This results in 1,108 individuals in the treated sample and 192,690 individuals in the comparison sample. We then assign weights for individuals in the comparison sample, where the weights are the inverse of the number of matches for person *i*, in the treatment group. The sum of these weights will equal the number of people in the treatment sample. We then repeat this matching process for our completers sample—that is Code Louisville participants who complete at least one module. This produces a treatment group of 635 individuals and a comparison group with 110,605 individuals.[16]

Table 2 provides basic summary statistics for the treatment groups and the weighted comparison groups. By construction, the weighted averages of the comparison group are identical for the exact match variables of gender, race, and education. The weighted average of age is also identical between the two groups because we also employed an exact match on age. There are small differences in average earnings in the year prior to enrollment between the treated and weighted comparison sample because this is the only variable where we did require an exact match, but the differences are small (less than 2% given our matching strategy).

Table 2 shows that we do not know education for 37.7% of the enrolled group and 38.6% of the completers. There are two potential reasons for unknown education. The first is that the

[15] Because KLDS does not use birth month when determining age, age is calculated as calendar year minus birth year and is treated as a continuous variable. Age is matched through subclasses where each subclass contains at most two different ages. 87.8% of subclasses contain two ages.

[16] We experimented with using propensity score matching with a caliper, nearest neighbor matching and coarsened exact matching on all four quarters or earnings prior to the zero quarter. However, all these other techniques produced a lower quality of matches.

individual completed their education in Kentucky prior to 2008, which is the first year of KYSTATS education data. This impacts both the treatment and comparison groups similarly so missing education should proxy for similar background characteristics. The second, and less common, reason is that an individual may have attended a private school or were educated outside of Kentucky, so no record exists in the state databases. Again, this should have a similar impact on the treatment and comparison groups. While a main source for race information is the school data, we can obtain race from other sources in the KLDS, so race is missing less often than education.

While slight differences between the enrolled treatment group and the completed treatment group exist, none are large. The enrolled group has a slightly larger percentage with some college (28.5%) than the completers (24.8%). Completers are also more likely to have a bachelor's degree (20.4% compared to 18.9%) or a master's degree (8.4% compared to 7.3%) suggesting more educated participants are more likely to complete at least one module of the program.[17]

In Figures 1 and 2 and we provide evidence on the evolution of earnings and employment for both comparison and treatment groups by gender. Figure 1 graphs earnings (for those with positive earnings) by quarter relative to enrollment for both those who enroll in the Code Louisville Program and the matched comparison group and Figure 2 plots the same information for our completers sample—individuals who complete at least one module—and their matched comparison group. In these figures we see that for both men and women earnings rise steadily

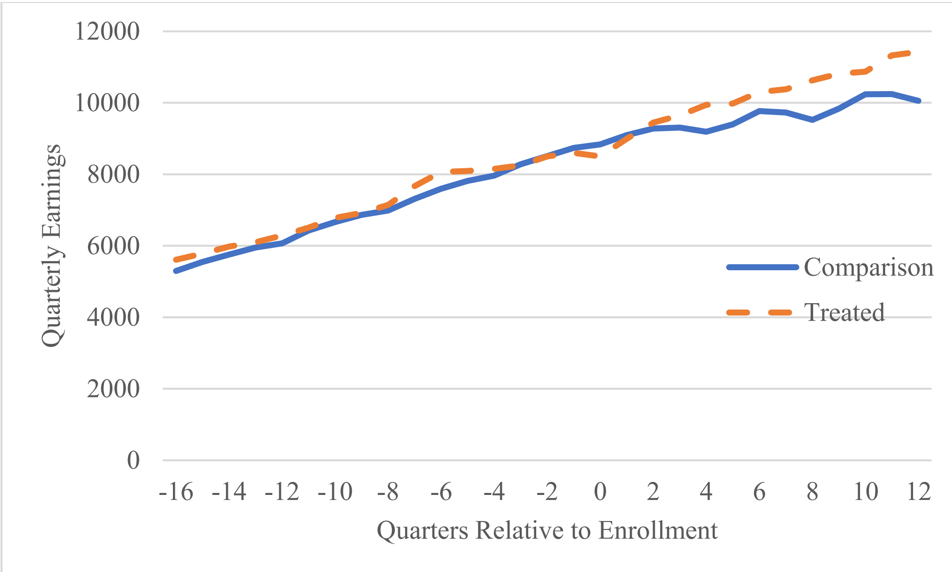
[17] Given that postsecondary education data are available only for students enrolled after 2008, the data are skewed towards younger people. The increased percentage in education by completers could suggest that completers are younger as opposed to more educated. We do not believe this is the case as the average age for both the enrolled and the completed treatment groups is 33.8 and the treatment groups should be similarly impacted by missing educational data.

throughout the study period. We also note the close match prior to enrolment for both groups. Given this successful matching, the differentials post- treatment are considered good estimates of the average treatment effect. Earnings growth for the comparison group appears to flatten during the last five quarters of the post-treatment period while earnings for the treated sample continue to grow, indicating earnings grew faster for the treatment group relatively to the earnings growth of the comparison group. We note that the earnings for women in particular rise rapidly for those who enrolled in Code Louisville, while the rise is slower but still evident for the men.

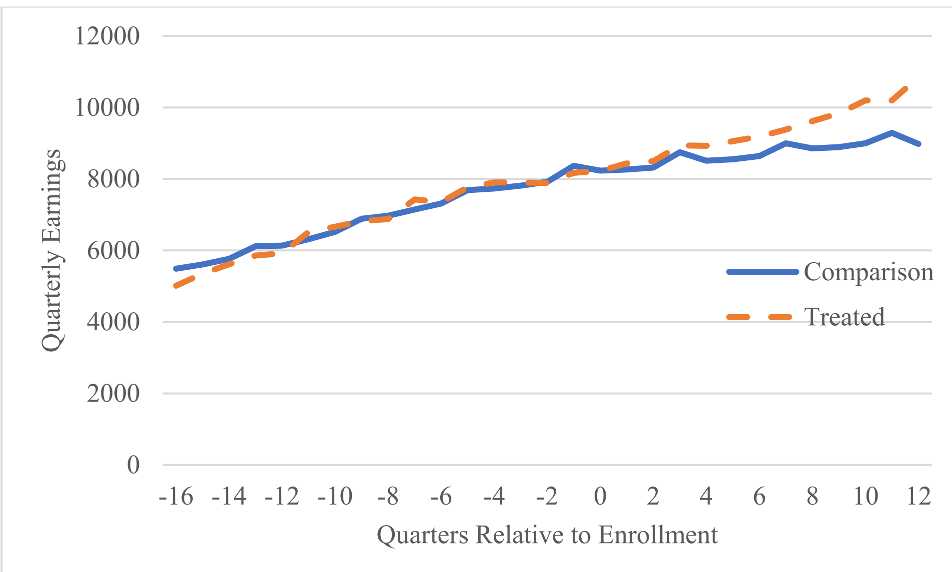
Table 2. Summary Statistics for the Matched Sample of Enrolled Individuals and Individuals Completing at Least One Module

	Enrolled			Completed		
	Treatment	Weighted Comparison	Std. Difference	Treatment	Weighted Comparison	Std. Difference
Female	0.333	0.333	0.000	0.324	0.324	0.000
Asian	0.020	0.020	0.000	0.024	0.024	0.000
Black	0.138	0.138	0.000	0.107	0.107	0.000
Other race	0.013	0.013	0.000	0.014	0.014	0.000
Two or more races	0.011	0.011	0.000	0.005	0.005	0.000
Unknown race	0.078	0.078	0.000	0.087	0.087	0.000
White	0.741	0.741	0.000	0.764	0.764	0.000
High school or less	0.046	0.046	0.000	0.041	0.041	0.000
Some college, no degree	0.264	0.264	0.000	0.236	0.236	0.000
Associates or certificate	0.042	0.042	0.000	0.041	0.041	0.000
Bachelor's degree	0.192	0.192	0.000	0.209	0.209	0.000
Master's or higher	0.079	0.079	0.000	0.091	0.091	0.000
Unknown education	0.375	0.375	0.000	0.381	0.381	0.000
Age	33.8	33.8	0.002	33.8	33.8	0.002
UI earnings 1 year prior to Enrollment	30011.67	30115.62	-0.004	31497.35	31539.47	-0.002
UI Earnings 2 years prior to Enrollment	27736.51	27309.76	0.016	28465.23	28583.94	-0.004
UI Earnings 3 years prior to Enrollment	24596.51	23930.62	0.026	24610.76	24842.71	-0.009
Employment 1 quarter after Enrollment	0.873	0.867	0.018	0.871	0.872	-0.004
Employment 1 year after Enrollment	0.776	0.763	0.031	0.787	0.774	0.033
Employment 2 years after Enrollment	0.765	0.724	0.097	0.781	0.734	0.114
Employment 3 years after Enrollment	0.741	0.704	0.084	0.772	0.715	0.136
UI Earnings 1 year after enrollment	34723.61	33802.38	0.032	36171.77	35274.14	0.031
UI Earnings 2 years after enrollment	38035.36	35240.82	0.090	39858.22	36749.45	0.099
UI Earnings 3 years after enrollment	38228.83	34772.88	0.103	41270.09	36374.55	0.145
Sample Size	1,108	192,690		635	110,605	

Figure 1. Quarterly Earnings by Quarter Since Starting Program, All Enrolled Participants
Panel A-Men



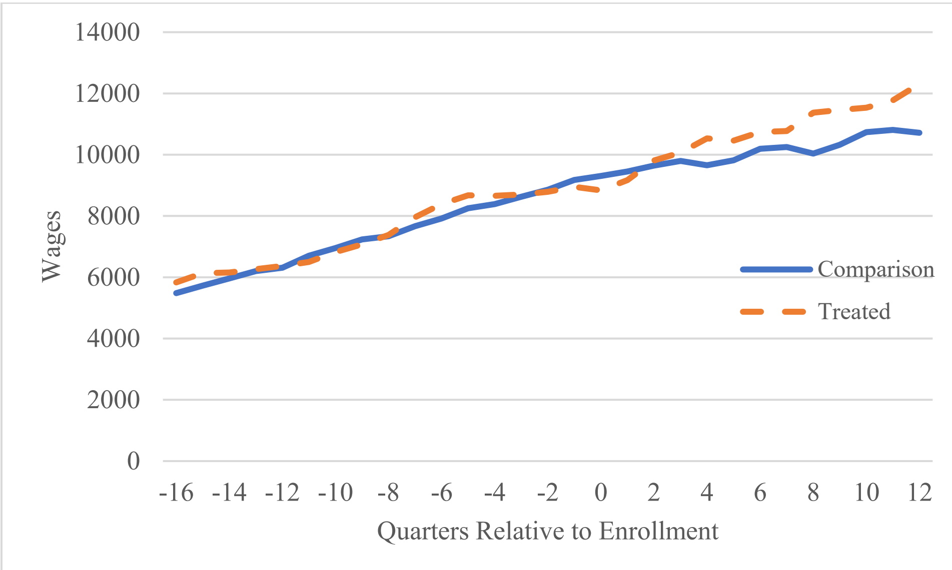
Panel B-Women



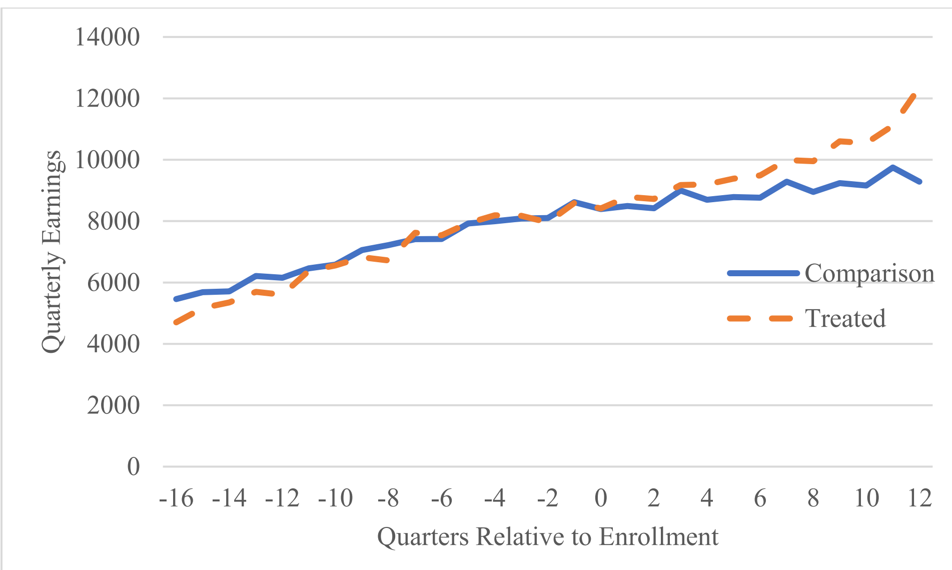
Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [https://kystats.ky.gov/.](https://kystats.ky.gov/)

Figure 2. Quarterly Earnings by Quarter Since Starting Program, Participants Completing At Least One Module

Panel A-Men



Panel B-Women



Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [https://kystats.ky.gov/.](https://kystats.ky.gov/)

In Figures 3 and 4 we plot the employment rates by gender for the enrolled and completers groups. Employment appears to rise relatively steadily for both groups until the treatment period when it begins to fall. This upward trend is the result of sample restrictions requiring some earnings in the four quarters prior to enrollment for matching purposes. Again, we note that pre-trends are nearly identical, particularly for men. Women in the treatment group have slightly lower employment rates than the comparison group, particularly 12 to 16 quarters prior to enrollment. However, the overall trends are quite similar, particularly in the last four quarters prior to enrollment.

Table 2 and Figures 1-4 demonstrate the advantage of using these large longitudinal state datasets for evaluating programs. Using simple matching it is possible to form large comparison samples that have observable characteristics that are nearly identical to almost any treatment sample.

Table 3 presents summary statistics for our treated enrollment sample (column 1 from Table 2), for KentuckianaWorks WIOA participants with an ITA or who participate in the M-TEC or CPT training programs (columns 3-4), and for individuals between age 20 and 64 in the Louisville MSA (column 5).[18] Comparing the enrolled treatment sample with WIOA training participants and individuals in the Louisville MSA shows that participants in the Code Louisville program are different from participants in WIOA programs and often different than the average individual of similar age in the Louisville MSA labor force. In particular, the Code Louisville program is composed of 33% women, which is less than the ITA sample and the Louisville metro area.

[18] Statistics for individuals in the Louisville MSA are obtained from the 2015 American Community Sample five-year panel.

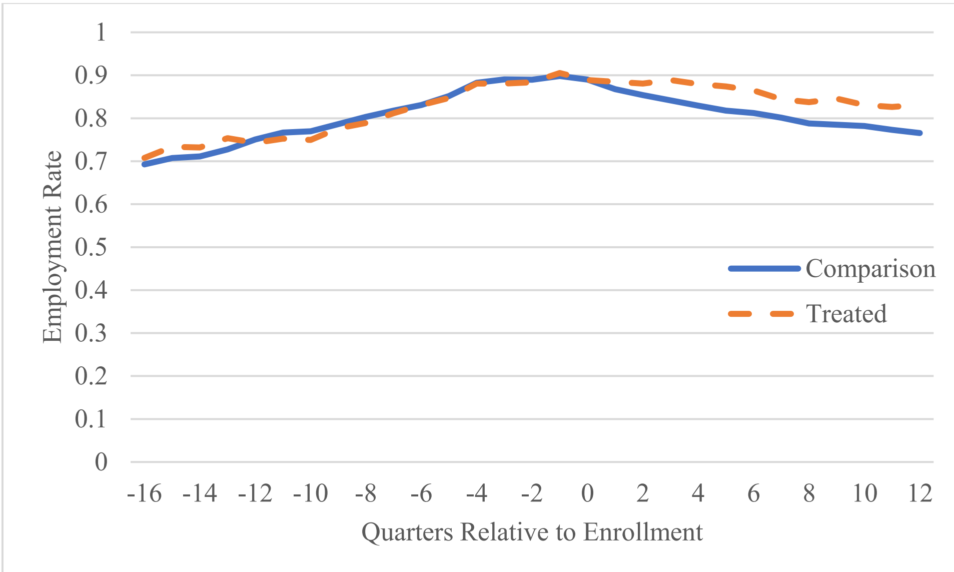
Missing data means that comparison to other WIAO programs at KentuckianaWorks or to statistics on the Louisville MSA is challenging. In making comparisons, we assume race and education data are missing at random and thus compare percentages for complete cases. We find that the participants in the Code Louisville program are slightly more likely to be white and less likely to be Black than the Louisville area, and much more likely to be white than any of the other three training programs.[19] The Code Louisville program has higher educational attainment – in particular the percent with Bachelors' degrees – than the Louisville area and especially compared to other training programs.

The Code Louisville group is slightly younger, at 33 years on average, than the typical worker in the MSA (even restricting the MSA sample to people between the ages of 20 and 64) but quite similar to the other job training programs. This is not surprising since younger workers are more likely to invest in training and education. Average earnings for 20–64-year-old labor force participants in the metropolitan area are $64,713 while Code Louisville participants have average earnings of $30,012 in the year prior to enrollment. Table 3 makes clear that participants in the Code Louisville program are more advantaged than the typical participant in a WIOA program but are somewhat less advantaged than the typical worker in the MSA.

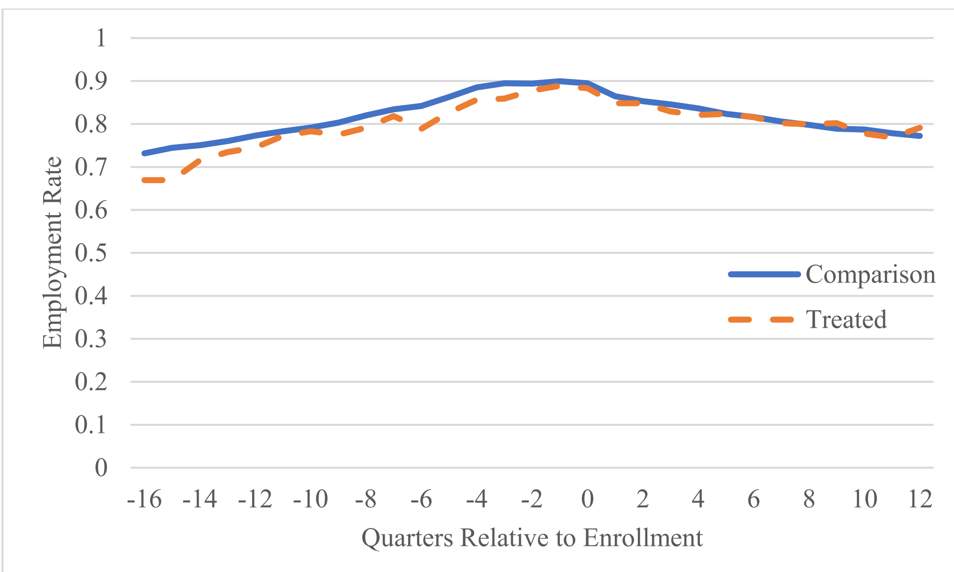
[19] It should be noted that missing race information is common for these other programs as well.

Figure 3. Rates of Employment by Quarter Since Starting Program, All Enrolled Participants

Panel A-Men



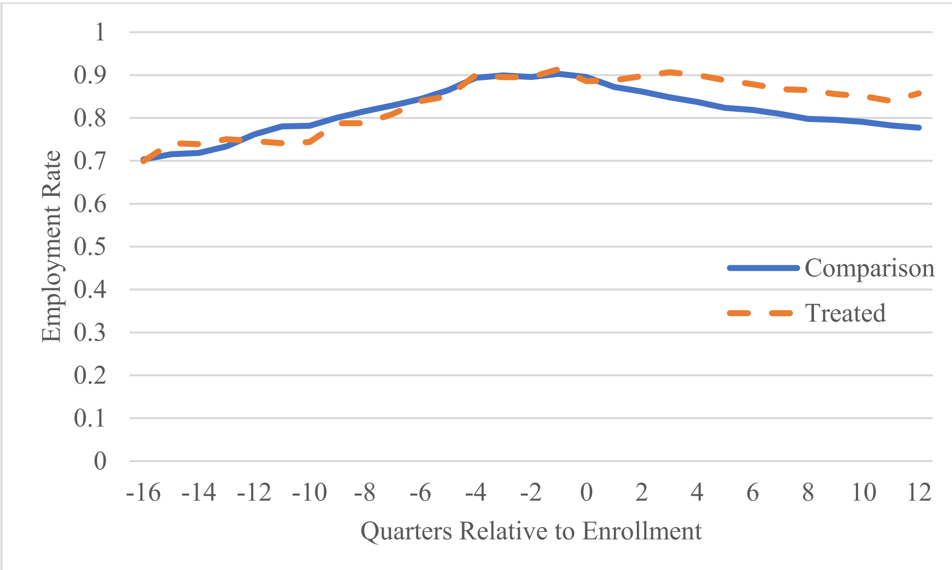
Panel B-Women



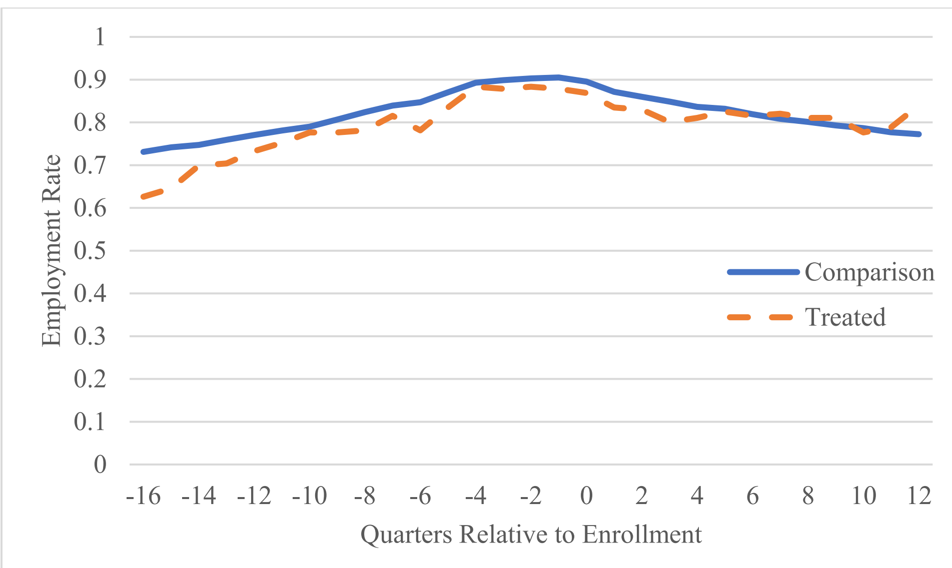
Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: https://kystats.ky.gov/.

Figure 4. Rates of Employment by Quarter Since Starting Program, Participants Completing At Least One Module

Panel A-Men



Panel B-Women



Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [*https://kystats.ky.gov/.*](https://kystats.ky.gov/)

Table 3. Summary Statistics for the Matched Sample of Enrolled Individuals in Code Louisville, Individuals in KentuckianaWorks WIOA Training Programs and Individuals in the Louisville MSA

	Matched Enrolled Treatment Sample	KetuckianaWorks WIOA Training Programs[a]			Louisville MSA[b]
		ITA	M-TEC	CPT	
Female	0.33	0.62	0.21	0.30	0.52
White	0.74	0.54	0.30	0.36	0.71
Black	0.14	0.43	0.65	0.61	0.23
Asian	0.02	0.00	0.04	0.01	0.02
Other race	0.01	0.03	0.01	0.09	0.04
Two or more races	0.01	N/A	N/A	N/A	N/A
Unknown race	0.08	N/A	N/A	N/A	N/A
High school degree or GED	0.05	0.61	0.57	0.53	0.40
Some college, no degree	0.26	0.16	0.20	0.17	0.20
Associates or certificate	0.04	0.07	0.05	0.07	0.08
Bachelor's degree	0.19	0.06	0.08	0.09	0.19
Master's or higher	0.08	0.00	0.00	0.00	0.14
Unknown education	0.38	0.01	0.06	0.02	0.00
Age	33.84	33.5	37.4	37.1	37.3
Earnings[c]	$30,012	N/A	N/A	N/A	$64,713

Notes: a-Data taken from Tables 9-15 in Bollinger & Troske (2019). Data originally provided by KentuckianaWork and are for participants in the program between 2015 and 2018. b-Data from 2015 American Community Survey (ACS) five-year sample. We restrict the sample from the ACS to individuals between 20-64 years old. c-Earnings for the Code Louisville treatment sample are from the year prior to enrollment.

METHODOLOGY

Our goal is to estimate the average effect of treatment on the treated (ATT) over time for participants in the Code Louisville programs using the matched data. Programs such as Code Louisville are voluntary, and individuals select into them based on their interests and expectations. ATT measures the impact of the training on the type of individual who chooses that training. A typical key assumption with matched data is that, conditional on observable characteristics used for matching, selection into treatment is independent of the outcome variable that would occur in the absence of treatment (Conditional Independence). If the conditional independence assumption holds then Figure 1 and 2 comparing earnings and employment post entry for our treatment and comparison samples are ATT estimates. We also estimate regression models because they provide two additional benefits to the matching. First, they improve precision since they include controls for known variation in earnings. Second, they improve robustness by controlling any remaining differences between individuals in the treatment and comparison sample. We used observed earnings for three years prior to enrollment for all individuals, and in our preferred model, individual fixed effects to further address the choice to enter training. In some models, instead of fixed effects, we condition on race and educational status.

We estimate models using the panel data on earnings, log earnings or employment—our three outcome measures—on samples containing individuals in both the treatment and comparison groups (the matched samples). We estimate weighted regressions using the weights described above. Conditioning on past earnings or employment as well as including a person-specific fixed effect, which we do in our preferred model, should capture any remaining differences between the treatment and comparison samples that are fixed over time. Equation (1) shows our preferred model:

$$y_{it} = \alpha_i + \delta X_{it} + \sum_{s=-4}^{12} \beta_s D_{st} T_i + \sum_{s=-4}^{12} \gamma_s D_{st} + \sum_{r=2012}^{2020} \sum_{q=1}^{4} \theta_{rq} D_{rq} . \quad (1)$$

The variable y_{it} represents our three outcome measures, earnings in a quarter t (for those with positive earnings), log earnings in quarter t or employment in quarter t (which equals 1 if someone is employed in the quarter). T_i =1 for individuals in the treatment group and 0 for individuals in the comparison group. The variable D_{st} = 1 if s=t. This is a series of 17 dummy variables indicating each of the quarters starting four quarters prior to enrollment, the enrollment quarter (t=0) and then the 12 quarters after enrollment. Other controls include a cubic in age (X_{it}) and a variable for calendar year-quarter (D_{rq}). The coefficients α_i are individual fixed effects. The coefficients β_s, measure the relative earnings or employment of the treatment group compared to the comparison group and provide our estimate of the effect of treatment on the treated in the quarter. The quarterly dummies for calendar time control for macro-economic effects such as overall wage growth or recessionary pressures. We include these controls because our matching requires treatment and matched individuals to live in the same counties, so essentially these controls capture any cohort effects.[20] This specification closely resembles the specification used in prior evaluations of job training programs such as Heinrich et al. (2013) and Andersson et al. (2022).

We also estimate several additional models to examine the robustness of our estimates from our preferred model. We start with Equation 2:

[20] County of residence is determined by the most recent residence as of 2021.

$$y_{it} = \alpha + \phi T_i + \sum_{s=-4}^{12} \beta_s D_{st} T_i + \sum_{s=-4}^{12} \gamma_s D_{st} + \sum_{r=2012}^{2020} \sum_{q=1}^{4} \theta_{rq} D_{rq} \quad (2)$$

where we include the treatment dummy separately from the interaction with D_{st} to capture possible differences in the outcome variable in quarters 16 to 5 prior to enrollment. We also estimate Equation 2 dropping the main T_i variable but keep the interaction between T_i and D_{st}.

As another robustness check we estimate Equation (3):

$$y_{it} = \alpha + \delta X_{it} + \phi T_i + \sum_{s=-4}^{12} \beta_s D_{st} T_i + \sum_{s=-4}^{12} \gamma_s D_{st} + \sum_{r=2012}^{2020} \sum_{q=1}^{4} \theta_{rq} D_{rq} \quad (3)$$

where X_{it} includes the cubic in age as well as dummy variables for the six race groups (with Asian being the excluded group) and dummy variables for the six education groups (with unknown education being the excluded group). We again also estimate Equation (3) dropping T_i but keep the interaction between T_i and D_{st}.

As we showed above, participants in the Code Louisville program tend to be more educated than nonparticipants. One possibility is that the return to the program varies by education level. In order to test whether effects are heterogeneous with respect to education we also estimate Equation (4):

$$y_{it} = \alpha_i + \sum_{s=-4}^{12} \beta_s D_{st} T_i + \sum_{s=-4}^{12} \gamma_s D_{st} + \sum_{s=1}^{12} \varphi_s ED_i D_{st} T_i + \sum_{r=2012}^{2020} \sum_{q=1}^{4} \theta_{rq} D_{rq} \quad (4)$$

where we add an interaction between the educational attainment of an individual using our six education classifications (ED_i), the training dummy, and number of quarters since treatment.

In order to allow heterogenous treatment effects by gender, we estimate all of our models separately for men and women. In addition, we also estimate separate models for all participants who start the program and those who complete at least one module.

MAIN RESULTS

Estimates for all enrollees

Our main specification provides a series of coefficients, β_s, tracing out the quarterly impact of enrollment or completion on the three main outcomes measures. As such, the most straightforward way to present our estimates is in graphs. We provide full sets of coefficients and standard errors from our estimation of Equation 1 in the online Appendix Tables 1 and 2 (see on line appendix).[21] For our initial results the treatment group includes everyone who started the program regardless of whether they complete any modules. For our results where earnings or log earnings are the dependent variable our analysis excludes quarters with zero earnings. We initially focus on the results from estimating Equation (1), since this controls for time invariant characteristics, before discussing our results from estimating the other specifications.[22] To reduce the number of figures in the main body of the paper we focus on the coefficients where log earnings or employment is the outcome variable. Figures showing the coefficients where earnings is the outcome are included in the online appendix (see on line appendix).

Figure 5 presents our main results showing the estimated effect of treatment on log earnings for men and women. In each graph the blue line represents the coefficient estimates, while the two dashed grey lines provide the upper and lower 95% confidence interval of

[21] https://gattonweb.uky.edu/faculty/Troske/Working%20papers/Online%20Appendix%20for%20Code%20Louisville%20Paper.pdf.

[22] While technically education is time variant, only a small portion of the sample had any changes in the degrees attained during our sample period.

coefficient estimates. We note here that Figure 1 provides very similar results, as we would expect given the matching. In many ways the main contribution of the estimates here is to reduce sampling variance by controlling for known covariates and for idiosyncratic effects.

For both men and women there is a decline in log earnings relative to the comparison group in the quarter prior to enrollment and the quarter of enrollment. Beginning with the first quarter post enrollment, log earnings relative to the comparison group begin to rise. For men, by three quarters past enrollment, log earnings are above parity with the comparison group while for women this occurs within two quarters. Both men's and women's earnings continue to rise relative to the comparison group, although the rise is most pronounced for women. By the last four quarters in our data, treated women earn over 15% more on average per quarter than their comparison counterparts and this difference is statistically significant. For men, the difference is less pronounced with the gain being less than 10% at the end of the data and only statistically significant in the 8^{th} quarter and 12^{th} quarter past enrollment.

Figure 6 presents results where employment is the dependent variable, with a 1 indicating someone is employed (has reported earnings in a quarter). These figures show that treated women have higher employment rates than women in the comparison group, but this difference is insignificant in the three quarters leading up to enrollment and in the quarter of enrollment. For men, the employment gain relative to the comparison group is immediate and rapid; by three quarters post enrollment, employment is 5 percentage points higher, on average, among treated men than their comparison group and employment remains between 5 and 6 percentage points higher for the remaining two years of the study. In contrast, women see much smaller gains in employment. The treated group's initial 2 percentage point advantage in employment rises to approximately 4 percentage points by the end of the data but remains largely statistically insignificant.[23]

Combining our results on earnings and employment we see that for men in the treatment group the gain is largely in employment, although men do experience modest gains in log earnings and the increase in earnings occurs later in the period. For women, we do not see significant gains in employment, but we see gains in log earnings among the treatment sample soon after enrollment (although the estimates are insignificant in the early years) and these gains continue to grow through the end of the data.

Our second analysis focuses on the subsample of individuals who enroll in the program and who complete at least one module of the program. Figures 7 and 8 present the coefficient estimates for men and women, for each of the two outcomes, log earnings and employment, from estimating Equation 1 including only data for completers and their matched comparison group.[24] The results, while similar to the results for all participants, tend to be larger in magnitude but also have larger standard errors due to smaller sample sizes.

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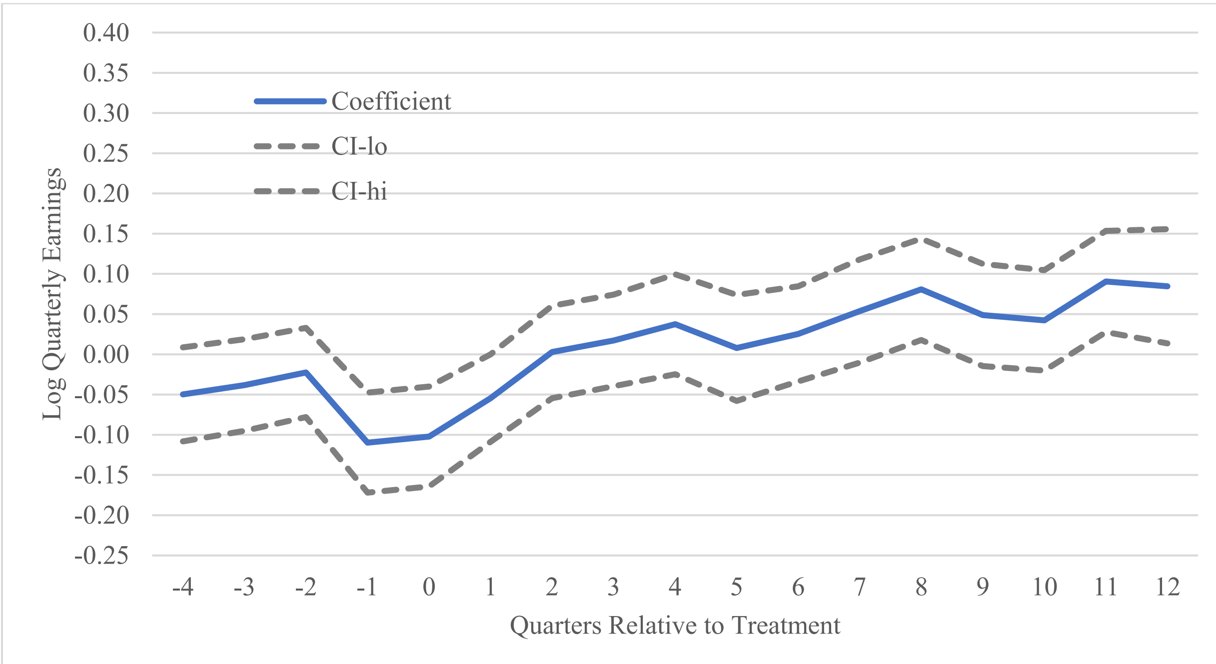
[23] It is possible that the small differences in employment prior to treatment seen in Figure 3 could affect these results, so we have less confidence that the results for women are causal then we do the results for me.

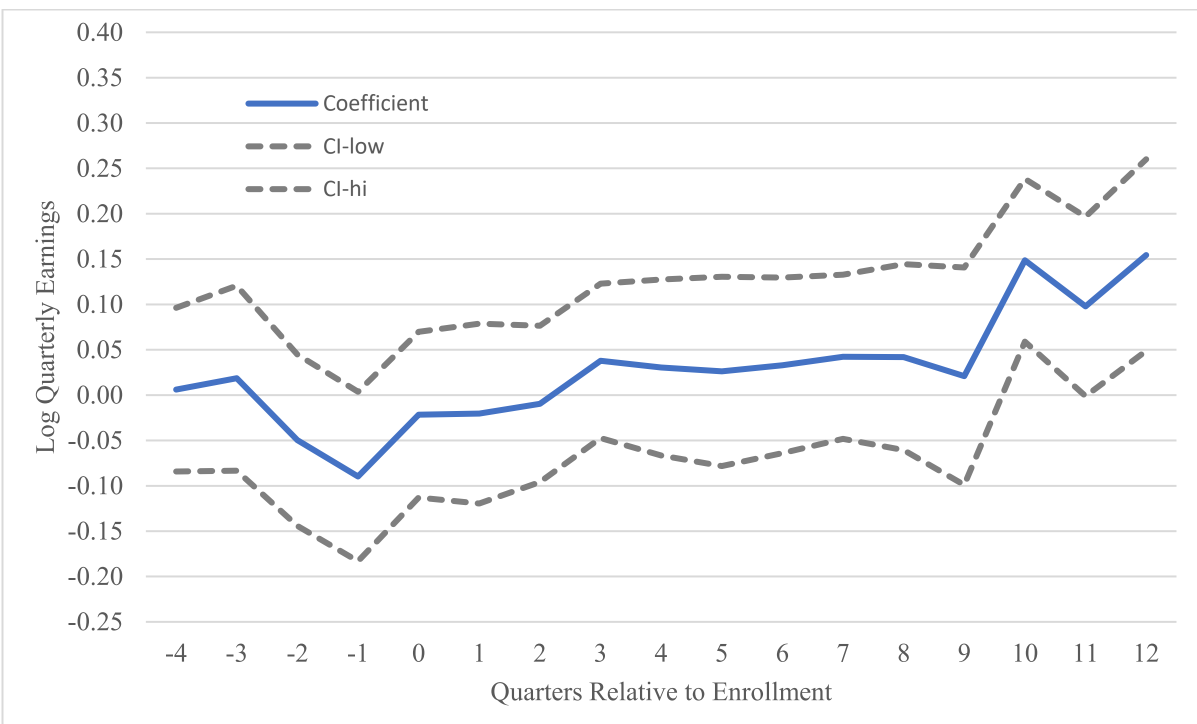
[24] Results where earnings is the outcome variable are included in the online appendix (https://gattonweb.uky.edu/faculty/Troske/Working%20papers/Online%20Appendix%20for%20Code%20Louisville%20Paper.pdf).

Figure 5. Effect of Treatment on Log Quarterly Earnings by Quarter, Estimation of Equation 1, All Enrolled Participants

Panel A-Men



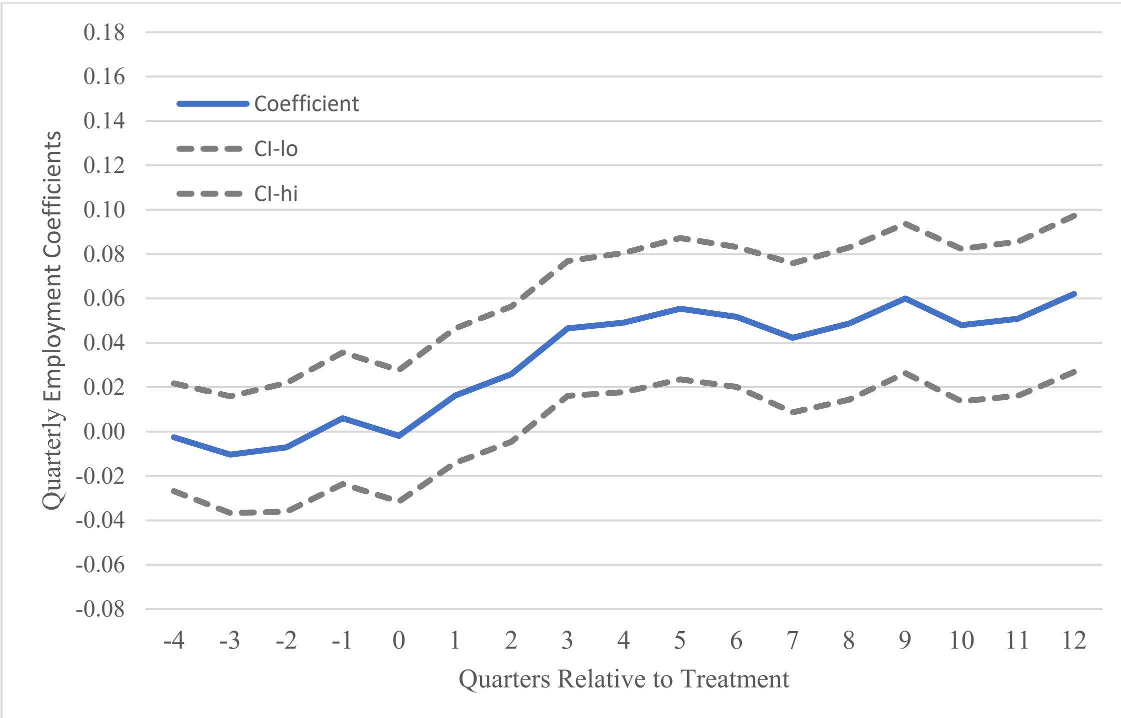
Panel B-Women



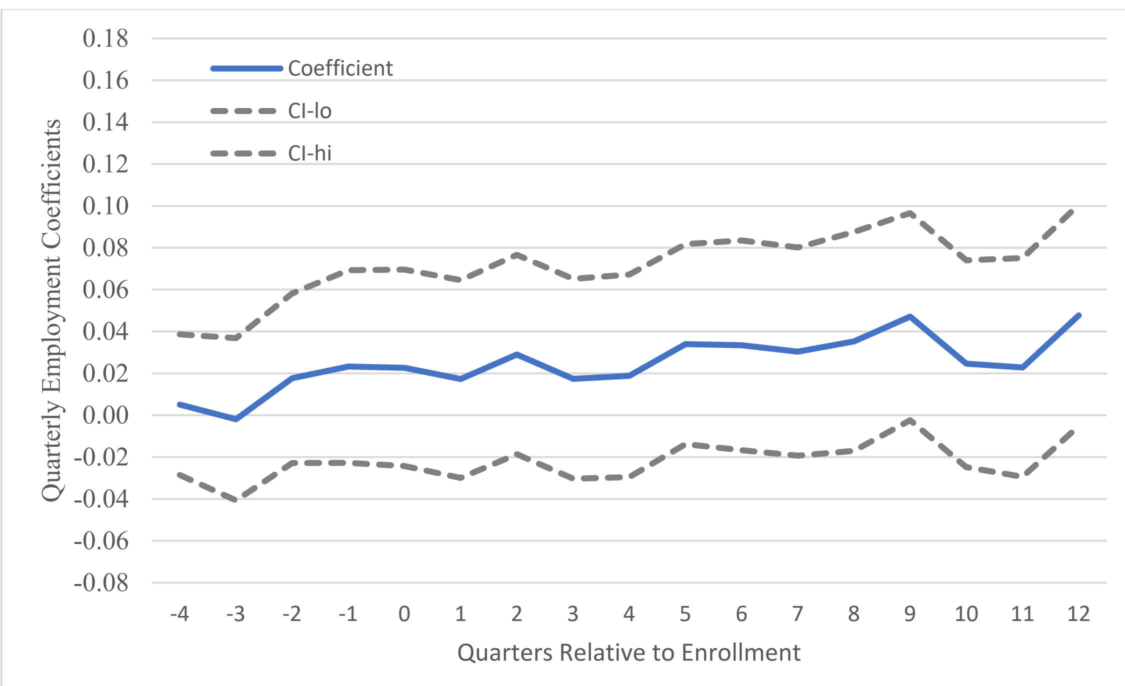
Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [https://kystats.ky.gov/.](https://kystats.ky.gov/)

Figure 6. Effect of Treatment on Employment by Quarter, Estimation of Equation 1, All Enrolled Participants

Panel A-Men



Panel B-Women



Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [https://kystats.ky.gov/.](https://kystats.ky.gov/)

Figure 7 again shows that men have smaller gains, on average, in log-earnings than women immediately after enrolling in the program. Men's log earnings gains do reach 5% by the last year of the study but are not statistically significant. Women's log earnings again start growing strongly soon after enrollment and this growth continues till the end of the data, with average log earnings gains reaching 20%. As with the enrolled group, men's employment (Figure 8) rises quickly to a nearly 8 percentage point gain, on average, relative to the comparison group by the end of the first year after enrollment and remains above the comparison group, and statistically significantly, through the remainder of the study period. Women are much slower to show gains in the probability of being employed but by the last two quarters of the data women's employment rises sharply to over 10 percentage points higher than the comparison group. However, large standard errors make most of these differences statistically insignificant.

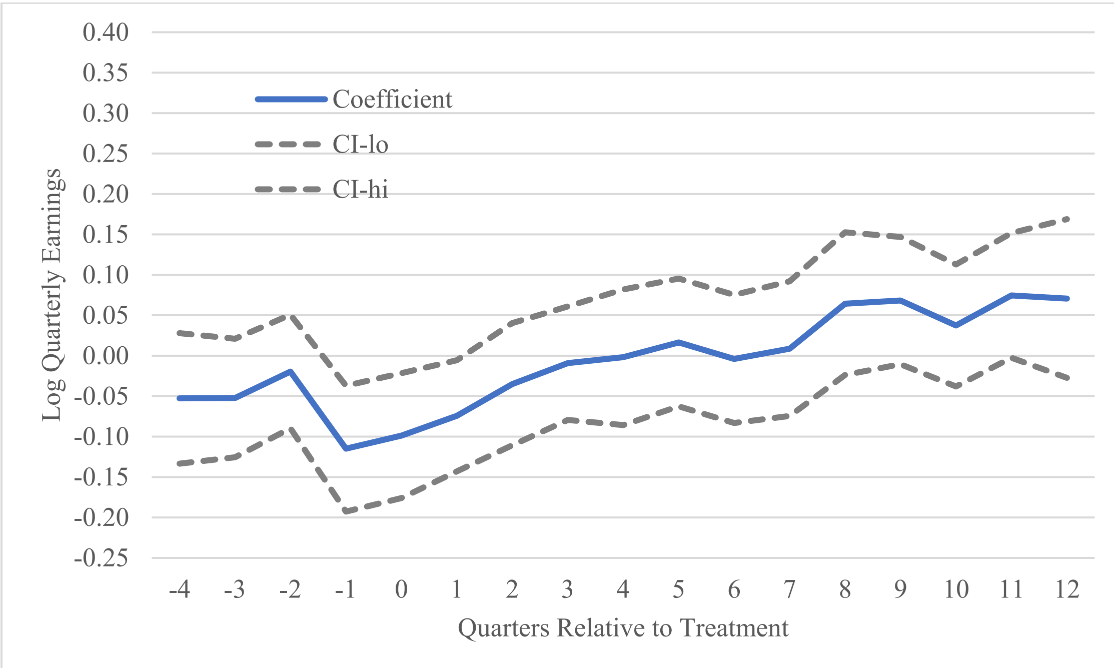
Estimates for completers

While we focus our attention on the enrolled group, focusing on intent to treat, it is clear that the differences in employment outcomes are largely due to the completers. The basic findings from the analysis on the enrolled are all larger among the groups that complete at least one module of the program.

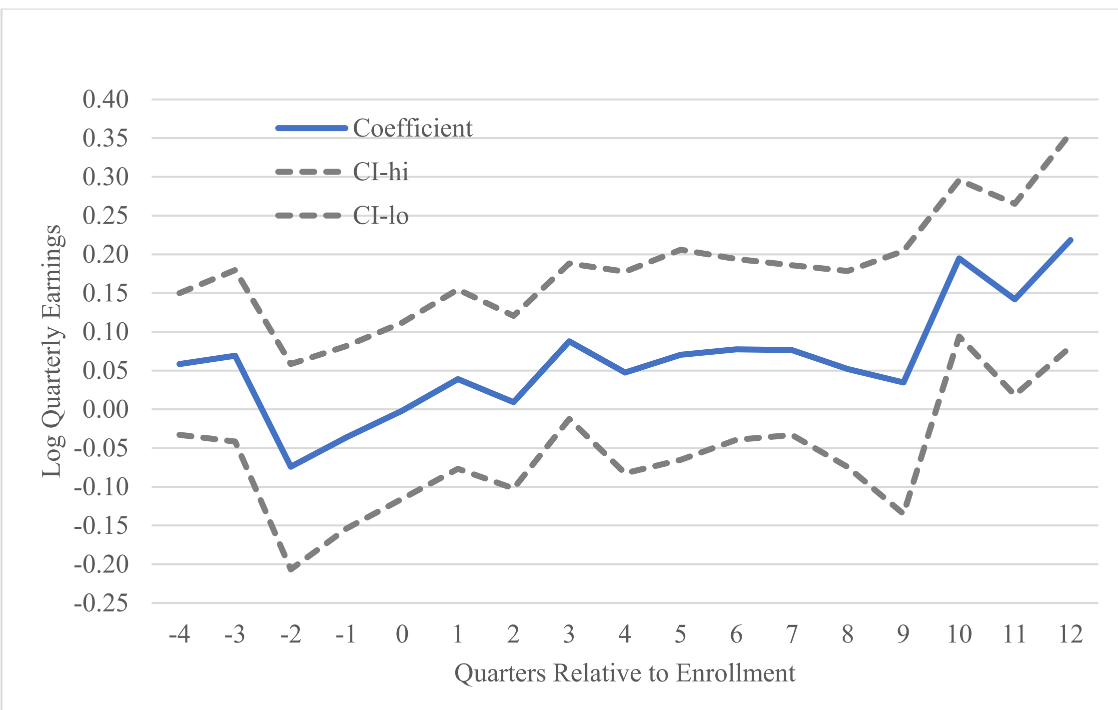
In addition to the results presented above, we conduct a number of robustness checks estimating Equations 2 and 3 both with and without the treatment dummy. These results are available in Appendix Figures 5 and 6 in the online appendix (and Appendix Tables 3 and 4). While some differences do appear, the coefficients on the treatment dummy largely parallel what we see in Figures 7 and 8, which lends support to our preference for the model that includes person-specific fixed effects. In addition, all of these models support our main conclusions−the largest gains from treatment for men occur in employment, while largest gains for women are in wages.

Figure 7. Effect of Treatment on Log Quarterly Earnings by Quarter, Estimation of Equation 1, Participants Completing At Least One Module

Panel A-Men



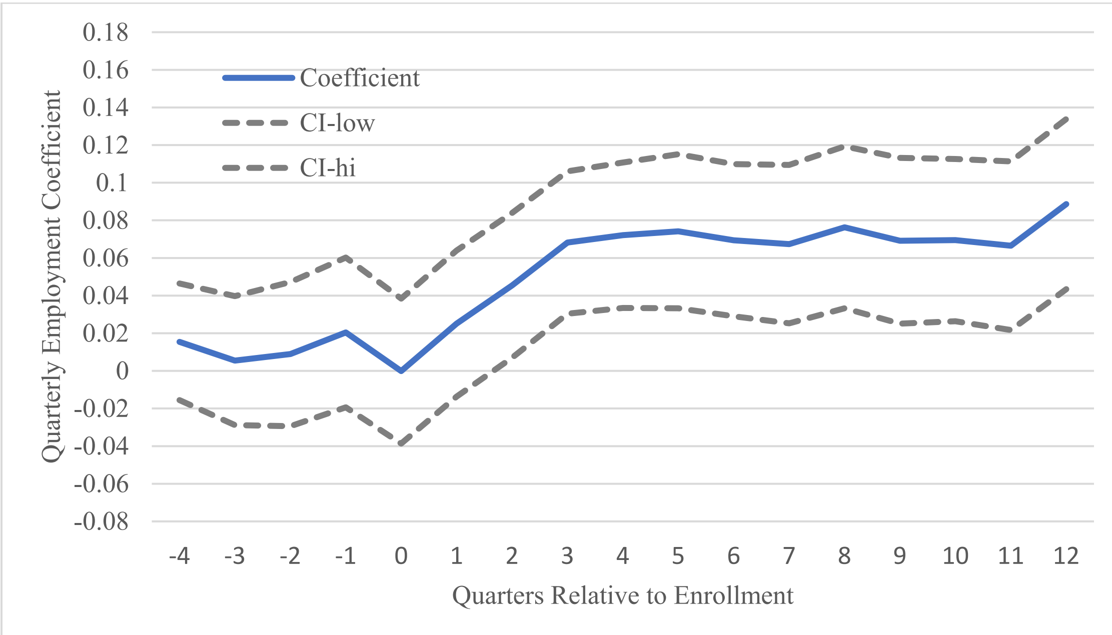
Panel B-Women



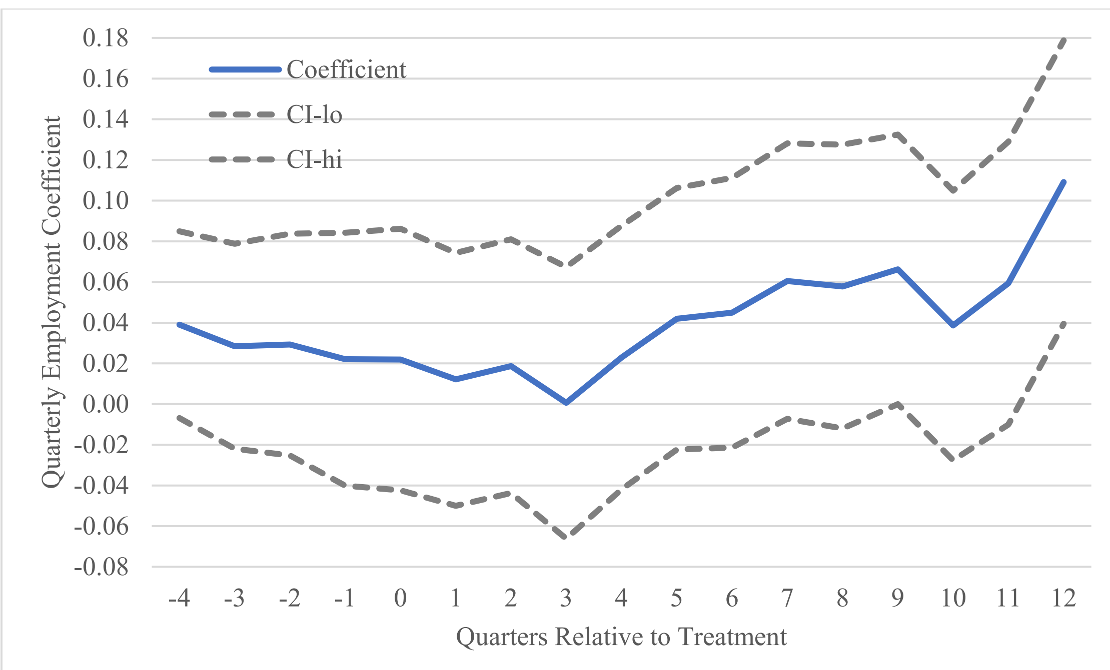
Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: https://kystats.ky.gov/.

Figure 8. Effect of Treatment on Employment by Quarter, Estimation of Equation 1, Participants Completing At Least One Module

Panel A-Men



Panel B-Women



Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: https://kystats.ky.gov/.

Heterogeneity by education

Next, we present our results from estimating Equation (4) in which we allow the quarterly impact of treatment to vary by the education of the participant prior to entry. One hypothesis is that the impact of the Code Louisville program may vary by educational attainment prior to starting the program, but a priori it is not clear whether the impact would be higher for those with more or less education.[25] Figures 9 and 10 present our results by education group and by gender for log-earnings and employment, respectively. Our separate estimates by education largely mirror our previous results. Looking initially at Figure 9, we continue to see the rise in earnings for men later in the period among all education groups except for individuals with missing education. The gains in log earnings are particularly large for those with a bachelor's degree and with just a high school degree, followed by those with a master's degree. All three of these groups experience gains in log earnings relative to the comparison groups of over 20% by four years after enrollment. We also see large gains in log earnings for women with master's and bachelor's degree. The gain in earnings for other groups are much more erratic over time reflecting the fact that we have too few women in these groups to obtain an accurate estimate of the gains in earnings.

In Figure 10 we see the employment gain for men is largest among those with a bachelor's or some college, but individuals with unknown educational level also experience some of the largest gains in employment. Since individuals with unknown education are either

[25] Examining the coefficients on the education variables from our estimations of Equation 3 (online Appendix Tables 7-10 https://gattonweb.uky.edu/faculty/Troske/Working%20papers/Online%20Appendix%20for%20Code%20Louisville%20Paper.pdf) shows no clear pattern of earnings or employment differences by education prior to entry. Generally, it is the case that individuals with more education have higher earnings and employment rates on average, but this is true for prime age workers. For younger workers, such as those in the code Louisville program, the pattern of earnings and employment by educational attainment is less clear.

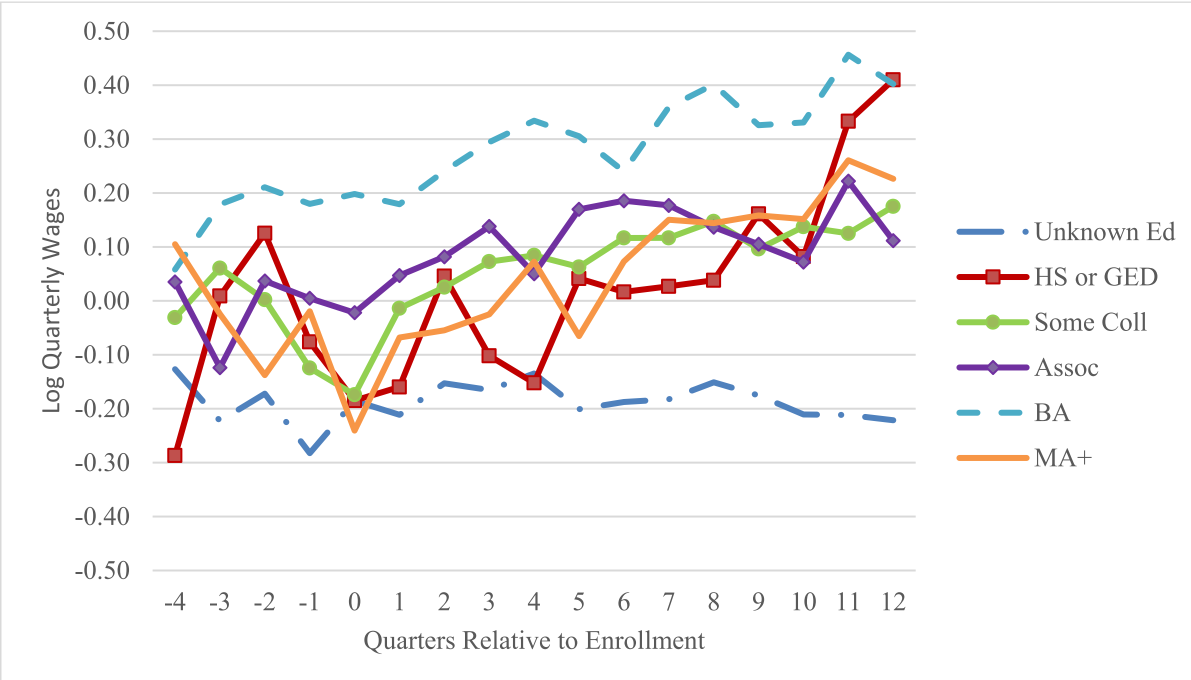
older or individuals who migrated to Kentucky after completing their education, one possibility is that many people in this group are investing in new skills so that they can switch to a new industry or occupation. We note that while initially the employment gain to those with a high school degree or less is variable and even negative, by the last year of the data it rises dramatically, although the differences are not statistically significant.

The changes in employment for women are more complicated. While for most educational groups, there is little employment effect among women, we see that woman with master's degrees have a dramatic increase in the probability of being employed. Conversely, women with an associate's degree or a high school degree appear to experience a decline in employment relative to people in the comparison group. Although not presented, the positive impact is largely driven by completers, while the negative impact is driven by those who fail to complete the program.

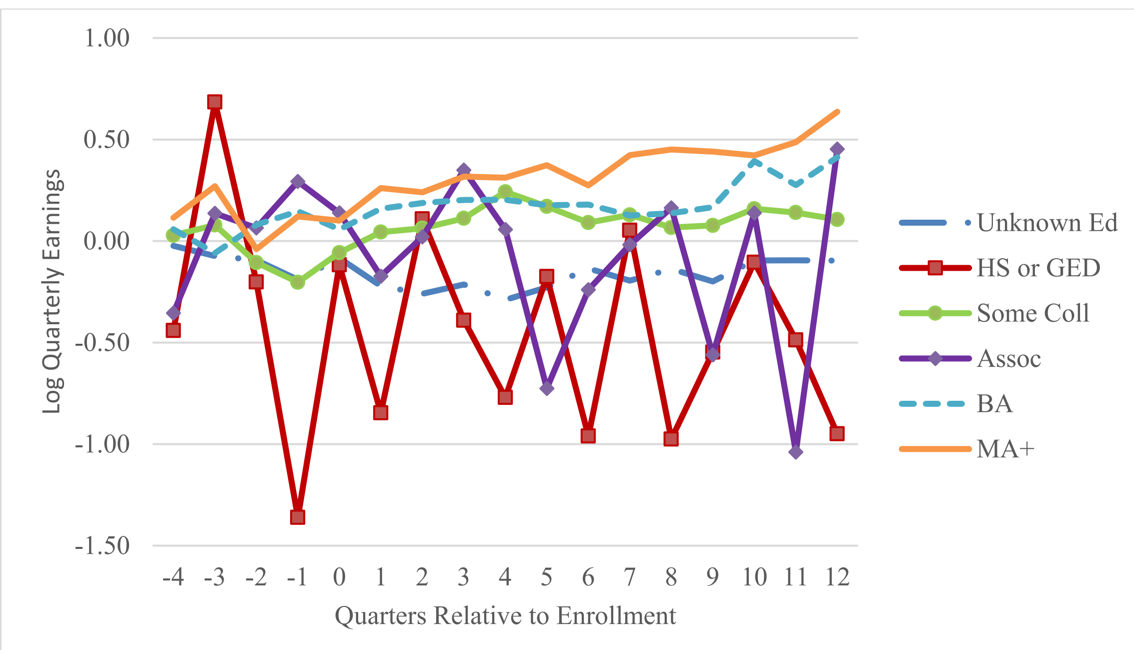
Overall, these results show that there is substantial heterogeneity in the estimated impacts of the Code Louisville program. People with a bachelor's degree or more experience the largest increase in earnings and employment and those with less education experience little measurable benefit. It should be noted that the standard errors for these estimates are quite large and thus some caution must be exercised in drawing strong conclusions. We cannot identify what the causal mechanism for these differences may be; however, one explanation is that women who are returning to the labor force find that job training aids their re-integration (see Doerr, 2022).

Figure 9. Estimated Effects of Treatment on Log Quarterly Earnings by Education and Quarter, All Enrolled Participants

Panel A-Men



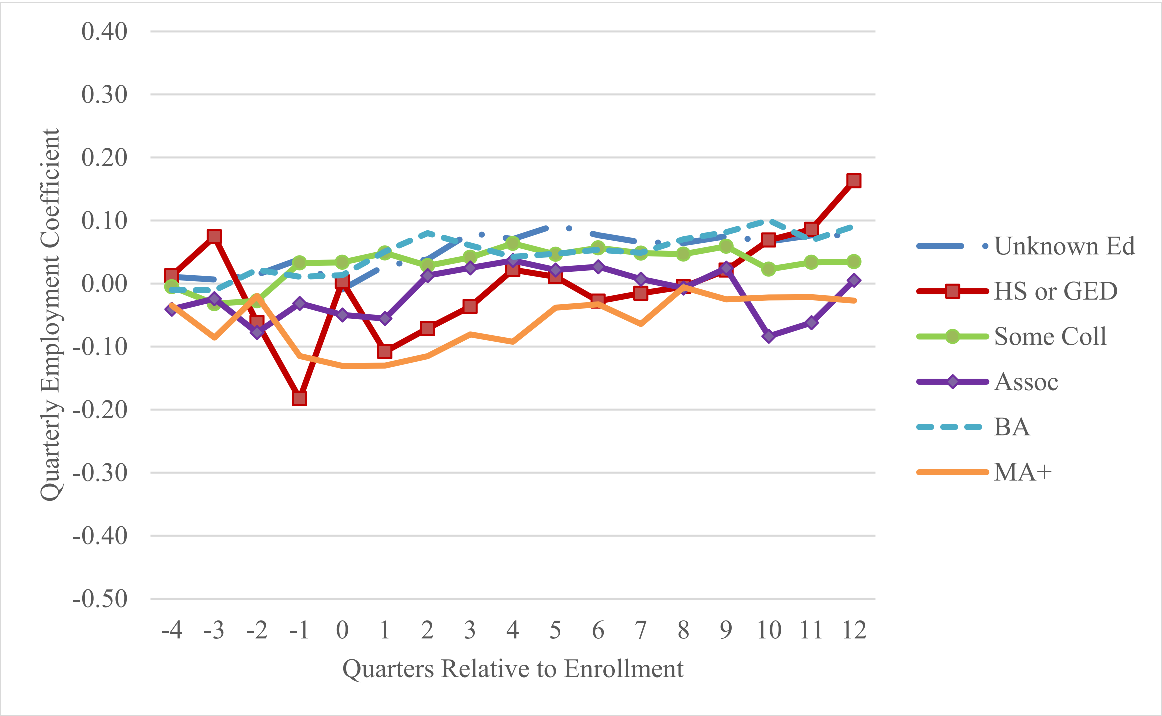
Panel B-Women



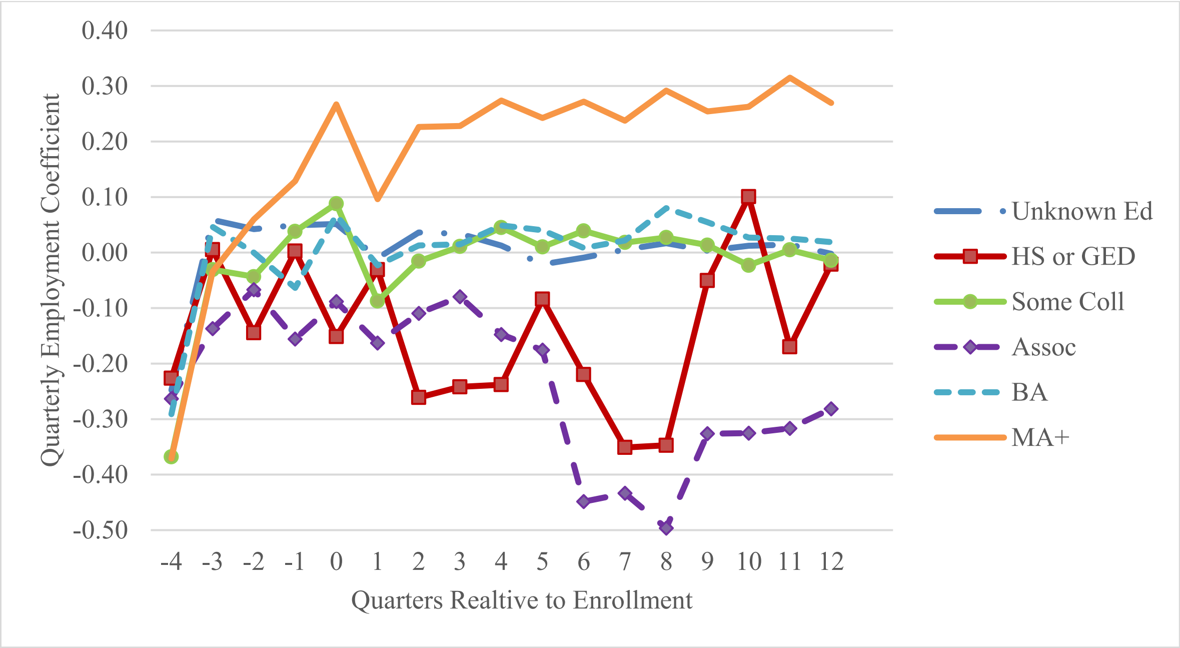
Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: [https://kystats.ky.gov/.](https://kystats.ky.gov/)

Figure 10. Estimated Effects of Treatment on Employment by Education and Quarter, All Enrolled Participants

Panel A-Men



Panel B-Women



Source: Kentucky Longitudinal Data System, Kentucky Center for Statistics: https://kystats.ky.gov/.

Comparison with other job training programs

The estimated impacts of the Code Louisville program are broadly similar to the estimated impact reported in recent evaluations of other job training programs. For example, the recent evaluations of WIA by Andersson et al. (2022) and Heinrich et al. (2013) report similar gains in earnings as those for participants in the WIA Adult Worker program. Both studies find that earnings differences grow over time, reaching a maximum 2-3 years after entering the program. In addition, both the Heinrich et al. evaluation and the Card et al. (2018) meta-analysis of job training programs find, like us, that earnings gains are larger for women compared to men. (Andersson et al., 2022, does not find differential effects for men and women). One notable difference between our study and these previous studies in that we find much larger employment effects for men.

Comparing our estimated effects to evaluations of other sectoral training programs, we find that our estimated impacts are somewhat more modest than the estimated effects from these other programs. For example, Baird et al. (2022) reports earnings effect from treatment of around 12% and employment effects of around 14 percentage points, while Katz et al. (2022) report impacts on earnings of between 12% and 34%. Bollinger & Troske (2019) find no statistical difference between the Code Louisville program and other training programs at KentuckianaWorks, although as noted above, the characteristics of participants differ dramatically between Code Louisville and these other programs. However, when considering the potentially smaller impacts for the Code Louisville program it is important to consider differences in the cost of operating the programs. Analysis in Bollinger & Troske (2019) shows that the Code Louisville program is substantially less costly to operate on a per-participant basis than traditional federal training programs.

CONCLUSIONS

This project provides researchers with an example of using matching estimators and state-level administrative data to evaluate a local job training program. Estimating treatment effects is a challenging endeavor. Our methodological approach allows for heterogeneous treatment effects both across demographic groups (by gender and education) and module completion. While a number of approaches are available, the approach we follow here (similar to that of Jepson et al., 2025) allows for greater flexibility than traditional approaches to estimate treatment effects.

While most recent evaluations of federal job training programs suggest that these programs produce positive labor market benefits for participants (Mueser & Troske, 2023) the impacts are fairly modest. One promising avenue for increasing the returns to training have been sectoral training programs which are designed to provide skills to participants that would enable them to obtain high paying jobs in growing sectors such as health care, advanced manufacturing and IT. However, many of these programs have been developed by non-governmental entities, leaving open the question of whether they can be implemented in federal job training programs such as WIOA.[26] In this paper we present evidence on the impact of the Code Louisville program, which is a program designed to provide participants with the skills necessary to obtain a job as a coder and is administered by the local Workforce Development Board in Louisville, KY.

Our estimates suggest that the Code Louisville program provides positive labor market benefits for both male and female participants, although the type and timing of benefits differ.

[26] See the Baird et al. (2022) for an example of a sectoral labor program implemented as part of WIOA.

Male participants see a fairly quick and large gain in employment relative to the comparison group of 5 percentage points within one year of enrolling in the program that persists through the end of the data but experience a fairly modest gain in quarterly earnings relative to the comparison group of between 5-10% by three years after enrollmentWomen experience an initial gain in quarterly earnings of approximately 5 within one year of enrollment (although the estimates are imprecise), which grows to between 10-15% by three years after enrollment. Women also experience around a 3-percentage point gain in employment relative to the comparison sample, by quarters 5-8 after enrolment. We further show that most of these increases accrue to participants who complete at least one module in the program. Participants who fail to complete any part of the program show insignificant benefits.

We also find that the biggest improvements in labor market outcomes occur for participants with the highest levels of education—a bachelor's degree or higher. Participants with less education typically do not show a statistically significant improvement in labor market outcomes, although male participants with an unknown amount of education do show a significant increase in the probability of being employed relative to the comparison sample. While we do not advocate further restricting entry into the program, we think these results suggest it may be beneficial to advise those with lower educational attainment that other programs may be of more benefit.

We speculate that one reason the Code Louisville program produces somewhat smaller returns than other sectoral training programs is that most of the training in the Code Louisville program is provided online as opposed to the in-person training provided in the other sectoral training program. However, while the Code Louisville program does produce somewhat lower returns than these other programs, this training appears to be provided at a significantly lower cost that the training provided in other programs (Bollinger and Troske, 2019) suggesting that online training may be an efficient way to provide training for certain types of occupations and for participants who are able to participate in online training.

We also find that data from the KLDS are valuable for conducting this type of program evaluation. Given the large size of the potential comparison group, we can form very close matches between the treatment and comparison groups, which strengthens the validity of the estimated effects. We believe these data, and similar data in other states, allow policy makers and researchers to conduct much more informative evaluations of a variety of programs.

Given the declining funding going to federal job training programs (Mueser & Troske, 2023) it is imperative that we continue to explore new and novel ways to provide job training programs to people in need of these services. Our estimates of the impact of the Code Louisville program provides some initial evidence that this program is providing positive improvements in the labor market outcomes for program participants, which we believe justifies continuing the Code Louisville program and expanding it to other locations in the country.

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