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Effect of Community and Technical College Course Work on Annual Earnings for the Training Benefits Program, 2006-2009

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Executive summary

Background

The purpose of this study is to analyze the effect of the Unemployment Insurance Training Benefits (TB) Program on the earnings of TB Program participants, with a particular focus on the training completed. The intent of the TB Program is to provide participants with the knowledge, skills and abilities to enhance their long-term earnings potential in high-demand occupations. People who are eligible for participation in the TB Program, as stated in RCW 50.04.075, include dislocated workers, U.S. military veterans, Washington National Guard members, mentally or physically disabled people and low income individuals. Overall, there have been 21,033 TB participants from 2002 through 2012.

Our findings, while exploratory, suggest that TB Program participation is generally beneficial from the standpoint of the participant. After applying statistical controls, our model estimates that post-training earnings of TB participants are $2,872 to $16,710 higher than their counterparts who did not participate in the program. In addition, we find evidence that the content of the training undertaken by TB participants matters. In particular, our model suggests that the pursuit of health-related (e.g. nursing, EMT training, home health care) credits may further enhance earnings. Finally, we find evidence that the beneficial effects of TB Program participation vary for specific categories workers.

Research questions and methodology

In this study we assess the effectiveness of the TB Program from the perspective of program participants. The main questions we answer in this report are as follows:

1) Does participation in the TB Program increase participants' future earnings?
2) Does the number of college credits completed while in the TB Program affect future earnings?
3) Do participants who take more science, technology, engineering and math (STEM) or health-related courses experience greater gains in earnings?

In order to calculate the net impact of the TB Program, we created a comparison group using propensity score matching to identify UI claimants who were statistically similar to TB participants. Next, we used fixed effects methods to estimate the net effects of the TB Program on participant earnings. Fixed effects methods are a class of econometric models which control for factors that the researcher cannot observe. By netting out all the unobserved differences between TB participants and non-participants we are better able to assess the effect of the TB Program on earnings.

Key findings

The TB Program contributes to an increase in earnings.

Our findings, while exploratory, suggest that TB Program participation is generally beneficial from the standpoint of the participant. Assuming TB participants and non-participants were statistically similar in terms of the fixed effects our model controls for, we estimate that TB participants would earn $2,872 to $16,710 more than non-participants.

Training in health-related fields appears to be especially beneficial.

We also find evidence that health-related college credits, and health-related programs of study, generate higher post-training earnings. This finding is unsurprising in light of recent occupational job growth projections. Indeed, Employment Security Department (ESD) projections forecast that two, of the top six, fastest growing major occupational groups in Washington state are health-related.[1] Further, at the national level, the U.S. Bureau of Labor Statistics projects that 20, out of the top 30, fastest growing occupations (e.g., personal care aides, home health aides, diagnostic medical sonographers, and occupational therapy assistants) are in health-related fields.[2]

TB participants who pursue a greater number of college credits experience steeper drops in earnings. However, this simply reflects the substitution of schooling for work.

Among TB participants, we find evidence that they earn less the more college credits they pursue. While this finding initially struck us as somewhat counter-intuitive, after close inspection we believe it reflects a trade-off between the amount of time individuals commit to the pursuit of training, and the amount of time people devote to work. Further, this negative effect appears to be partially offset for TB participants who enter the program with prior college credits. We suspect this is because workers with prior credits are closer to degree or certificate completion. Further, workers who are closer to completing an educational credential at the outset of the TB Program are likely to re-enter the labor force earlier than others.

Participation in the TB Program impacts the earnings of workers differently.

Finally, we find that the effects of TB Program participation differ across demographic categories of workers. In other words, certain groups of workers may be more (or less) likely to benefit from participation in the TB Program when compared to others. For example, our analyses suggest that the year in which one was admitted into the TB Program, gender, and low income status all affect the relationship between program participation and earnings.

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[1] See https://fortress.wa.gov/esd/employmentdata/docs/industry-reports/employment-projections-2015.pdf

[2] See http://www.bls.gov/news.release/ecopro.t04.htm

Overview of the Training Benefits Program

In 2000, the Washington State Legislature enacted Substitute House Bill 3077 (SHB 3077), which created the TB Program. The goal of this program is to retrain unemployed individuals who qualify for unemployment benefits, but whose skills are no longer in demand. The TB Program is ultimately designed to provide TB participants with knowledge, skills, and abilities that enhance their long-term earnings potential in high-demand occupations.

SHB 3077 (2000) authorizes the Washington State Employment Security Department (ESD) to allocate up to $20 million each year from the Unemployment Insurance Trust Fund for the provision of additional unemployment benefits to qualified UI claimants who wish to receive job training. The bill defines a qualified UI claimant as a dislocated worker whose occupation is in decline in his or her local labor market and who needs training for a new occupation. Until June 30, 2002, SHB 3077 (2000) also made additional benefits available to claimants who had exhausted their benefit eligibility and who were employed in aerospace, forest products and fishing industries during their base year.[3]

In 2009, the Washington State Legislature passed Engrossed Substitute House Bill 1906 (ESHB 1906) which substantially increased the number of individuals who qualify for the TB Program. In addition to dislocated workers, U.S. military veterans, Washington National Guard members, mentally or physically disabled people, and low income individuals qualify for the TB Program as of April 2009.

In 2011, Engrossed House Bill 1091 (EHB 1091) further expanded the number of individuals who qualify for the program by removing the requirement that claimants demonstrate a long-term attachment to the labor force. EHB 1091 (2011) also amended the law, such that TB Program payments are not charged to employers for purposes of calculating their experience-rated UI taxes.[4]

Upon entering the program, TB participants must enroll in training that prepares them for a high-demand occupation in their local workforce development area (WDA). On an annual basis, ESD develops a list that identifies occupations that are "in demand," "balanced" and "not in demand" in each WDA. Local workforce development councils (WDCs) then review, adjust and approve that list according to their knowledge of local labor market conditions.[5]

Under current law, UI claimants who qualify for the TB Program receive up to 52 weeks of unemployment benefits. These 52 weeks include 26 weeks of regular benefits and an additional 26 weeks of benefits paid out of a portion of the trust fund set aside for the TB Program. Unemployment benefit eligibility reached a peak of 125 weeks for TB participants, and 99 weeks for all other UI claimants, during the period of federal benefit extensions that lasted from June 2008 through December 2013.[6] During the period of federal extensions, participants had to exhaust both their regular unemployment benefits and extended benefits (EB) before they drew Training Benefits.

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[3] For a detailed explanation of TB Program eligibility requirements prior to 2009, see SHB 3077 (2000) Sec. 8. For a detailed definition of a dislocated worker, see RWC 50.04.075.

[4] RCW 50.20.043.

[5] As required by RCW 50.22.150 and 50.22.155.

[6] U.S. Department of Labor, Employment and Training Administration (ETA), "Emergency Unemployment Compensation (EUC) Expired on January 1st, 2014," www.workforcesecurity.doleta.gov/unemploy/supp_act.asp: accessed July 2, 2015.

TB participants do not have to look for work as long as they are enrolled full time and making satisfactory progress in their approved training programs. Direct costs of training – such as tuition, books, tools, supplies and transportation – are not supported by the program.

Until April 5, 2009, all TB participants could receive Training Benefits for up to two years after the end of their regular UI claim year, which is 12 months from a UI claimant's effective claim date. TB Participants approved during the period of federal benefit extensions could receive Training Benefits for up to three years after the end of their regular UI claim year.[7]

In some cases, TB participants included in this study exited training before receiving Training Benefits from the trust fund. TB participants who did not draw Training Benefits from the trust fund were likely still receiving federal unemployment benefit extensions when their training ended.

Prior to 2011, all UI claimants had to submit a training plan within 90 days of receiving their TB Program eligibility notice in order to qualify. All claimants were also required to enroll full time in an approved training program within 120 days of receiving their eligibility notice.

EHB 1091 (2011) amended the training plan submission and enrollment deadlines. Claimants who qualify as dislocated workers with an effective date of claim on, or after, July 1, 2012, must submit a training plan and enroll in an approved training program prior to the end of their claim year. The bill also waives the full-time enrollment requirement for dislocated workers.

Since April 2009, all qualifying claimants can receive a waiver for missing the training plan submission and enrollment deadlines if the Employment Security Commissioner (ESC) determines they have good cause for doing so. Similarly, the ESC can waive the full-time enrollment requirement for those who have a physical, mental, or emotional disability.

Data sources

Data in this report are drawn from two separate sources: the Employment Security Department's (ESD) administrative records, and training data from the State Board of Community and Technical Colleges (SBCTC), which was provided to ESD by the Office of Financial Management (OFM).

In this report, we analyze the educational and labor force histories of individuals who received unemployment benefits from the years 2006 through 2009. People are assigned to a cohort based on the year in which they first received unemployment benefits – hence, a person whose initial unemployment benefits payment occurred in 2007 would be classified as belonging to the 2007 cohort.

Our selection of the years 2006 through 2009 was motivated by the data provided to us by the OFM. The OFM provided us with educational data for the years 2005 through 2014. We chose 2006 through 2009 because we wanted to ensure that 1) there was at least one year of pre-TB Program educational data for each participant; and 2) there were at least four years of educational (and earnings) data for each participant in the years

[7] See RCW 50.22.010

following their entrance into the TB Program. Note however that the years we have chosen to analyze in this report share some overlap with the years in which the Great Recession most severely impacted Washington state. We expect the economic realities of the time period under consideration to be reflected in this report.

For each cohort, we analyzed three years of prior earnings data. For example, we have earnings data for the years 2004 through 2006 for individuals belonging to the 2007 cohort. In addition to earnings data in the three years prior to an individual's first unemployment benefit payment, we looked at earnings data for each individual through the year 2013. *Figure 1* provides a graphical depiction of the structure of our data.

For each person-year we have a measure of the total number of college credits earned, the number of STEM credits earned and the number of health-related credits earned. These measures allow us to track the educational achievements of individuals over time.

In addition, our ESD administrative records collect a wealth of demographic information from UI claimants. In this report, we use information pertaining to individuals' sex, age, ethnicity, veteran status, disability status, place of residence (as measured by workforce development area) and occupation. *Appendix 1* provides further details regarding the demographic composition of TB participants.

Figure 1. Study data: years for which earnings data were analyzed
Washington state, 2003 through 2013
Source: Employment Security Department/LMPA

Cohort	Participants	Pre-unemployment period			Year of initial unemployment benefit payment	Follow-on period						
2006	2,166	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
2007	1,756	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	
2008	3,374	2005	2006	2007	2008	2009	2010	2011	2012	2013		
2009	8,040	2006	2007	2008	2009	2010	2011	2012	2013			

For each individual, we have a minimum of eight years of data. We use earnings and education data from 1) the three years prior to each individual's year of initial unemployment benefit payment; 2) the year of initial unemployment benefit payment; and 3) each year after initial unemployment benefit payment through 2013.

Note the distinguishing characteristic of our data is that it follows individuals as they progress through time. In other words, for each individual we have multiple years of data. Many researchers refer to data that follows individuals through time as *panel data*. Panel data is unique because it allows us to use the person-year combination as the primary unit of analysis. The benefits of using person-year panels will become apparent in the methodology section we present later in this report.

Finally, consistent with prior research (see Card et al., 2010; Hollenbeck & Huang, 2006) we elected to define the period in which TB participants are "in training" as three years in duration. So, for example, a participant who enters the TB program in 2006 is counted as being "in training" through 2008. In addition to being consistent with prior research, we chose this design because we do not expect the positive effects of training on earnings to be instantaneous. Because it takes time to develop new skills we chose not to assess the effects of training on earnings until sufficient time has elapsed for individuals to complete their training. (See *Appendix 2* for a more detailed description of our treatment of the training period).

Analytic strategy

Most theoretical explanations regarding the relationship between education and earnings claim that people who pursue education should see an increase in earnings. (See *Appendix 3* for greater detail.) Indeed, several studies of government-sponsored training programs have produced results consistent with this theoretical expectation. (See *Appendix 4* for a review of the literature.) In what follows, we describe an exploratory analytic strategy for assessing the impact of TB Program participation on post-unemployment earnings. First, we describe our strategy for selecting non-participants for our sample comparison group.

Statistical matching: Selecting non-participants from the comparison pool

Because our goal in this report is to compare earnings outcomes between TB participants and non-participants, it is beneficial to match individuals who participated in the TB Program with people who did not. We use propensity score matching to identify UI claimants who are statistically similar to TB participants for inclusion in our study samples. We refer to matched non-participants as the comparison group throughout this report.

A propensity score is the estimated probability that an individual will participate in a training program, regardless of whether or not that individual actually participated in training. Thus, a training participant will often have the same propensity score as a non-participant in the sample.

To generate the propensity score, we specify a logit regression model, where the dependent variable takes the value of "one" for those who participate in the program and "zero" for non-participants. This regression model is called a propensity function, and it includes independent variables believed to predict whether or not an individual will enter the training program. A correctly specified propensity function yields estimated participation probabilities that are greater than zero (absolutely certain not to participate) and less than one (absolutely certain to participate).

It is important to include variables in the propensity function that both predict participation in the program and influence the dependent variable in the net impact models. Using variables that influence both participation and the dependent variable in the net impact models reduces selection bias. This is because each participant and his or her matched non-participant are more likely to be similar on most of the observed variables included in the propensity function.[8] *Appendix 5* summarizes the variables we include in the propensity function.

[8] See Stuart, Elizabeth A., "Matching Methods for Causal Inference: A Review and a Look Forward," *Statistical Science*, Vol. 25, No. 1, pp. 3ff.

Statistical methodology: The fixed effects model

Because we are working with panel data (as introduced previously in the discussion of data sources), we have selected a method that is capable of modeling both the individual and time components of our dataset. Specifically, the method we have selected to test our research questions is called a "fixed effects" model. A fixed effects model is a generalized form of ordinary least squares regression (OLS) that is primarily useful in a panel data setting because of its ability to net out the effects of unobserved heterogeneity.

In the context of this report, unobserved heterogeneity refers to all of the characteristics inherent to workers that we cannot or do not observe but, nevertheless, affect earnings. An example of unobserved heterogeneity would be worker motivation. Motivation is a trait that we expect to vary across workers. Some workers are likely to set extremely high personal standards for the quality of work they produce, whereas others are likely to be content with a minimally acceptable performance. The fixed effects model uses the person-year structure of panel data to net out the effects of factors, such as motivation, that we cannot observe, but still expect to be associated with earnings.[9] *Appendix 6* provides a detailed specification of how we constructed our fixed effects model.

The statistical details of the fixed effects model are highly complex, so we have elected not to present the technical documentation here. Instead, we provide technical documentation of the fixed effects model in *Appendix 7*. Readers who are interested in a formal explanation of our methodology should direct their attention to the appendix.

Scope: Focus on TB participants with earnings

Because our interest lies in estimating the effects of TB Program participation on earnings, we have excluded all workers in our sample for each year in which they report zero earnings. For example, if a worker reports positive earnings in 2006, 2007 and 2009 – and also reports zero earnings in 2008 – information pertaining to that worker in 2008 is excluded from our analyses. This exclusion is justified because we cannot estimate the effects of training on earnings for workers who report no earnings.

Further, our data do not allow us to make the distinction between workers who actually have zero earnings in a particular year from workers whose earnings do not show up in our data since their employment is not covered by Washington state's unemployment insurance system (e.g., those who are self-employed, moved out of state, etc.). Because of this flaw in our data, we elected to take a conservative approach by treating all "zeros" in our data as missing. Because it is very likely that some individuals who are coded as having zero earnings in a particular year actually received some income over the course of that year, our model estimates are likely underestimating the effects of training on earnings.

[9] The fixed effects model further assumes the unobserved characteristics of individuals (such as worker motivation) are time-invariant. In other words, workers who are highly motivated, remain highly motivated as they progress through time and vice versa. While we could imagine a situation in which a formally unmotivated worker endeavors to change his mental approach towards work, our models do not allow for the analyses of unobserved factors that undergo change over time. See the technical supplement *in Appendix 7* for more details.

Finally, in order to account for outliers and impose greater linearity on the relationship between earnings and college credits, we opted to exclude the top 5 percent of earners in our analysis so as to avoid inaccurately positive results. However, we re-ran our models without excluding the top 5 percent of earners, and found no substantive differences from the results presented below.

Findings

Figure 2 displays selected results for our model with additional results presented in *Appendix 8*. Our findings, while exploratory in nature, suggest that TB Program participation has a positive effect on post-training earnings. Specifically, our model suggests that participants enjoy an increase in earnings of $2,872 to $16,710 relative to their non-participant peers.[10] This positive estimated effect of TB program participation is not trivial – indeed, it represents an increase in earnings of 5.2 percent to 30.5 percent of average (2014) household earnings for the entire state.[11]

Several additional dynamics are present in our model. First, our model shows the relationship between total credits earned and earnings is negative, meaning that the more credits a participant took the less he or she earned. We interpret this negative relationship as indicative of a trade-off between time spent working, and time spent pursuing education. In other words, people who pursue training see short-term declines in earnings because time spent pursuing education comes at the expense of time spent working for pay.

Second, our model suggests the negative effects of time spent pursuing education on earnings are less severe for TB participants who earned college credits prior to entering the TB Program. We suspect this reflects the fact that individuals who earned college credit prior to re-training are closer to degree completion, and thus more likely to re-enter the labor force earlier. That is, people who are closer to earning an associate degree, or certification, may not require the full three years our model allocates to the training period (see *Appendix 2*).

Health-related training is associated with higher earnings

Third, TB participants who pursue health-related training appear to enjoy additional earnings gains. Our model suggests each additional health credit earned by TB participants generates an additional $19 to $367 in post-training earnings.

Fourth, our model suggests that the positive effects of pursuing health-related credits may be further enhanced if TB participants specialize in a health-related field. For our purposes, specialization in a health-related field is different from pursuing health-related credits. For example, a TB participant who takes a nursing course will have earned credits in a health-related field. However, a participant who pursues a degree or certificate in nursing is counted as having specialized in a health-related field (see *Appendix 6* for a more detailed description of our definition of health-related training.) We estimate TB participants who specialize in health-related training will enjoy an additional increase in earnings of $1,282 to $10,648.

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[10] The reported range is based on a 95% confidence interval.

[11] Range is based on an average household income of $54,829 (2014). This estimate is derived from internal ESD wage records.

The effects of TB participation on earnings vary for specific categories of workers

In addition to estimating the effects of education on earnings, our model allows us to assess the effects of TB Program participation, and type or intensity of training, on workers with different backgrounds. For example, workers admitted in 2009 appear to be especially disadvantaged. Our model suggests that TB participants who entered the program in 2009 are likely to see a reduction in earnings of $93 to $3,327 compared to workers who began the program in 2006. Of course, 2009 was one of the years in which the effects of the Great Recession were felt the hardest. Thus it comes as no surprise that workers who entered the TB program in 2009 fared worse than workers who entered prior to the full on-set of the Great Recession in Washington state.

TB participation and low-earning individuals

Further, participation in the TB Program appears to exert unambiguously positive effects on earnings among low-wage populations. Our model suggests that people entering the TB program at low wages experience an additional $4,529 to $7,227 increase in post-training earnings when compared to those with higher wages before entering the program.

TB participation and gender

Finally, our model also suggests men disproportionately benefit from participation in the TB Program. While this finding is consistent with prior work, we expected to see women close the gap as they attained more total credits (see *Appendix 4*). We find no evidence for this. Our model suggests that men benefit more from training at all levels of college credits undertaken.

Figure 2. Fixed effects model results
Washington state, 2007 through 2013
Source: Employment Security Department/LMPA

Type of earnings gain (loss)	Estimated benefit (loss)	Effect on post-unemployment earnings
Earnings gain associated with participation in TB Program	$2,872 - $16,710***	Positive
Additional earnings gain associated with health-related training	$1,282 - $10,648*	Positive
Earnings gain per health credit taken	$19 - $367**	Positive
Earnings loss associated with entering the TB Program in 2009	(-$93) – (-$3,327)***	Negative
Earnings gain associated with low-earner status	$4,529 – $7,227***	Positive
Earnings gain associated with being male (gender gap)	$1,575 - $3,417***	Positive

** p<.1; ** p < .05; *** p < .01 (one-tailed tests).*

TB Program participation, and the pursuit of health-related college credits, are most strongly associated with positive earnings outcomes.

Appendix 1: Participant demographics

In this section we describe the demographic characteristics of the 2006 through 2009 TB participant cohorts. Further, in order to highlight the differences between TB Program participants and non-participants, we compare the characteristics of these two groups.[12] When compared to the general population of Unemployment Insurance beneficiaries, TB participants are more likely to be female. Indeed, 49.5 percent of the pooled 2006 through 2009 cohorts of TB participants were women – as compared to approximately 35.4 percent of the total population of UI claimants.

Both Whites and Asian/Pacific Islanders are over-represented in the TB Program relative to their presence in the wider UI universe. Approximately 74.5 percent of TB participants identify as White, compared to roughly 67.2 percent of the total population of UI claimants. Similarly, Asian/Pacific Islanders comprised about 7.6 percent of the 2006 through 2009 TB participant population, compared to only 6.3 percent of total UI beneficiaries. Conversely, African-Americans and Hispanics are under-represented among the 2006 through 2009 TB population when compared to the racial/ethnic make-up of the general UI population. African-Americans and Hispanics respectively comprise 4.9 percent, and 6.7 percent, of all 2006 through 2009 TB participants, whereas these two groups' share of the total UI population is about 5.4 percent and 14.8 percent, respectively.

The average age of TB participants does not significantly differ from the average age of the general population of UI claimants. TB participants (2006 through 2009) are, on average, 41.7 years old. This is comparable to the average age of 42 among the total population of UI claimants. *Appendix figure A1-1* summarizes these results.

Appendix figure A1-1. Demographic characteristics
Washington state, 2006 through 2009, 2015
Source: Employment Security Department/LMPA

Demographics	TB participants 2006 through 2009	All unemployment insurance claimants 2015
Sex		
Male	50.5%	64.6%
Female	49.5%	35.4%
Ethnicity		
African-American	4.9%	5.4%
Asian/Pacific Islander	7.6%	6.3%
Hispanic	6.7%	14.8%
Native American/Alaska Native	1.4%	1.9%
White	74.5%	67.2%
Other	4.9%	4.5%
Average age	41.7	42.0

Individuals approved for the TB Program were more likely to be female compared to all UI claimants. Participants were also more likely to be White or Asian-American/Pacific Islander.

[12] Because the demographic characteristics of the general UI population exhibit remarkable stability over time (see https://fortress/wa/gov/esd/employmentdata/reports-publications/special-reports/training-benefits-report) we have elected to use the demographic features of the most recent recipients of unemployment benefits payments as our point of comparison. The demographic make-up of the 2015 UI claimant population is sufficiently similar to that of the 2006 through 2009 cohorts to warrant this comparison.

TB participants appear to be roughly similar to the overall population of UI beneficiaries in terms of educational attainment. TB participants appear to be more likely to have completed either some college, or an associate degree, when compared to non-participants. Further, while TB participants appear to be slightly less likely to have completed a bachelor's degree relative to the general population of UI claimants, they are also less likely to have dropped out of high school. *Appendix figure A1-2* compares the educational achievements of 2006 through 2009 TB participants with the wider population of UI claimants.

Appendix figure A1-2: Educational attainment
Washington state, 2006 through 2009, 2015
Source: Employment Security Department/LMPA

Educational attainment	TB participants, 2006 through 2009	All UI claimants, 2015
Less than high school	8.4%	13.5%
High school diploma	35.0%	36.9%
Some college, no degree	23.0%	12.6%
Associate degree	16.1%	14.4%
Bachelor's degree or higher	17.5%	22.7%

TB participants were less likely to have a bachelor's degree (or higher) than UI claimants overall, but they were also less likely to have less than a high school diploma as well.

Appendix figure A1-3 displays the geographical distributions of TB participants and general UI claimants. Note the counties in *Appendix figure A1-3* are grouped by workforce development area (WDA). WDAs are groupings of counties that fall under the jurisdiction of one of the state's Workforce Development Councils (WDCs). As is evident from *Appendix figure A1-3*, TB participants appear to be slightly more concentrated in urban areas of the state than are their non-TB counterparts. For example, 57.3 percent of TB participants live in King, Pierce and Snohomish counties, compared to the 44.5 percent of the general UI population. However, Spokane County appears to be exceptional in this regard. Whereas 7.2 percent of all UI claimants hail from Spokane County, it contributes only 1.8 percent of total TB participants.

Appendix figure A1-3. Geographic distribution
Washington state, 2006 through 2009, 2015
Source: Employment Security Department/LMPA

County of residence	TB participants 2006 through 2009	All UI claimants 2015
Jefferson, Kitsap and Clallam	4.6%	3.6%
Grays Harbor, Mason, Pacific, Thurston and Lewis	11.5%	6.9%
Whatcom, Skagit, San Juan and Island	5.5%	5.6%
Snohomish	12.1%	9.7%
King	32.9%	23.3%
Pierce	12.3%	11.5%
Wahkiakum, Cowlitz and Clark	5.4%	5.9%
Okanogan and Chelan	1.4%	2.5%
Douglas, Grant and Adams	1.5%	3.3%
Kittitas, Skamania, Yakima and Klickitat	5.5%	7.3%
Ferry, Stevens, Lincoln and Pend Oreille	1.4%	1.2%
Walla Walla, Whitman, Columbia, Garfield and Asotin	1.7%	1.0%
Benton and Franklin	2.5%	4.8%
Spokane	1.8%	7.2%
Data not available	0.0%	6.3%

TB participants were concentrated in King, Snohomish and Pierce counties.

Over half (55.1 percent) of the 2006 through 2009 cohorts of TB participants were previously employed in the following four occupational groups: office and administrative services; management; production; and sales. Further, workers employed in each of the above listed occupations were disproportionately represented among TB participants when compared to the overall make-up of the broader UI population. Workers in the following occupational groups constitute less than 1 percent of the 2006 through 2009 TB participants: building and grounds maintenance, community and social services; education, training and literacy; healthcare practitioners, healthcare support; legal and protective services. *Appendix figure A1-4* summarizes the occupational distributions for both TB participants, and the broader UI population.

Appendix figure A1-4. Occupational distribution
Washington state, 2006 through 2009, 2015
Source: Employment Security Department/LMPA

Occupational groups	TB participants 2006 through 2009	All UI claimants 2015
Architecture and engineering	3.2%	1.8%
Arts, design and entertainment	3.0%	1.6%
Building and grounds maintenance	0.4%	2.6%
Business and financial services	6.8%	2.8%
Community and social services	0.6%	0.8%
Computer and mathematical	4.2%	3.1%
Construction and extraction	7.3%	17.0%
Education, training and literacy	0.9%	1.3%
Farming, fishing and forestry	1.4%	5.7%
Food preparation and service	1.1%	4.3%
Healthcare practitioners	0.9%	1.6%
Healthcare support	0.9%	1.5%
Installation, maintenance and repair	4.7%	4.6%
Legal	0.8%	0.5%
Life sciences	1.0%	1.1%
Management	11.2%	9.4%
Military specific	1.4%	0.8%
Office and administrative services	20.0%	10.5%
Personal care and services	1.1%	2.2%
Production	18.0%	11.3%
Protective services	0.7%	1.2%
Sales	5.9%	5.5%
Transportation and material moving	4.3%	8.1%
Data not available	0%	0.6%

Over one-half of all TB participants worked in the following occupational groups prior to TB Program participation: office and administrative support; production; management; and sales.

Appendix 2: Structure of the data

We begin by structuring our panel data according to the logic displayed in *Figure 1* in the main text of this report. Specifically, for each individual in our panel, we specify three separate periods: a pre-unemployment period (Period I), an unemployment/training period (Period II), and a post-unemployment period (Period III). We define the transition from Period I to Period II as having occurred when an individual receives their initial unemployment benefits payment. However, because the positive effects of training on earnings cannot be expected to result in instantaneous productivity enhancements, we have elected to define the training period (Period II) as three years in duration. Hence the transition from Period II to Period III occurs three years after an individual's initial unemployment benefits payment. This definition is consistent with prior research on the length of time individuals in government-sponsored training programs need to complete their training (see *Appendix 4*). Further, because we do not expect the effects of training to be manifested prior to the conclusion of the three-year training period, we imposed a three-year aggregated lag on total credits earned during Period II. In other words, for the purposes of our analysis, all college credits an individual earns while in training (Period II) are not counted until the completion of training (the on-set of Period III).

To better illustrate this point visually, the structure of our data is represented in *Figure A2-1*. For each individual in our data set, we have a minimum of 8 years of information. The first 3 years represent the pre-training period (Period I), the following 3 years are designated as the training period (Period II), and any remaining years are classified as the post-training period (Period III). We have the fewest years of data for the 2009 cohort, with only 2 years (2012 and 2013) in Period III since Period I begins in 2006.

As depicted in *Figure A2-1*, a training program participant is flagged as completing training in year 7 of the panel. Our analyses seek to ascertain the effect of participation in the TB Program in Period II, on earnings in Period III. In order to best assess this question, we assign each individual his or her aggregated college credits to the first year of the post-training period (year 7). This allows us to isolate the effects of accumulated credits on earnings in Period III.

However, without further adjustment, this approach has the disadvantage of including credits earned prior to TB Program participation. In order to net out the effects of pre-TB Program credits, we assign each individual the number of college credits he or she completed prior to TB Program participation for each of the first 6 years of the panel.[13] For example, person A (see *Figure A2-1*) entered the TB Program having previously earned 0 college credits. During the training period (years 4, 5 and 6) this individual completed 180 credits. However, because we are interested in the effects of credits earned during Period II on earnings in Period III we elect to lag aggregated credits until the onset of the post-training period. As a consequence, we assign the 180 credits earned by person A during the training period to year 7 – the first year of the post-training period.

[13] There are a few cases in which the aggregated number of credits earned changed over the first 3 years of the panel. In these few cases, we allowed for the accumulation of total credits during Period I. However, in order to isolate the effects of training undertaken in Period II, each individual's pre-TB Program credits (credits earned prior to year 4) are held fixed at their year 3 levels for each of the years designated as part of the training period.

Alternatively, person B entered the TB Program having already completed 80 credits worth of college coursework. While participating in the TB Program, person B earned an additional 100 credits. Because we want to separate the effects of person B's pre-TB Program credits from the effects of credits earned under the auspices of the TB Program, we assign the 80 credits earned prior to program participation to the first 6 years of the panel, and the total accumulated 180 credits to the final (Period III) years. This approach allows us to separate the effects of 1) credits earned prior to TB Program participation from 2) the effects of credits earned during Period II on 3) earnings in Period III.

Figure A2-1: Illustration of data structure
Source: Employment Security Department/LMPA

Year	Training flag	Total credits earned		Period
		Person A	Person B	
1	0	0	80	Period I (Pre-training)
2	0	0	80	
3	0	0	80	
4	0	0	80	Period II (Training)
5	0	0	80	
6	0	0	80	
7	1	180	180	Period III (Post-training)
8	1	180	180	

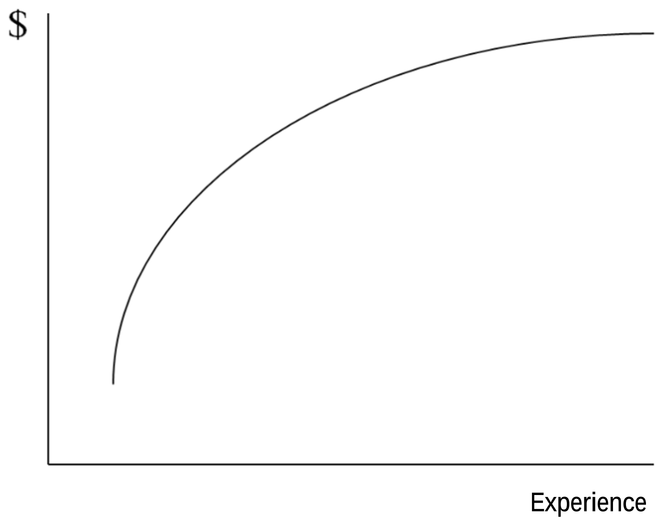
For each individual we have a minimum of 8 years of data. Training program completion is flagged in year 7. Credits earned during training are aggregated and applied to individuals in year 7.

Appendix 3: A human capital orientation to understanding the relationship between training and future earnings

Our goal in this report is to assess the relationship between participation in the TB Program and future earnings. With this in mind, it may be useful to briefly review the logic underpinning much of the prior research on the relationship between training and earnings.

The dominant theoretical orientation regarding the relationship between training and earnings was originally advanced by Becker (1964). Becker argues workers are paid in proportion to their productivity, hence we should expect more productive workers to command higher wages. Further, as depicted in *Figure A3-1*, Becker claims there is a curvilinear relationship between work experience and productivity/earnings.

Figure A3-1. Age-earnings profile
Source: Employment Security Department/LMPA



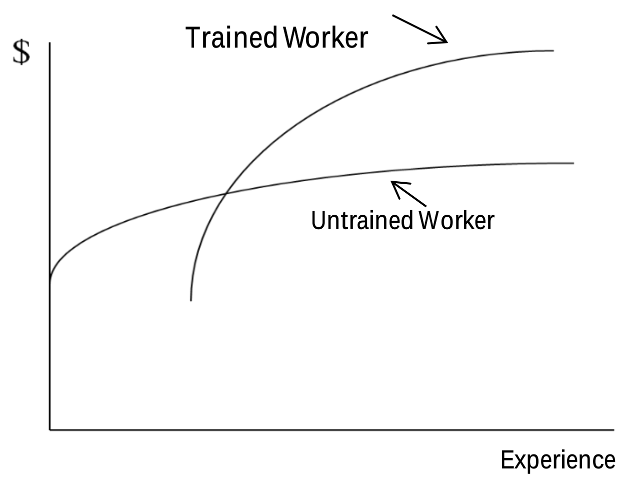
Earnings are expected to increase in conjunction with experience, but at a diminishing rate.

Economists often refer to the relationship depicted in *Figure A3-1* as an "age-earnings profile". Note that the age-earnings profile rises quickly with the first few years of experience, and then subsequently flattens out. *Figure A3-1* suggests that when a person is young (or new to a job) he or she is relatively unproductive – and paid a wage commensurate with his or her low levels of productivity. However, with each passing year, we expect workers to become "better" at their jobs, enhancing their productivity and exerting upwards pressure on the wages they are able to command. However, at some point, the additional productivity/wages associated with an additional year of experience becomes subject to diminishing marginal returns. In other words, once a worker has been on the job for a sufficient period of time, he or she has already learned all there is to learn, and his or her productivity consequently fails to grow at the same pace as when he or she was younger/newer.[14]

Training adds another layer to the relationship between earnings and experience depicted in *Figure A3-2*. Training often has substantial benefits for both workers and employers. Training can provide new skills, improve existing skills, and make it possible for workers to engage in a broader array of duties. As a consequence, training tends to make workers more productive – and therefore more valuable – to their employers.

Graphically, we can depict the expected effect of training on productivity by juxtaposing the age-earnings profile of a worker who undertakes training with the age-earnings profile of an identical worker who forgoes training. This juxtaposition is presented in *Figure A3-2.*

Figure A3-2. Expected effects of training on age-earning profiles
Source: Employment Security Department/LMPA



Age-earnings profiles are expected to be steeper for trained workers than for untrained workers.

Note that the slope of the age-earnings profile is steeper for the trained worker than for the untrained worker. We expect training to be associated with a steeper age-earnings profile because training may confer scarce skills to its recipient that allow for greater over-time productivity enhancements[15]. In terms of worker earnings, the wage premium associated with training is indicated by the area between the curves. In other words, this area represents how much "better off" the trained worker is on account of his or her training.

[14] We might even expect the marginal productivity of an additional year's experience to be negative at some point along an individual's age-earnings profile. As workers approach retirement age, they may choose to allocate less time to working, and more time to alternative pursuits.

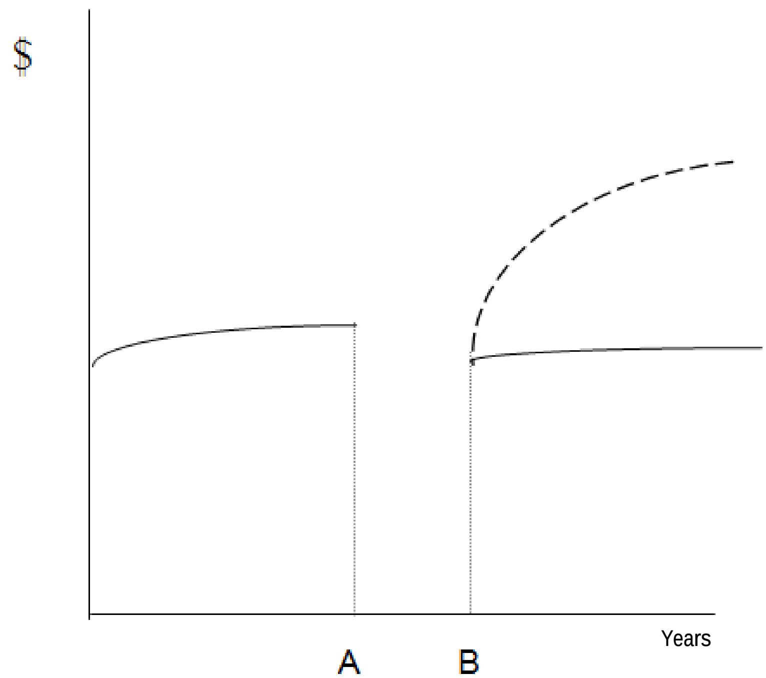
[15] Also, note that the untrained worker begins receiving a wage at an earlier time than does the trained worker. This reflects the time the trained worker spends in pursuit of training. Becker (1964) informs us that the forgone earnings associated with the pursuit of training are, in fact, an opportunity cost that a rational person should account for when making the decision whether to pursue training. However, in this report, we are primarily concerned with whether training positively impacts earnings among a group of individuals who have already made the decision to pursue training. Therefore, we will not dwell on the cost-benefit dynamics of rational-choice decision-making as they pertain to job-related training.

Becker's theory of human capital can be generalized to extend to the questions under consideration in our present report. In our case, we are interested in the effects of training on earnings among a group of individuals who have experienced recent unemployment. Most accounts of the human capital model claim that workers who become unemployed are likely to experience a decline in earnings even after securing subsequent employment. The orthodox explanation for this decline claims that post-unemployment wage reductions come about because job-related skills have a tendency towards atrophy during the period of unemployment (Edin & Gustovsson, 2008; Jacobson, LaLonde & Sullivan, 1993; Mincer & Polachek, 1974).[16] The question we seek to resolve in this report concerns whether the beneficial effects of training on earnings are sufficient to offset the negative effects of prior unemployment.

Figure A3-3 graphically depicts the dynamics of the human capital model as it pertains to unemployment and training. *Figure A3-3* can be interpreted as follows: the period prior to point (A) represents a period of initial employment. At time (A) the individual in question becomes unemployed, and remains unemployed until re-employment occurs at time (B). Note that two separate age-earnings profiles are presented in the post-unemployment period. Further note that both post-unemployment age-earnings profiles exhibit earnings deterioration relative to the pre-unemployment period. This deterioration reflects the unemployment-induced skills atrophy discussed above. However, for our purposes, what is really important is the slopes of the post-unemployment age earnings profiles. Consistent with the human capital model, we expect the flatter age-earnings profile to be associated with workers who forgo training, whereas the steeper profile belongs to workers who pursue training while unemployed.

[16] Alternative (and generally more heterodox) explanations for the decline in post-unemployment earnings do exist. These explanations usually appeal to the signaling effects of unemployment regarding the potential productivity of unemployed job applicants (see Agell & Bennmarker, 2007; Blinder & Choi, 1990).

Figure A3-3. Unemployment, training and age-earnings profiles
Source: Employment Security Department/LMPA



Post unemployment, we expect trained workers' age-earnings profiles (dashed line) to grow at a faster rate than untrained workers (solid line).

Appendix 4: Prior research

Much of the prior research assessing the impact of government-sponsored occupational training is consistent with the logic of human capital theory. For instance, Hollenbeck and Huang (2006) estimated net training outcomes for several types of workers and training programs for two different time periods. The statistical methods and data used in their studies are similar to the methods used in this study in that the authors attempt to adjust for selection bias by matching based on estimated propensity scores. When their data allow, they further reduce classical selection bias by transforming their outcome variable(s) using the method of difference-in-differences (DID).[17]

Hollenbeck and Huang show net effects at approximately the beginning of the third year after entry into a training program. For the 2006 study, the net positive estimates to participation in training benefits program range from a low of $1,421 for participants in the Community and Technical College Worker Retraining program, to a high of $3,591 for the Workforce Investment Act (WIA) Title I-B Dislocated Worker program.[18]

In addition, Jacobson, LaLonde, and Sullivan (2005) estimate the net effect of community college education on displaced workers in Washington state. Displacement is defined as being permanently laid off from a firm after three or more years of employment. This definition of displacement is more stringent than the more recent (2011) definition of dislocated workers in the TB Program under consideration in this report.[19] However, the Jacobson et al. definition does not require the worker be severed from an occupation that is defined as declining in demand. The authors assess the net effects of job training on five cohorts of displaced workers who are eligible for unemployment benefits, starting with the 1990 cohort and ending with the 1994 cohort. Individuals are followed for up to 16 quarters after the quarter of initial layoff.

Jacobson et al. estimate that it takes about three quarters after leaving training for net earnings effects to become positive. Thereafter, annualized in 2012 dollars, men earn an additional $2,307 to $3,616, and women an additional $1,318 to $1,736 per year.

A critical finding of Jacobson's 2005 study was the estimate that "technically oriented and/or scientific and/or health-related courses" provided much higher net benefits compared to "all other community college courses." Further, this finding was much more pronounced for women than for men. Among women, the effect of one academic year or more of technical credits increased their earnings by 22 to 28 percent, compared to an estimated increase of only 5 to 7 percent for all other community college courses.

In addition to studies that focus directly on the effects of training in Washington state, a number of prior studies have sought to evaluate the efficacy of government-sponsored training programs across the United States. For instance, Ashenfelter (1978) estimated that men earned an additional $1,082 to $3,603 (constant 2012 dollars) in the first year after

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[17] Imberns, Guido M. and Jeffery M. Wooldridge. 2008. "Recent Developments in the Econometrics of Program Evaluation" *NBER Working Paper No. 14251*. pp. 64.

[18] Expressed in constant 2012 dollars.

[19] Substitute House Bill 3077 (2000) initially required "earning a plurality of wages in a particular occupation or using a particular skill set during the base year and at least two of the four 12-month periods immediately preceding the base year." Engrossed House Bill 1091 (2011) then defines a dislocated worker as "… any individual who: (a) has been involuntarily and indefinitely separated from employment as a result of a permanent reduction in operations at the individual's place of employment, or has separated from a declining occupation; and (b) is eligible for or has exhausted entitlement to unemployment compensation benefits."

training, although these earnings premiums did appear to deteriorate over time. Women were estimated to earn an additional $2,164 to $4,327 (constant 2012 dollars) in the first year after training, with no evidence of over-time deterioration.

Heckman, LaLonde, and Smith (1999) reviewed nine studies assessing the efficacy of the federal Comprehensive Employment and Training Act (CETA). These studies varied considerably in the data and statistical methods used, as did the results. A summary of Heckman's meta-analysis is provided below.

- For men, the net estimates range from -$1,555 per year to $1,638 per year (constant 1977 dollars), with the median estimate being $61 per year. Note that net negative earnings accruing to training are possible if:
  - Foregone earnings during training exceed the future stream of positive earnings benefits,
  - Relative to the control or comparison group, the treatment group members lose ground in the labor market due to lost on-the-job training opportunities while engaged in formal classroom training or
  - Some other statistical error or economic misspecification exists, including an incorrect comparison group match, non-random measurement error, etc.
- Net benefits to training among women ranged from $24 per year to $2,220 per year (constant 1977 dollars).

Since we did not have standard errors for the disparate results reported by Heckman et al., we report the median of this set of estimates in inflation-adjusted 2012 dollars. For men, the median estimate is $87 per year. For White women the median estimate is $1,831 per year. For non-White women, the median estimate is $3,800 per year.

Friedlander, Greenberg and Robins (1997) report on 16 classical experiments conducted for the federal Job Training Partnership Act (JTPA) program that operated in various locations throughout the United States. The experiments began in November, 1987 and extended through September, 1989. Participant men were estimated to earn, on average, $1,455 extra per year (constant 2012 dollars) whereas participant women were expected to see an additional $584 per year.

Bloom et al. (1997) reported on the National JTPA Experiment. This classical random assignment experiment reported results for people eligible to enroll in the JTPA program and for people who actually did enroll in the JTPA program. In constant 2012 dollars, participant men and women were estimated to earn an additional $1,242 and $1,424 per year, respectively.

Mueser, Troske, and Gorislavsky (2007) evaluated the returns to training for adults in Missouri for the period July 1994 through June 1996. Mueser et al. estimated that training participant men earned an additional $1,141 per year, and women an additional $1,211 per year, in constant 2012 dollars.

Heinrich et al. (2008) analyzed the net effect of the federal Workforce Investment Act (WIA) of 1998. Data from 12 states were analyzed. Participants were compared to individuals who received core and intensive job-search services from their respective state employment agencies. In 2012 dollars, Heinrich et al. found that men earned an additional $2,467 per year, starting 10 quarters after program entry. Similarly, female participants earned and additional $3,498 per year. Finally, participation among dislocated workers was estimated to generate a $2,379 earnings premium.

King et al. (2009) evaluated a large set of different training and training-type programs in Texas under the auspices of the WIA. Estimated net earnings surpluses for participant men and women combined were $2,199 per year. However, because so many different types of training and education were combined into one measure of "training" in this estimate, it is difficult to interpret the policy meaning of the estimated net outcome.

Card, Kluve, and Weber (2010) conducted a meta-analysis of 97 studies of active labor market policies (ALMP) that contained 199 program estimates. The studies range across the globe, but are concentrated in the United States, Canada, Great Britain and Western Europe. The authors conclude the following:

- Longer-term evaluations (more than one year after treatment) of ALMPs tended to be more favorable than shorter-term evaluations (one year or less after treatment), since training does not begin to yield benefits until the medium- or longer-term period – say, three years or so.
- ALMP programs did not appear to have differential effects on men versus women.

Finally, in a meta-analysis that focused only on the United States, Greenberg, Michalopoulos and Roins (2003) found that adult men had an estimated net training benefit of $2,469 per year; adult women, $3,498 per year; displaced men, $2,318 per year; and displaced women, $2,379 per year (all expressed in constant 2012 dollars). This meta-analysis combined the results of both experimental and non-experimental studies and carefully adjusted for other differences in period of analysis and statistical methods.

In summary, a review of the literature lends strong support to the human capital arguments advanced above. On the whole, net earnings premiums in the neighborhood of $2,000 per year, for both men and women, appear to be typical among training program participants. Our findings are generally consistent with the literature. However, our estimates for the positive effects of training are somewhat larger than those reported elsewhere. While we have no way to directly assess the sources of these discrepancies, we note that many of the prior studies examining the effects of government-sponsored training on earnings outcomes were written in the 1970s, 1980s and 1990s.

Appendix 5: Variables used in the propensity function

We use the following variables in our propensity function to match TB Program participants with similar non-participants.

1) The Ashenfelter dip;
2) Earnings lost in the two quarters prior to the unemployment benefits payment date we use to define cohort membership;
3) Each individual's previous occupation;
4) Previous earnings for each of the 12 quarters prior to the unemployment benefits payment date we use to define cohort membership;
5) Working to not working transactions between the third and second quarters prior to the unemployment benefits payment date we use to define cohort membership.

All five of these variables potentially influence the probability of finding work or earnings levels after becoming unemployed.

In addition to the variables previously listed, we also include the following variables in the propensity function:

1) The age and squared age of each individual on the date of the unemployment benefits payment we use to define cohort membership;
2) Formal educational level on the date of the unemployment benefits payment we use to define cohort membership;
3) Each individual's WDA on the unemployment benefits payment date we use to define cohort membership;
4) The individual's ethnicity;
5) U.S. veteran status;
6) Low income earner status;
7) Disability status.

Including each individual's age serves as a proxy for on-the-job experience that may influence earnings over time. Including an individual's squared age adjusts this proxy for the fact that a worker's productivity tends to increase, reach a maximum, and then decrease over time. Formal education is one of the strongest predictors of a person's earnings ability, and is an essential variable in a propensity function designed to reduce bias in an earnings net-impact model.

The pre-training WDA variable accounts for local differences in the method of delivering services to potential TB participants. It also serves as a statistical control for labor market conditions in the WDA at the time a participant enters the program. Many studies reveal that including a proxy for local labor market conditions reduces selection bias in net impact estimates of job training programs.

We include the ethnicity/race variable to adjust our estimates for differences in average earnings that are a function of race or ethnicity, rather than a function of training.

The U.S. veteran status, low income earner status and disability status variables adjust our estimates for differences in earnings and employment that are a function of these variables, rather than a function of training.

Prior to matching participants and non-participants on their propensity scores, we separate our participant and non-participant pools by gender and annual cohort. Separating the samples by gender accounts for the fact that men and women have different experiences in the labor market. Separating the sample into annual cohorts reduces bias in our estimates by adjusting for any changes to the regulation and administration of the TB Program. It also adjusts for labor market conditions that might affect an individual's decision to participate in the TB Program in a given year.

Some selection bias remains in our estimates of net program effects, because unmeasured variables that predict participation in the TB Program, or that influence the dependent variable in the net-impact models are not accounted for in the matching process. Propensity score matching reduces bias in net impact estimates that are attributable to observed variables. However, it cannot replicate the results of a random assignment experiment.

Appendix 6: Modeling specification

In this section, we specify our fixed effects model. Our model includes the following measures:

1) An aggregated measure of the total number of credits a respondent completed as detailed in *Appendix 2*.
2) An aggregated measure of the total number of STEM credits a respondent completed.
3) An aggregated measure of the total number of health-related credits a respondent completed.[20]
4) Interaction terms for TB Program participation and total credits earned, STEM credits earned and health credits earned.
5) Interaction terms for TB Program participation and total-, STEM-, and health-credits earned prior to entrance into the TB Program (see pp. 12-13 for greater detail).
6) Dummy variables indicating whether an individual pursued a STEM-, or health-related course of study.[21]
7) Interaction terms for TB Program participation and STEM-, or health-related course of study.

In addition to the measures listed above, we also include the control variables detailed in *Figure A6-1*. We include these controls because we expect each of them to be associated with worker earnings. The large number of interaction terms we include in our model are of particular interest. The interaction terms capture the effect of TB Program participation, as well as the intensity/content of training undertaken for different categories of workers. Hence the inclusion of the interaction terms into our model allows us to assess the effectiveness of TB Program participation, and training intensity/content, for demographically distinct subsets of the overall sample. Note, however, that we are unable to include the actual dummy variables for our demographic sub-samples because the fixed effects model does not allow for the inclusion of independent variables that do not vary over time. (See *Appendix 7* for technical documentation on the fixed effects model.) However, because participation in the TB Program (as well as credits earned) do vary over time, we are able to model the effects of program participation (and course intensity/content) across demographic subsets via the inclusion of the interaction terms.

[20] We treat the aggregated measures for STEM and health-related credits the same as we treat the aggregated measure of total credits.

[21] A respondent is flagged as having pursued a STEM-, or health-intensive course of study if they fall in, or above, the 75th percentile in terms of either STEM credits, or health credits, respectively (among respondents reporting > 0 total credits earned).

Figure A6-1. Control variables
Source: Employment Security Department/LMPA

Control variable	Description
Age	The age of the respondent, in years
Age^2	The squared age of the respondent, in years
Sex	Dummy variable: *Female is the reference category*
Sex x TB Program participation	The interaction of sex and TB Program participation
Sex x Total credits	The interaction of sex and total credits earned
Sex x STEM credits	The interaction of sex and STEM credits earned
Sex x Health credits	The interaction of sex and health credits earned
Ethnicity	Unordered factor: *African-American is the reference category*
Ethnicity x TB Program participation	The interaction of cohort and TB Program participation
Ethnicity x Total credits	The interaction of ethnicity and total credits earned
Ethnicity x STEM credits	The interaction of ethnicity and STEM credits earned
Ethnicity x Health credits	The interaction of ethnicity and health credits earned
Cohort	Unordered factor: *2006 is the reference category*
Cohort x TB Program participation	The interaction of cohort and TB Program participation
Cohort x Total credits	The interaction of cohort and total credits earned
Cohort x STEM credits	The interaction of cohort and STEM credits earned
Cohort x Health credits	The interaction of cohort and health credits earned
Educational attainment	Unordered factor: *Associates degree is the reference category*
Educational attainment x TB Program participation	The interaction of Educational attainment and TB Program participation
Educational attainment x Total credits	The interaction of Educational attainment and total credits earned
Educational attainment x STEM credits	The interaction of Educational attainment and STEM credits earned
Educational attainment x Health credits	The interaction of Educational attainment and health credits earned
U.S. Veteran	Dummy variable: *Non-veteran is the reference category*
U.S. Veteran x TB Program participation	The interaction of U.S. veteran and TB Program participation
U.S. Veteran x Total credits	The interaction of U.S. veteran and total credits earned
U.S. Veteran x STEM credits	The interaction of U.S. veteran and STEM credits earned
U.S. Veteran x Health credits	The interaction of U.S. veteran and health credits earned
Disability	Dummy variable: *No disability is the reference category*
Disability x TB Program participation	The interaction of disability and TB Program participation
Disability x Total credits	The interaction of disability and total credits earned
Disability x STEM credits	The interaction of disability and STEM credits earned
Disability x Health credits	The interaction of disability and health credits earned
Low income	Dummy variable: *Non-low income is the reference category*
Low Income x TB Program participation	The interaction of low income and TB Program participation
Low Income x Total credits	The interaction of low income and total credits earned
Low Income x STEM credits	The interaction of low income and STEM credits earned
Low Income x Health credits	The interaction of low income and health credits earned
WA state workforce development area (WDA)	Unordered factor: *WDA 1 (Jefferson, Kitsap, Clallam counties) is the ref.category*
WDA x TB Program participation	The interaction of WDA and TB Program participation
WDA x Total credits	The interaction of WDA and total credits earned
WDA x STEM credits	The interaction of WDA and STEM credits earned
WDA x Health credits	The interaction of WDA and health credits earned
Occupation	Unordered factor: *Agriculture is the reference category*
Occupation x TB Program participation	The interaction of occupation and TB Program participation
Occupation x Total credits	The interaction of occupation and total credits earned
Occupation x STEM credits	The interaction of occupation and STEM credits earned
Occupation x Health credits	The interaction of occupation and health credits earned

Note the (x) symbol refers to an interaction effect.

Appendix 7: The fixed effects model – technical supplement

The fixed effects model is a method that uses the person-year structure of panel data in order to net out the effects of unobserved heterogeneity. As mentioned in the main text of this report, unobserved heterogeneity refers to concepts which researchers expect may have an association with the dependent variable, but are very difficult (or impossible) to measure. In addition, the fixed effects model further subdivides unobserved heterogeneity into two sub-categories: (1) factors that change over time; and (2) factors that are time-invariant. Using (i) to denote the individual and (t) to denote the time period we can specify the following equation:

$$y_{it} = \beta_j x_{it} + a_i + u_{it}, \qquad (\mathbf{1})$$
$$for\ (t) = 1,2,\dots,T$$

In equation (**1**), the dependent variable (y_{it}) represents the i^{th} individual at the t^{th} time period. Similarly, x_{it} denotes a vector of *observed* characteristics measured for person (i) at time (t).

(a_i) represents all *unobserved*, *time-constant* factors that are thought to affect y_{it}. In other words, (a_i) denotes the time-invariant component of unobserved heterogeneity. Note that (a_i) does not include a subscript for (t). This is because the factors comprising (a_i) are assumed not to change over time.

(u_{it}) represents all *unobserved, time-variant* factors that are thought to affect y_{it}. In this regard (u_{it}) is very much like the stochastic component of an Ordinary Least Squares (OLS) regression.

Hence, as stated above, the fixed effects model formally divides the error term (unobserved heterogeneity) into two sub-components: the time-invariant component (a_i), and the time-variant component (u_{it}).

In order to estimate coefficients for the β_js, the fixed effects model first averages all measured (y)s and (x)s for each individual (i) across all time periods (t). More simply, the fixed effects model estimates the following equation:

$$\bar{y}_i = \beta_j \bar{x}_i + a_i + \bar{u}_i \qquad (\mathbf{2})$$

Note that because (a_i) does not change over time, it is unaffected by the time-demeaning implied by equation (**2**). After resolving for equation (**2**) the fixed effects model then subtracts the time demeaned equation (**2**) from the original equation (**1**) resulting in the following:

$$y_{it} - \bar{y}_i = \beta_j (x_{it} - \bar{x}_i) + (u_{it} - \bar{u}_i) \qquad (\mathbf{3})$$

The most important thing to note about (**3**) is that the time invariant component of composite error term (unobserved heterogeneity) has been subtracted out. This transformation is commonly referred to by applied econometricians as the *within* transformation. Essentially, what the within transformation accomplishes is a netting out of all unobserved factors inherent to individuals (i) that do not change over time periods (t). This netting out allows for estimates of β_j that are less prone to omitted variable biases. Less formally, we can think of the fixed effects estimator as a method that subtracts out all the things we cannot measure about an individual – provided these things do not change over time. Note however, that any measured variable that does not change over time would also be subtracted out by the within estimator. This is why we are only able to include measures that change over time in our fixed effects models.

Appendix 8: Extended model results

Figure A8-1. Extended fixed effects model results

Source: Employment Security Department/LMPA

Variable	Model estimate	t-value	Effect on post-unemployment earnings
TB Program participation	9,790.58	3.29***	Positive
TB participants who pursue health-related training	5,965.28	1.63	Positive
Number of health credits taken	192.98	1.82	Positive
TB participants who take more total credits	-57.80	-4.85***	Negative
TB participants who start program with more total credits	35.03	1.81	Positive
TB participants who start program with more health-related credits	150.79	1.71	Positive
TB participants who entered the program in 2008	-1,373.64	-1.77	Negative
Individuals who received their first unemployment benefits payment in 2008 who take more total credits	-34.72	-3.00**	Negative
Individuals who received their first unemployment benefits payment in 2008 who take more health-related credits	-69.66	-2.93**	Negative
TB participants who entered the program in 2009	-1,709.88	-2.46*	Negative
Individuals who received their first unemployment benefits payment in 2009 who take more total credits	-32.47	-3.14**	Negative
Individuals who received their first unemployment benefits payment in 2009 who take more health credits	-114.49	-5.26***	Negative
U.S. veteran TB Program participants	-2,790.43	-3.33***	Negative
U.S. veterans who take more total credits	26.17	2.07*	Positive
Low-income TB Program participants	5,878.37	10.13***	Positive
Low income individuals who take more total credits	42.87	4.77***	Positive
Gender = Male	2495.87	4.45***	Positive
Men who take more total credits	-6.40	-.69	No effect

** p<.05; ** p < .01; *** p < .001 (two-tailed tests).*

TB Program participation, and the pursuit of health-oriented college credits are most strongly associated with positive earnings outcomes.

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