Return on Investment for Virginia's Workforce Programs

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I. Introduction and Overview of Report

The two primary goals of the public workforce system are to connect jobseekers to employment and to help businesses connect to the workers they need to be competitive. Developing competitive workforce and making sure that businesses have the talent they need is critical for any state wishing to maintain a strong economy. However, funding for most public workforce programs has been dwindling. Therefore policy makers must make well informed decisions on the most productive use of taxpayer dollars to ensure that their investment yields a return. The state of Virginia is one of only a few states that require a return on investment analysis (ROI) be performed on its public workforce programs. In 2012, the state's total allocation for its 24 workforce programs was $362.8 million. The funds came from a combination of federal allocations (60.2%), state allocations (36.9%) and local sources (2.5%).[1] Understanding the returns on investment in public workforce programs and how those returns differ across various populations and service models is critical for ensuring continuous improvement and efficiency.

This report analyzes return-on-investment (ROI) for three of Virginia's publicly funded workforce programs: Workforce Investment Act (WIA), Wagner Peyser (WP), and Trade Adjustment Assistance (TAA). The goal is to evaluate the impact of the programs from a government budgetary perspective using administrative data for program exiters during the 2008 to 2012 program years. The analysis employs a combination of before-and-after models and propensity matching models to calculate ROI. We also use OLS and logistic regression analysis to estimate the dollar influence of each demographic and service related variable on earnings and employment outcomes. The three key research questions for this study and a brief synopsis of our findings for each follow.

A. Key Findings

In summary, WIA and WP generally show positive returns on investment while TAA shows negative return. We find that even when the ROI is negative, certain service related factors such as training and earning credentials can improve ROI outcomes. The three programs differ tremendously in terms of the characteristics of the clients they serve. Both after-program earnings outcomes and employment odds are influenced by the demographic (race, gender, education) and qualification (employment and wages prior) variables that have been thoroughly discussed in previous literature as highly influential on labor market outcomes. The regression results triangulate and offer further explanation for the ROI outcomes by estimating the dollar influence of each variable on earnings and each variable's specific impact on odds of employment.

Research Question #1: What is the return on investment to government for providing public workforce development services to VA jobs seekers?

[1] Graham & Harper-Anderson, 2013

Using the propensity matching method, investment in both WIA and TAA results in a positive ROI after 5 years and after 10 years as compared to the control group. Among WIA participants, cost savings from reduced reliance on public assistance benefits are extremely significant and help to increase returns over the cost of the program. The TAA program's positive results can in large part be attributed to the fact that the wages for TAA participants are significantly higher than those for the control group (WP). Therefore, tax benefits based on the program effect (as measured by wages) tend to outweigh TAA costs.

When program effects are measured by post-program wages of each group compared against their own prior earnings trajectory (before-and-after approach), ROIs for the WIA and WP programs are positive, but TAA has a negative ROI. For WIA participants, many of whom either did not have a job prior to the program or had a low paying job, the smallest earnings increase comparing their earnings before to their earnings after the program contributes to a positive ROI. As mentioned previously, savings from public assistance benefits also boost returns from this group. On the other hand, TAA earnings were relatively high before the program but dropped significantly after, which resulted in a large impact when program effects were measured based on comparison of before and after earnings. The drop in wages is partially driven by the state of the economy during the study period (2008 to 2012 corresponding to The Great Recession); and partially driven by the nature of TAA wherein participants are eligible because they are losing jobs (often well-paid, skilled jobs) for which there is no equivalently paid replacement position to be found. In addition, partial explanation for TAA negative outcomes is related to the program's high training costs. TAA training costs per person are about five times the WIA costs. When wage effects are already negative, adding extensive costs to the equation increases the magnitude of negative ROIs for TAA even more.

Research Question #2: How does ROI differ across service levels, demographic groups, and LWIA?

Participant demographic characteristics and employment history both have important influences on wages and employment, and hence, ROI outcomes. Groups that have traditionally been disadvantaged in the labor market such as women, disabled populations, certain racial ethnic groups, and individuals with limited education, yield the more favorable ROIs in WIA and TAA than their more job-ready counterparts do. Wage replacement rates are much higher for groups that start from a lower wage base and their employment is more likely to yield savings from forgone public assistance. Both of these factors contribute to higher ROIs. However, these same groups see the exact opposite effects in programs without significant service intervention such as in WP. In WP, groups that traditionally have had more secure connections to the labor market had higher ROIs. For example, for WIA and TAA, ROIs decrease the higher one's education prior to the program; women have higher ROIs than men; and Black and Hispanic participants have higher ROIs than do White and Asian participants. All of these patterns are reversed in the WP program. It is important to point out that while disadvantaged populations have higher ROIs in WIA and TAA, their actual wages and employment levels continue to lag behind groups with more labor market advantages. Therefore, these groups continue to need additional support and targeted resources.

Research Question #3: What roles do demographic, service and economic factors play in employment and earnings outcomes for workforce program participants?

The impact of demographic, service and economic factors for the three programs is consistent with previous literature on labor market outcomes. Low levels of education (less than high school); disability and gender (female compared to male) all have negative impacts on earnings that are statistically significant across all programs. Higher levels of education all have increasingly large and positive impacts on earnings that are statistically significant across all programs. Consistent with earnings, many of these same factors also negatively impact odds of finding employment after exiting the program. Women however, had increased odds of finding employment over those of men in all three programs. While achievement of credentials did not prove to have a statistically significant effect on earnings in most cases, earning certain credentials related to occupational skills increased the odds of employment after the program.

In brief we recommend that Virginia policy makers take note of and build on factors which have proven successful such as training and credential achievement with particular emphasis on reaching out to disadvantaged groups with information and support. We also recommend ROI analysis be incorporated into a broader performance measurement system which allows for innovative metrics that value the challenges of serving certain demographic groups. Finally we recommend that processes are put in place for linking the appropriate sources to improve the quality and quantity of data available for ROI analysis.

B. Report Overview

In the remainder of this first section of the report, we briefly discuss previous approaches to using ROI to evaluate workforce programs including relevant-related issues raised. We next provide an overview of the Virginia workforce system followed by key highlights of the WIA, TAA and WP programs. In Section II, we discuss the methodology and data employed in this analysis. Section III is a discussion of the results including ROI results by program and the regression outcomes. In the final section of the report we offer our conclusions and policy recommendations.

C. ROI and Workforce Development

Applying ROI to workforce programs is still a relatively new process although it has recently gained traction in a handful of states as governments have increased their expectations of accountability and transparency. Texas appears to have had one of the earliest starts on ROI workforce calculations. The state published their first study in 2003, followed by an improved study in 2008[2]. Along with Texas, Arizona, Colorado, Minnesota, Indiana and Ohio are the states that have made the most significant progress to date. While most publicly funded workforce programs are held accountable for meeting federal and state performance measures, some scholars and policy makers have argued that the measures are vague and only tell part of the story. Framing program evaluation in terms of an ROI allows taxpayers to view

[2] See King and O'Shea, 2003 and King, Tang, Smith & Schroesder, 2008

program funding as an investment with the expectation of future benefits rather than simply a subsidy.

According to Hollenbeck, King and Stevens (2012), ROI is basically the net benefit of investment and is similar to a cost-benefit analysis but expressed as a percentage (p. 1). Existing studies to calculate ROI for workforce programs seek to do two things. First they estimate the impact of program participation on earnings and employment outcomes. In other words, what is the difference between what would have happened to this job seeker without the program compared to their outcomes having participated in the program? Net impact estimates benefits minus program costs. Next, using net impact amounts, researchers estimate the percentage return that investors can expect to receive as a result of funding the program. Previous workforce ROIs have estimated returns to various audiences including the individual participant, the taxpayer, and/or society as a whole, depending on the researcher or policy maker's interest. As ROI increases (greater return for every dollar invested), the value of the workforce program is presumed to increase as well.

While the basic premise behind ROI is simple, estimating costs and benefits can get extremely complicated. With multiple workforce programs per state, each with its own unique data collection process and cost structure, aggregating costs and benefits into one figure that is both methodologically rigorous and useful to policy makers can be a challenge. Most ROIs for workforce programs include a number of debatable assumptions. The Minnesota Governor's Workforce Development Council (MGWDC) (2011) noted the difficulty of "finding a balance for models that are both transparent and simple, and both rigorous and accurate." They also suggested that one model may not be equally useful to both workforce program managers and policy makers.

Given these complexities, approaches to calculating ROI for workforce programs vary tremendously. Hollenbeck et.al. (2012) warn that because workforce administrators tend to prefer a high ROI that demonstrates program effectiveness, it is common for estimates to be based in assumptions that artificially raise the final percentage.[3]

1. Methods of Calculating ROI

Approaches to calculating ROI for workforce programs vary tremendously from extremely simple to extremely intricate and complex. At least some of the variation results from differences in data availability, ability to match data from various sources, the nature of specific programs to be evaluated, preferences of the researcher, and purpose for the ROI. Existing literature suggests ROI analysis for workforce development generally involves analysis of secondary cost/benefit data, propensity matching of cases in treatment and control groups; and/or regression analysis.

[3] Hollenbeck, King, & Stevens, 2012

The simplest way of calculating ROI is to use secondary data to estimate costs and benefits which can be applied to the basic ROI formula:

$$ROI = (Benefits - Costs) / Costs * 100$$

Some of the most commonly considered benefits include increased wages and fringe benefits from finding employment, savings on public assistance costs when unemployed people find jobs; and added tax revenue from earnings and spending of increased wages. Some researchers have taken the analysis a step further to project the multiplier effect of returns on the broader economy.

Indiana, Texas and Colorado utilized propensity matching to calculate the ROI of workforce development programs. In this method a control group is comprised of unemployed individuals who do not receive the given program benefits. The treatment group consists of program participants. Cases from treatment and control groups are matched based on a host of chosen variables believed to impact outcomes using a logistic matching procedure. Once treatment and control groups are created, a net impact evaluation of both is conducted with emphasis on the difference in net impact.

Previous studies have differed in their definition of treatment and control groups. In the Texas and Indiana studies, for example, treatment and comparison groups were differentiated by the level of services received by program participants. In the Colorado study, on the other hand, comparison groups were characterized by whether an individual received services or not. Minnesota differentiated between the two groups by the source of data.

2. Data Issues with ROI

Several data related issues have been raised in relation to using ROI for workforce programs. Hollenbeck et al. 2012 point out that ROI estimates are based on many assumptions. Brooks (2010) acknowledges Colorado's assumptions about cost/benefit projections (e.g., selected tax rates) and comparison groups (e.g., the services they used or did not use) as well as projected average earnings. Beyond assumptions, which are inherent to the ROI process, states generally found data difficult to collect. King et al (2011) and GWDC (2008) both acknowledge the reality that each workforce program has a different mission, target population, reporting requirements and accountability. In other words, aggregating data across programs is problematic due to different formats, methodologies, and participant characteristics. Further, the necessary workforce data are often not available at all. [4] Finally, there are also concerns regarding missing data. For example, the Colorado study substituted average annual wages for the population at large in place of the actual wages of those exiting programs due to data limitations. Additionally, no state is entirely comprehensive in the workforce programs they evaluate, raising questions of generalizability. [5]

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[4] King et.al 2008; Brooks, 2010; and GWDC 2011
[5] Brooks, 2010

In addition to methodological variations that may influence ROI outcomes, previous literature suggests that workforce participation patterns and program outcomes in WIA, TAA and WP vary significantly across demographic groups defined by race, gender, age disability status and education level. The demographic variation makes meaningful comparison of ROI results across programs complex at best.

In sum, while states are in the beginning stages of developing ROI models for workforce development, final ROIs should be viewed through a cautionary lens rather than at face value given the multitude of data challenges and methodological complexities. Further ROI should be viewed as one tool in among a many for evaluating the effectiveness of workforce programs.

D. Overview of the Virginia Workforce System

The Virginia workforce system serves approximately 1.1 million participants each year across twenty-four different workforce programs spread across several different agencies. The total allocation across all workforce programs in the Commonwealth was $362 million for 2012. Funding for the Virginia workforce system includes approximately 60% from federal allocations, 37% from state allocations, 2.5% from local allocations and less than 1% from other private sources. The system is made up of fifteen local workforce areas (LWIA) each governed by its own local workforce investment board(LWIB) which each works alongside local employers and service providers to meet the workforce needs of the state's rapidly growing and diverse population (see Appendix B for list of Virginia's LWIA). The Virginia Workforce Council is the state-level board that provides strategic leadership for the entire state workforce system. The Virginia workforce system serves job seekers ranging from teens through adults.[6] Included are several programs specifically designed to serve populations with more specialized service needs (such as veterans or the vision impaired clients)? The state of Virginia, well known for its efficiency and fiscal responsibility, is one of only a few states in the country that requires a return on investment analysis for its public workforce programs.

E. Overview of WIA, TAA and WP Programs

This study focuses on three federally funded workforce programs implemented in the state of Virginia, the Workforce Investment Act program, Trade Adjustment Assistance Act program and Wagner Peyser program. The Workforce Investment Act of 1998 established the one-stop delivery system that mandated that certain workforce partner programs make their services available through local One-Stop Career Centers. While all three programs examined in this report are mandated partners of the one-stop system, the WIA program is administered by the local WIB while both TAA and WP are administered locally by the Virginia Employment Commission. Table 1 summarizes the main features of each program.

The *Workforce Investment Act* Programs (WIA) provides workforce development services to adults, dislocated workers and youth. WIA programming is housed within the One-

[6] For the purposes of our report, we only include participants 18 yrs. or older.

Stop Career Centers, along with other workforce service programs. The WIA programs offer a tiered system of services including core, intensive and training services. Intensive services are provided to those clients unable to find employment using core services or who need hands-on assistance. Those WIA participants meeting the eligibility requirements for intensive services but who are still unable to find a job may qualify for one of several training options. Funding for WIA programs is distributed to local Workforce Investment Boards (WIBs) via the state WIB. Each local area must meet performance targets negotiated with the State WIB. In the state of Virginia in program year 2012, the budget allocation for WIA Adult and Dislocated Worker programs was $30,853,626, which constitutes 9% of its total workforce budget. The program served 12,916 program participants statewide in 2012.

Table 1: Workforce Program Overview

Program	**WIA**	**TAA**	**WP**
Legislation	*Workforce Investment Act* of 1998	*Trade Act* of 1974; 2002 and *Trade and Globalization Adjustment Assistance Act* of 2009	*Wagner-Peyser Act* of 1933 and *Federal Unemployment Tax Act*
Description	Reformed the national job training system creating the One-Stop Career System for adults, dislocated workers and youth[1]	Assists workers who have lost their jobs due to foreign trade impacts, i.e. increase in imports, shifts in production or employer lost business	Established nationwide system of employment offices - Employment Services
Services Offered	Core services: -job search -placement assistance -career counseling -labor market information -assessment of needs & skills, -follow-up services related to job retention Intensive Services: -individual employment plans -counseling -case management -prevocational services -Training (on-the-job, entrepreneurial, skill upgrades, job readiness and adult education or literacy)	-Rapid response assist. -reemployment services -job search allowances -relocation allowances, -training income support -health coverage tax -credit training -job search -relocation allowances -health coverage -tax credit	-employment assistance -facilitated self-service -career counseling -job match process -work test for UI circulation of job-related information
VA Participants (2012)[2]	12,916	8,113	405,230
VA Program Budget (FY 2012)[2]	$30,853,626	$11,486,161	$15,912,960

[1]While to WIA program includes youth, this study only covers the adult and dislocated worker populations. Budget figures reported here only include adult and dislocated worker allocations.
[2]Source: Harper-Anderson, Graham 2013

The *Trade Adjustment Assistance* (TAA) is a federally funded workforce program which assists workers who have lost their jobs due to foreign trade impacts. Nationally, the majority of petitions for TAA assistance come from employees of the manufacturing sector (66%), with the second highest originating from Professional Scientific and Scientific Services (14%). [7] Workers who qualify for TAA benefits may access a wider variety of services than those available through WIA (see Table 1). Of all the benefits and services available, the most common approved are income support and training. In Virginia, TAA is administered by the Virginia Employment Commission. The TAA program served 8,113 program participants in 2012 with a budget of $11,486,161.

The *Wagner-Peyser Act* of 1933 established a nationwide system of employment offices called the Employment Service (ES). The Workforce Investment Act of 1998 made the ES the foundation of the One-Stop Career Center system. Wagner-Peyser funds are distributed to states for labor exchange programs, but each state has some discretion on exactly how they allocate funds. Services to job seekers generally involve the job match process (for both the unemployed and employers), work test for Unemployment Insurance programs, and the preparation and circulation of job-related information.[8,9] In 2012, the state of Virginia served 405,230 participants through the WP program with a budget of $15,912,960.[10]

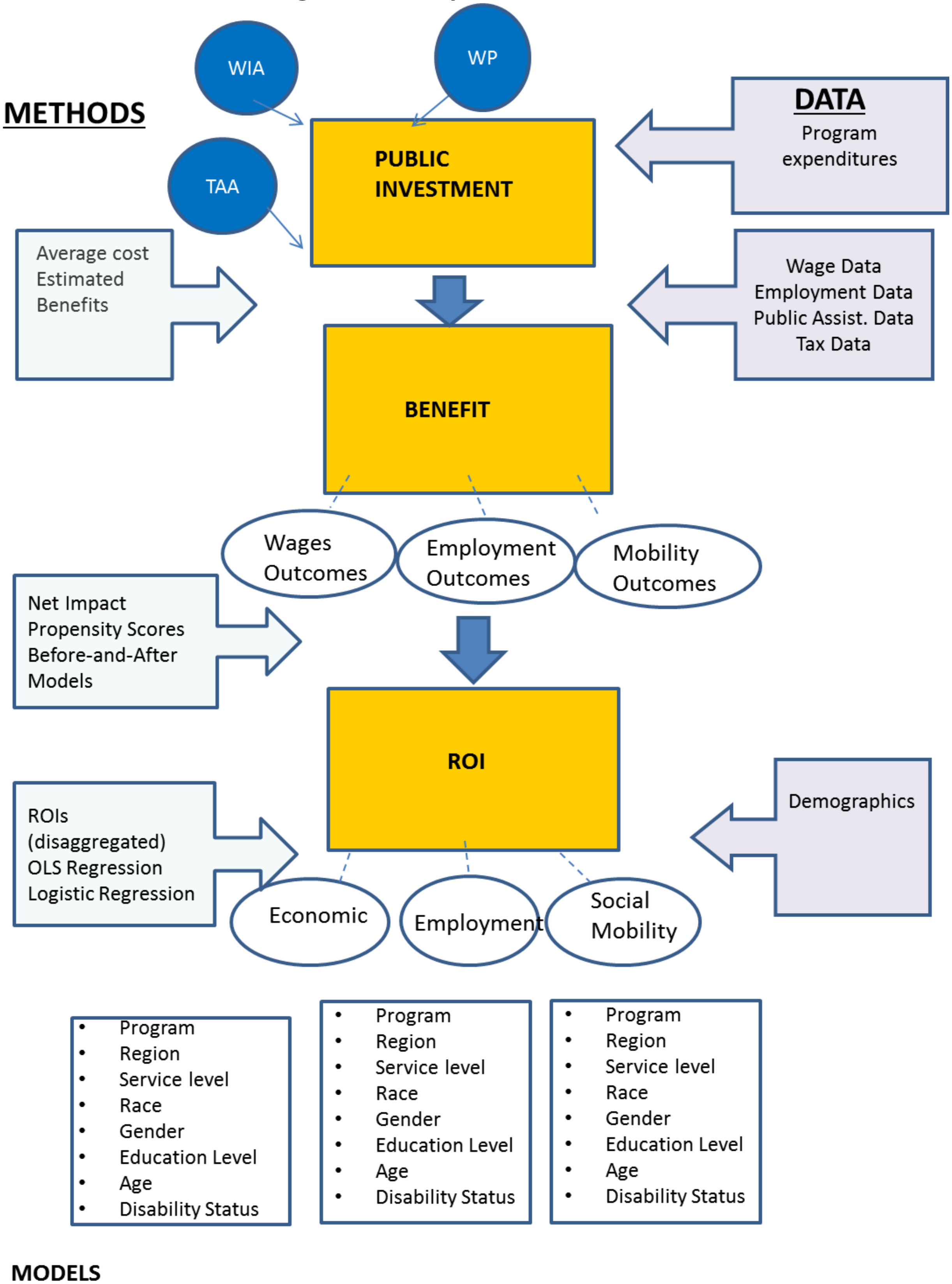
[7] Source: http://1.usa.gov/13nzuBt
[8] O'Leary and Eberts, 2008
[9] Source: http://1.usa.gov/RK6wsG
[10] Graham &Harper-Anderson, 2013

II. Methodology and Data

A. Overview of Study Approach

This study uses a multi-method approach to assess the program impacts and returns on investing in workforce development programs. Based on administrative data from WIA, WP and TAA programs we estimate 5-year and 10-year ROI for dollars expended on Virginia's workforce development participants for each program. To answer Research Question #1, we used two approaches to estimate ROI for each of the three programs. Each approach has different strengths and weaknesses. The first method uses regression adjusted propensity scores to create treatment and control groups that are comparable across a number of demographic and labor market characteristics. In this approach the wage difference between the treatment and control group is considered to be the program effect. The second approach estimates incremental program impacts based on deviations of program participants from their past earnings trajectories— commonly referred to as the before-and-after approach. The differences between earnings before program participation and after are considered the program effect. Each approach is discussed in greater detail below. To answer Research Question #2, we further disaggregate the ROI results from the before-and –after approach along demographic and service related categories. To address Research Question #3, we use OLS and logistic regression to estimate the effects of each demographic, service and employment related variable on after-program earnings and likelihood of employment. Figure 1 provides an overview of the analytical process discussed in more detail in the next section.

Figure 1: Analytical Framework



B. Data

This study is based on administrative records for program exiters from the Workforce Investment Act (WIA), Wagner-Peyser Employment Services (WP), and Trade Adjustment Assistance (TAA) workforce programs in Virginia. The WIA file combined records from WIA adult and dislocated worker populations. Records were provided for participants who exited each program between January 2008 and July 2012. Generally, each record included data on demographics, program participation, and program outcomes. Specific variables available differed across programs.

Each administrative record also contained Wage Record Interchange System (WRIS) data, commonly referred to as Unemployment Insurance (UI) data. According to USDOL "WRIS facilitates the exchange of wage data among participating states for the purpose of assessing and reporting on state and local employment and training program performance, evaluating training provider performance, and for other purposes allowed under the WRIS Data Sharing Agreement". Each workforce program in our study normally includes WRIS data in their administrative files for a set number of quarters before program participation and after program exit as a basis for assessing participant outcomes. In this analysis, researchers were only provided WRIS data available from the state of Virginia. If participants worked outside of the state for any time during the period that records normally cover, wage data from other states was excluded from the totals. Therefore, any participant records containing a flag indicating that all or part of the wage data had been excluded were considered inaccurate and excluded from the analysis (10% of original WIA records, 13% of WP and 4% of TAA).

The data cleaning process for administrative records required elimination of any duplicate case files and addressing dual enrollment in programs. We also limited our analysis to participants who were at least 18 years of age when they enrolled in the program. Table 2 shows the final number of records included in the analysis for each program. Greater detail on the data cleaning process can be found in Appendix A.

Table 2: Number of Records per Program

Program	*# Records*
WIA	37,940
TAA	9,096
WP	1,319,326

<u>1. Variable Definitions</u>

In order to identify the most important factors that influence program outcomes, variables covering demographic measures, employment experience prior to program entry, program achievement, and program service levels are included in this analysis. To find a description of each specific variables included and an explication of the coding strategy please see Appendix C.

C. Measuring Costs and Benefits

The first step in conducting an ROI is to determine the net impact of the program. The net impact estimates final impact of program treatment once costs are taken into consideration. Net impact and ROI were calculated for each individual participant and averaged. Table 3 lists the averages for costs and benefits by program.

Table 3 : ROI Expenditures and Returns per Year by Program

	WIA	TAA	WP
Expenditures			
Avg. Costs			
Program	$643	$374	$41
Training	$435	$3,366	N/A
Returns			
Taxes Rates			
State and Local Income[11]	9.70%	9.70%	9.70%
FICA	7.7%	7.7%	7.7%
Federal Income[12]	5.0%	5.0%	5.0%
Public Assistance Benefits[13]			
TANF +SNAP	$5,436	$5,436	
SSI + SNAP	$10,872	$10,872	
SNAP Only	$3,432	$3,432	
UI Only			$2,082

1. Costs

Each program provided figures for overall program costs, training costs and number of participants served in each year under consideration. For WIA, individual participants were assigned estimated costs based on average program costs across participants for their participation year. If they received training, an additional amount was added for average training costs that year. The TAA dataset included a total training expenditure variable as a part of each participant's record. That figure was combined with the average program cost to estimate total cost for each TAA participant. The WP program does not provide training therefore cost per participant were based on average program cost.

2. Benefits

Increases in earnings for workforce clients are assumed to lead to additional tax revenue to the local, state, and federal government and reduction in dependence on public assistance programs. Benefits or returns in this analysis are a function of tax revenues attributable to

[11] Based on averages obtained from Davis et.al 2013
[12] Based on data from Marr and Frentz 2013
[13] Based on averages obtained from McMakin 2013

program effects and program savings resulting from clients attaining employment and presumably leaving public assistance rolls. Benefits include estimates for Virginia state and local taxes (combines state income, sales and property), FICA, and federal income taxes all based on average rates paid by Virginians for each. Tax benefit is calculated based on the program effect, which for the before-and-after models, means the difference in income between earnings prior to the program and earnings after. In other words, if a participant was earning $5,000 in the quarter prior to the program and earned $12,000 in the second quarter after, tax benefit is calculated based on the additional $7,000 that is now being earned presumably as a result of benefits derived from participation in the program. If a participant's earnings decrease after program participation, the tax effect could be negative. For the propensity matching model, the program effect is measured by the wage difference between the treatment group and the control group in the matched dataset. For example, if the mean difference between WIA and the control group is $1,000, average tax rates are applied to this figure for each tax included in the analysis.

In this analysis participant wages in the quarter immediately preceding program participation were compared to wages in the second quarter after exit. The assumption was that the goal of each workforce program is to improve workers earnings and likelihood of employment from their starting point (when the worker first enters the program) and therefore the quarter immediately preceding treatment is the most appropriate before measure. Given that job seekers may require some time after completing services to secure employment, the second quarter after program exit is used to measure the after-effect to allow time for participant job search. Quarterly wage differences were used to estimate yearly wage differences.

Another presumed benefit is savings from clients leaving public assistance rolls once they obtain employment. Again, data availability varied between programs. WIA and TAA data included a dichotomous indicator of whether an individual received TANF or not. The data also contained a catch-all variable indicating whether a participant received other types of public assistance (SNAP, SSI and/or General Assistance). TANF clients were assigned the average monthly TANF award for Virginia residents based on the 2012 annual report of the Virginia Department of Social Services. Further, the assumption was made that TANF recipients who indicated that they were also receiving "other public assistance", were receiving SNAP and the average SNAP amount was added to their benefits total. Disabled individuals who were not receiving TANF but indicated they were receiving public assistance, were assumed to be receiving SSI and SNAP. Again, SNAP amounts were based on averages for SSI recipients. Program participants who were not receiving TANF and were not disabled but indicated that they were receiving public assistance were assumed to be receiving SNAP. They were assigned the average amount of SNAP for those who were not receiving other assistance.

The WP dataset did not include variables that would allow for consideration of TANF and SNAP benefits but did include a variable to indicate whether the participant was an Unemployment Insurance (UI) clamant. UI savings were calculated based on average UI amounts in Virginia and average length of time participants spend on UI. The assumption was made, that if the participant secured employment (as indicated by their administrative record), they were no longer eligible for UI and the remaining benefit amount is counted as benefits saved. This program saving along with the additional taxes generated by the wage increase (or decrease) makes up the benefits figure for the WP program.

D. Analysis

Once benefits and costs were determined, the formula below was applied to estimate the return on investment for each program using propensity score matching and before-an-after approaches. Benefits were then converted to dollars for ease of interpretation.

ROI = (Benefits –Costs) /Costs *100

The most basic method employed to calculate ROI was the before-and-after design based on prior earnings trajectory. This approach estimates incremental program impacts based on deviations of program participants from their past earnings trajectories. The differences between earnings before program participation and after are considered the program effect. While this method is straight forward, there is no comparison control group causing some researchers to point out possible threats to internal validity from confounding variables. However, since WP data (control group) is missing many important variables available in the WIA and TAA datasets and therefore limits the extent to which these can be examined in the quasi-experimental method, the before-and-after method allows for the disaggregation of results in ways that are more meaningful

Propensity score matching uses regression adjusted propensity scores to create treatment and control groups that are comparable across a number of demographic and labor market characteristics. Propensity score matching is considered a superior approach for reducing potential bias for workforce ROIs. Random assignment, which is the gold standard in experimental research, assumes there is no systematic statistically significant difference in the two groups being studied. Propensity matching attempts to simulate random assignment by matching cases from the treatment group and control group that are as similar as possible on variables that may influence results. Participants are matched based on an estimate of the probability that the individual receives treatment (the propensity score). The propensity score is thus a balancing score for individual characteristics, assuring that for a given value of the propensity score, the distribution of individual characteristics will be the same for both participants and comparison cases.[14] In this approach, the wage difference between the treatment and control group is considered to be the program effect and therefore used to estimate benefits.

[14] Heinrich, Mueser, and Troske, 2008

Why Calculate ROIs Using both Before-and-After and Propensity Score Matching Methods?

We calculate ROI using both methods because each has strengths and weaknesses. The table below summarizes the pros and cons of each.

	Pros	*Cons*
Before-and-After	• Straightforward/Easy to apply • Uses all available cases in each dataset • Reflects true population served by program	• No control group • Possible internal validity issues
Propensity Matching	• Simulates random assignment • Balances individual characteristics • Commonly accepted method	• Limited to cases with matches • Data does not reflect true population served • Accuracy contingent on quality of matches • Only looks at post-program results

The matched dataset for WIA participants included 67,974 cases. The matched sample for TAA included a total of 16,934 individuals, evenly distributed in the two groups (TAA participants versus control group). Testing implied that matching improved overall balance among key variables between the treatment group and control group in both datasets. See Appendix D for a more detailed discussion of propensity score matching process and specific statistics related to test outcomes.

In each case WRIS data for quarterly earnings was used to estimate yearly earnings. Based on yearly earnings and employment status, we projected ROI for 5-years and 10-years after program exit. Across the analysis we discount future benefits at the 3% rate suggested by OMB (2002).

Finally, using OLS and logistic regression we analyze the influence of participant characteristics and service related variables on earnings and employment outcomes. First, we used linear multiple regression models (OLS) to examine the influence of variables on earnings. Next, we used binary logistic regression to examine the impact of the variables on the likelihood of employment after exit.

We combine the analysis above to draw conclusions about the impact of WIA, TAA and WP programs, their ROI and how various factors influence their outcomes.

E. Study Limitations

This study represents an important first step toward understanding ROI for Virginia's workforce programs and it offers a foundation upon which to build more robust models and processes for future analysis. Three key limitations are worth noting to contextualize results and offer insight for improvements to future ROI studies.

One limitation of this study is the dearth of data available. Because administrative data were used from all three programs, standard wage and employment outcome data covered a maximum of four quarters after exit whereas other ROI studies for workforce development have covered several years. Further, because of limitations on WRIS data discussed above, the number of useable records was further decreased. Evaluating outcomes over longer time periods with a greater number of data points would allow for a more robust analysis. Another important point is that One-Stop Centers serve clients at the core, intensive and training levels. However, administrative records for workforce programs only cover those who are "enrolled" in intensive level services and training. This leaves a significant number clients who are benefiting from the One-Stop Center (and the resources spent on them) unaccounted for in this analysis. The result is that the true impact is underestimated. This is not an issue with this study per se but more with data collection policies in the public workforce system.

Second, lack of primary data from agencies other than workforce such as social services and tax records limit the precision of estimates. Due to the inability to link data systems, there was no way to verify accuracy of public assistance benefits received or tax paid. Alternately, we relied on each workforce program's administrative records, which are largely based on participant reporting. Further in the absence of data on benefit amounts, we had to estimate yearly amounts for TANF, SSI and SNAP (food stamp) benefits based on assumptions and averages taken from public reports. The ability to link workforce records to actual social service and tax records would enable more accurate estimates of benefit amounts and hence more precise ROIs.

Finally, inconsistency in the types of data collected across programs and compatibility of data formats limited the types of comparative analysis that could be performed across programs. More uniform data collection practices could improve the comparability of results across programs. Despite these limitations, the analysis in this report provides important insights into the impacts and outcomes of workforce programs in Virginia.

III. Results

A. Demographics of Participants in WIA, TAA and WP Programs

Prior research has shown that certain demographic characteristics are correlated with labor market outcomes. Programs participants in WIA, TAA and WP have varied demographic make-ups which will undoubtedly play a role in return on investment for each program. In short, the research shows that race, gender, education, age, disability status and employment experience each has an impact on earnings and employment. It is therefore important to understand who is enrolled in each workforce program as a framework for contextualizing program performance. Table 4 lists detailed descriptive statistics for each program. Below is a short summary of the demographic highlights for each.

WIA had a higher percentage of African Americans than the either TAA or WP (45% compared to 28% and 37% respectively). The majority of WIA participants were women and the percentage of women in WIA (57%) was the highest among the three programs. Half of the WIA participants were between the ages of 21 and 45 when they began the program. Another 37% were between 45 and 64 years old. WIA participants had fairly low education levels with 64% only having a high school diploma or less and only 11% with a Bachelor's degree or more.

The TAA population tended to be white (67%) with the lowest percentage of blacks among the three programs (28%). They also tended to be older with a majority of the participants between the ages of 45 and 64 years old (56%), mostly male (59%) and the group had lower levels of prior education than the other two programs (only 9% with Bachelor's degrees or above but 67% high school graduate or less).

WP participants fell in the middle of values of the other two programs on percentage of African Americans participants (36%) and percent female (47%). Participants in WP were generally on the younger end of the age spectrum with the largest proportion of the participants in the 21-45 age groups (61%). Their education levels were higher than the other two groups within 15% holding a BA or above (Compared to 9% and 11% in TAA and WIA respectively).

All three programs tended to have low levels of participation from Asians, Native Americans, and Hawaiian/Pacific Islanders (each group less than 3% per program). WIA, TAA and WP also had comparable levels of participation by veterans (8% to 9% each) and they each had less that 5% participation by people with disabilities.

Table 4: Demographic Statistics by Program

	WIA		TAA		WP	
	Frequency	%	Frequency	%	Frequency	%
Race						
American Indian	418	1.10	56	0.64	20,023	1.52
Asian	888	2.34	229	2.61	26,717	2.03
Black	17,050	44.98	2,474	28.19	486,303	36.86
Hawaiian	103	0.27	10	0.11	4,626	0.35
White	18,209	48.04	6,055	69.00	728,693	55.23
Age Group						
18 to 20	4,637	12.2	27	0.30	84,219	6.38
21 to 44	18,937	50.0	3,780	41.48	802,008	60.79
45 to 64	14,047	37.1	5,118	56.16	411,247	31.17
65 and over	285	.8	188	2.06	21,852	1.66
Educational Attainment						
Less than High School	5,478	14.49	1,174	12.96	157,499	11.38
HS Grad/GED	18,810	49.75	4,892	53.98	640,711	46.27
Some Coll./No Degree	7,170	18.96	1,564	17.26	127,500	9.21
Cert/Deg. LTBA	2,082	5.51	631	6.96	251,046	18.13
BA or above	4,272	11.30	801	8.84	207,829	15.01
Gender						
Male	16,057	42.36	5,402	59.28	731,394	52.71
Female	21,849	57.64	3,711	40.72	656,240	47.29
Disability Status						
No Disability	36,236	95.59	9,094	99.88	1,320,591	96.51
Individual with Disability	1,670	4.41	11	0.12	47,703	3.49
Veteran Status						
Not a Veteran	34,858	91.96	8,295	91.02	1,262,671	90.99
Veteran	3,048	8.04	818	8.98	124,963	9.01
Employment Status						
Not employed	30,663	80.89	7,128	78.22	1,139,661	82.13
Employed at time of service	7,243	19.11	1,985	21.78	247,973	17.87

B. Program Outcomes

Program effects on wages and employment vary depending on whether they are being examined as change over time for the same individual or outcomes for programs participants in the treatments group are being compared to outcomes for a control group. Examining pre and post program wages suggests that the impact of WP and WIA have been positive (albeit small) while the impact of TAA has been largely negative. However, when wages are measured after program participation comparing WIA and TAA to non-participants, both programs show positive and statistically significant wage effects. The specific outcomes of each program will be discussed in greater detail below.

<u>1. WIA Outcomes</u>

Employment and Wages

WIA program outcomes suggest mixed results in both wages and employment after participation in the program. Among all WIA exiters, average wages increased by $416 after participation compared to the before (from $15,252 per year to $15,668 per year). The average wage earnings for WIA participants in the matched dataset ($11,629)[15] were also slightly higher than their counterparts in the control group ($10,785) — $844 higher. While overall WIA exiters were more likely to be employed after the program than before the program (67% and 19% respectively), WIA participants in the matched treatment group were less likely to be employed compared to the control group (odds of .88). In other words, while on average participant's odds of employment were higher after exiting the program than before, WIA participants' odds were still compared to the control group.

WIA Return on Investment

Both approaches to calculating ROI suggest that the WIA program yields a positive return on government investment both over the five year and ten year time periods. However the precise amounts differ based on reference group.

Table 5: WIA ROI Results

	Propensity Matching[16]		Before-and-After	
	5 Year	Ten Year	5 Year	Ten Year
Average Cost	$901		$901	
Net Gain/Loss	$2,386	$6,110	$1,544	$3,249
Returns in Dollars	$2.65	$5.78	$1.72	$3.60

Table 5 lists key cost and return information based on both methods employed in this analysis. Costs per WIA participant were $901 on average, which includes both program costs and training costs when applicable.[17] Among the matched sample, total benefits including

[15] Wage difference were calculated based on quarterly wages and translated into yearly wages multiplying by 4

[16] For more details on calculations for this model see Appendix G

[17] Each participant's costs was calculated separately based on average administrative and training costs for their program year with total costs for all participants averaged at the end.

additional tax revenue based on earnings and savings from public assistance averaged $720 per year. Total returns over a 5-year period expressed in present value terms (at a 3% discount rate) were $3,287. Once costs are considered the present value of the net return was $2,386. This outcome suggests that for every dollar invested in the WIA program, $2.65 will be returned over five years in the form of increased taxes and foregone public assistance benefits compared to the control group. After 10 years, the return was $6,110, which results in a net return of $5,209. Every dollar invested in WIA is predicted to yield a $5.78 ROI over a ten year period compared to the control group.

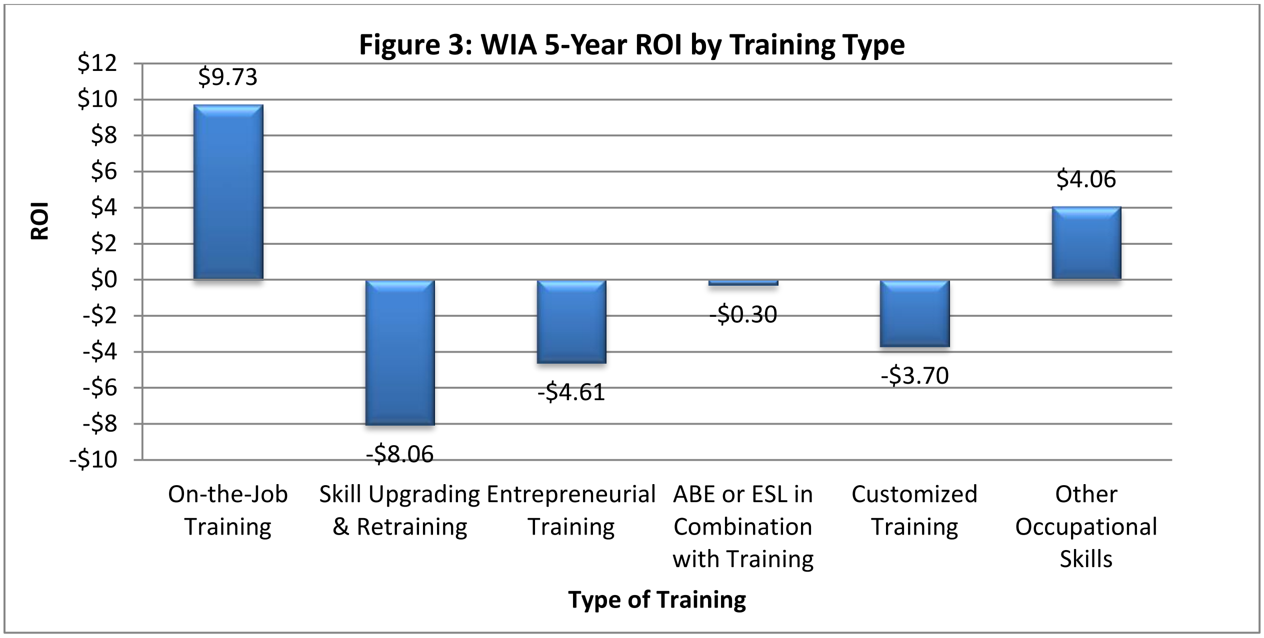
Comparing earnings of WIA participants after the program to their prior earnings trajectories, also yields positive ROI results but are of a much smaller magnitude. Table 5 shows that over the five year period the returns after participation in WIA were projected to be $1,544 on average. Once costs were considered, the average net returns per WIA participant were 172% or $1.72 over five years and a 360% return over a 10 year period or $3.60 for every dollar invested in the program.

WIA ROI by Service level and Training Type

While the ROI showed positive results for WIA, the outcomes are differentiated by service level, service type and participant achievement. Not only did training yield much higher ROI than not-training, specific types of training (on the job training and occupational skills training) yielded the most favorable ROIs. Further, earning occupational skills licenses and other occupational skills certifications yielded higher returns than any other type of recognized credential earned as a result of WIA funded training.

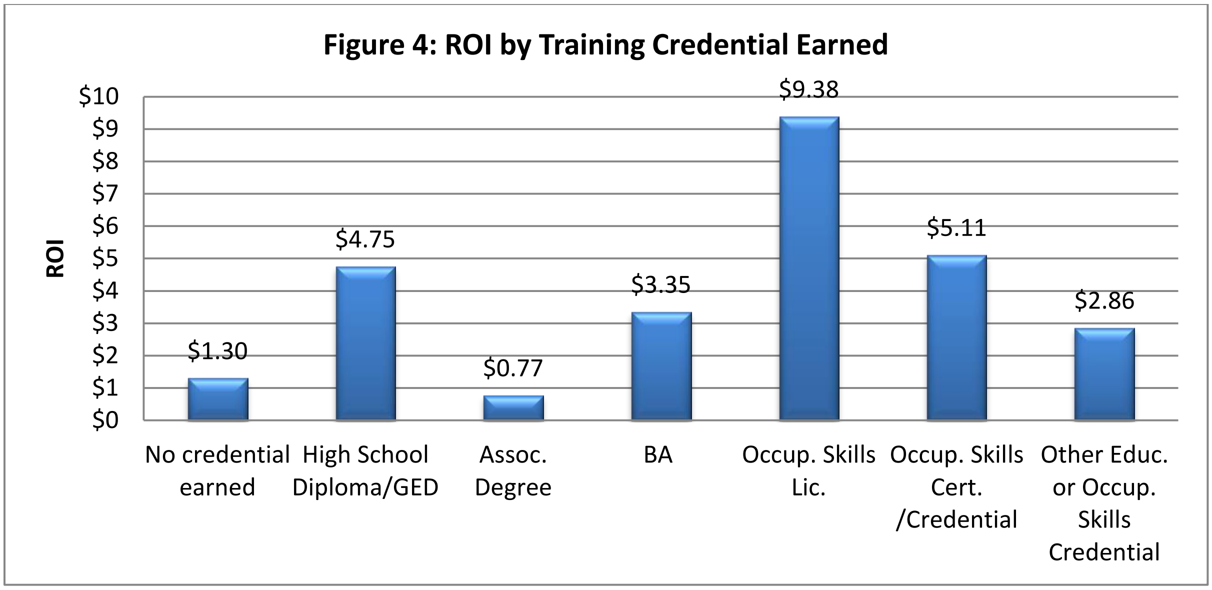
Figure 2: WIA ROI by Training Status

As illustrated in Figure 2, ROI for those participants receiving training both 5-year and 10-year ROIs were positive and much higher ($3.86 and $7.82) than the ROIs for participants who did not receive training through the WIA program (-$1.95 and -$2.62 respectively). The results suggest that investment in WIA participants who train yields a $3.86 return over the five year period for every dollar invested while those who do not train yield a loss over the same period of $1.95 per dollar invested.



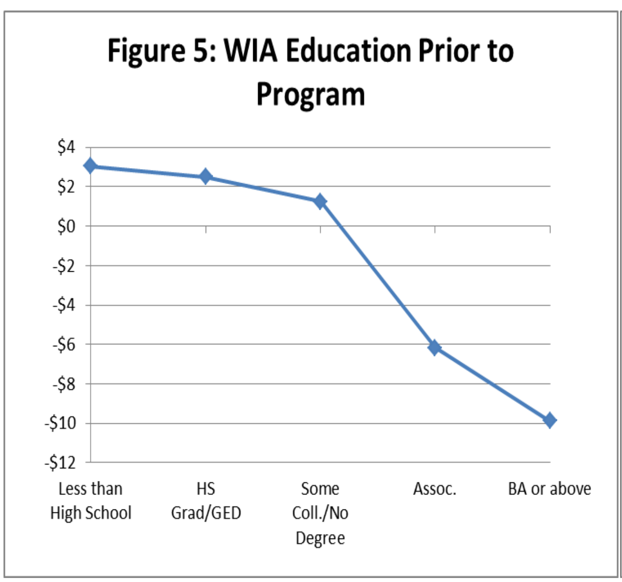
As Figure 3 shows not all training yielded equal or positive returns. The WIA program offers six types of training. The highest ROI resulted from on-the-job training ($9.73) and other occupational skill training ($4.06) over a 5-year period. The other types of training each showed a negative ROI with the largest negative return coming from the Skills Upgrading and Retaining category.

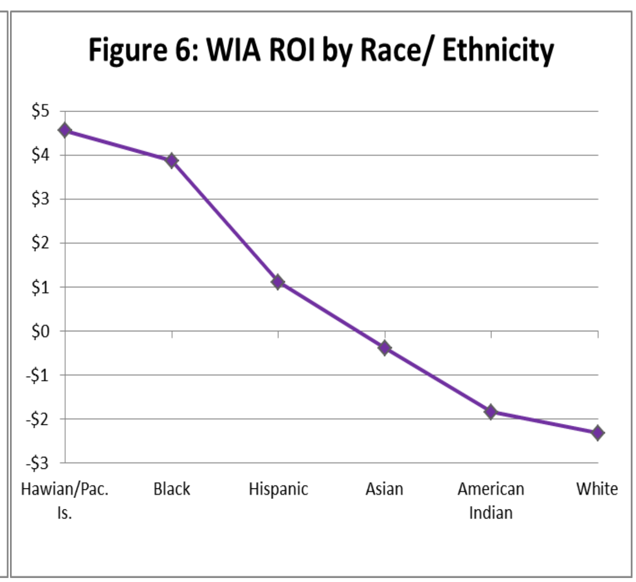
Actual achievement also mattered for the WIA ROI. Obtaining a credential as a result of WIA sponsored training yielded notably higher returns than training that did not result in a credential, except in the case of the Associates degree. Figure 4 illustrates that earning an occupational skills license yielded the highest ROI by far ($9.38), followed by obtaining other certifications and credentials relate to occupational skills ($5.11). Obtaining a high school diploma and Bachelor's degree yielded the third and fourth highest returns respectively, while earning an Associate's degree yielded returns lower than training but not earning a degree at all ($.77).



WIA ROI by Demographic Groups

Disadvantaged populations appear to yield the highest ROIs for the WIA program. While participants without a high school diploma yield ROIs above 300% or $3.00 for every dollar invested, Figure 5 illustrates how the ROIs decrease as education level increase until those with a Bachelor's degree or above yield negative returns to investment in the WIA programs. Similar patterns can be observed for race. Whereas racial groups that traditionally do well in the labor market (Whites and Asians) yield negative ROIs, traditionally disadvantaged race and ethnic groups with the most to gain (blacks and Hispanics) yield higher returns (see Figure 6). Park (n.d.) points out that Hispanics and blacks enrolled in workforce programs may have higher wage replacement rates due to their lower earnings prior to entering the program. Native Americans also yielded surprisingly low returns. Results for Native Americans and Hawaiian Pacific Islanders must be viewed with caution given the very small proportion of each group in the participant pool (1.10% and .27% respectively).





Disaggregated ROI outcomes for individuals with disabilities followed the same patterns as other groups who are traditionally disadvantaged in the labor market. While the ROI for individuals without disabilities was 47.23% or a return of $.47 over five years for every dollar invested, the ROI for individuals without disabilities was 653% or $6.53 return for every dollar investment over the same period suggesting that those with the lowest initial wages yield higher returns. While, the National Association of Workforce Boards (n.d.) found that adults with disabilities tend to have lower participation rates in workforce programs and less favorable workforce outcomes than other adults (National Association of Workforce Boards, n.d.), they are often starting from a much lower wage position. For example, among WIA exiters in this study, the quarterly wages of individuals with disabilities prior to entering the program were only 33% of the wages of exiters without disabilities ($1,544 and $4,632 respectively)

WIA ROI by LWIA

Regional employment conditions and program implementation are likely to have an impact on workforce program outcomes and consequently ROI. Disaggregating ROIs by Local Workforce Area (LWIA) is quite telling. Five year ROI for Virginia LWIA ranged from -10.39 to 12.39. Eleven of fourteen[18] LWIA yielded positive ROI by year 5 for WIA —the highest being New River/Mt. Rogers at $12.29 per dollar invested. Three LWIA yielded negative returns. See Appendix H Table H1 for full details.

In summary, the WIA program shows a small but consistent return on government investment. Training significantly increases WIA ROIs, and particularly when the training is on-the-job. Further, earning a certificate or other credential also yielded higher returns than training without earning the credential. Disadvantaged demographic groups yield the highest ROIs despite continuing to lag behind other groups in actual performance. Across LWIA, ROI results varied tremendously with 11 out of 14 showing positive results.

<u>2. TAA Outcomes</u>

TAA Wages and Employment

On average wages for TAA program participants dropped tremendously between the quarter prior to participation and the second quarter after exiting (- 42%). The average yearly wages for TAA participants prior to entering the program were about $31,872. Like WIA, TAA participants in the matched dataset also showed a statistically significant earnings effect over the control group in the second quarter after participation (t (16540) = -12.02, p < 001). The comparison showed a gap between the average earnings of TAA participants and non-TAA participants of $5,049 per year. TAA exiters were far more likely to be employed after program participation (62%) than they were before program participation (22%). However, the odds of finding employment in second quarter after exit were 1.48 times greater for the control group participants than for TAA in the matched data. This finding is consistent with the majority of the literature which says that TAA participants struggle to find employment more compared to

[18] Although Virginia contains more than 14 LWIA not all records included a value for LWIA. I suspect that LWIA not represented in results are included in records missing this identifier.

other program participants due to the lengthy application process and longer period of program participation.

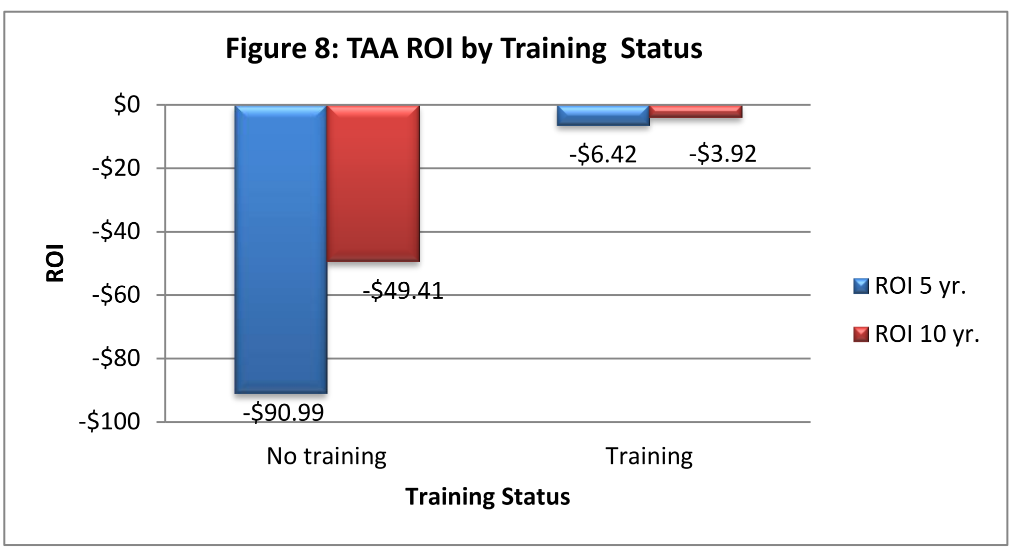
TAA Return on Investment

ROIs for TAA yielded mixed results. In comparison to the control group, TAA yielded positive returns. However, when comparing TAA participants to their own earnings trajectories, returns after program participation were consistently negative. Table 6 summarizes key ROI outcomes for each method. The difference reflects the substantial decline in wages for TAA workers over the study period.

Table 6: TAA ROI Results

	Propensity Matching Method (Compared to Control Group)		Before-and-After Method (Compared to Own Trajectory)	
	5 Year	Ten Year	5 Year	Ten Year
Average Cost	$2,055		$2,055	
Net Gain/Loss	$3,111	$7,547	-$15,991	-$27,904
Returns per Dollar Invested	$1.51	$3.67	-$34.86	-$63.94

Table 6 lists the average costs, returns, and ROIs for the TAA program participants in the matched dataset and before-and-after models projected over 5 years and 10 years. See Appendix G for full calculation details. Results show that TAA has relatively high average program costs ($2,055). Based on administrative records training cost reached as high as $16,000 for some participants. When returns are estimated based on matched cases and discounted at a rate of 3% yearly, the present value of gains TAA participants experience are $3,111 over 5 years and $7,574 over 10 years compared to the control group. These gains result in an ROI of151% or $1.51 over five years for every dollar invested and $3.67 over 10 years for every dollar invested compared to the control group.

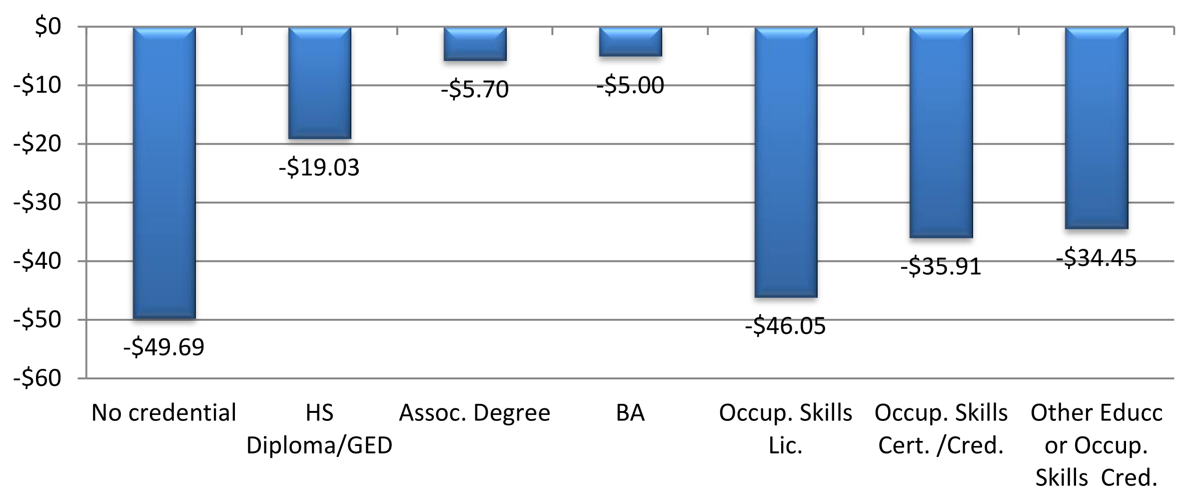


For the before-and-after model, TAA returns are negative and large. Over a five-year period each dollar invested in TAA yields loss of $34.86 and over ten years the loss is $63.94 per dollar invested.

As Figure 8 shows, while the ROI for TAA is negative whether a participant receives training or not, the negative impact is substantially reduced for participants who received training compared to those who did not. Further, ROI by training type was fairly close for 3 of the 4 types offered through TAA (-$13 for on-the-job-training, -$15 occupational skills training and -17 for remedial). Customized training however, yielded a -$297 loss over a five year period.

As with WIA, ROI for TAA also varied by the type of credential earned. Among TAA participants, earning a Bachelor's degree had the most favorable outcome (i.e. least detrimental return) (-$5.00 over 5 years). As Figure 9 shows, this was followed by the ROI for earning an Associate's degree and next a high school diploma. Occupational Skills Licenses and Occupational Skills certificate fell near the bottom of the list in 5th and 6th place with earning no credential yielding the most extreme negative return (-$49.69).

Figure 9: TAA ROI by Credential Earned

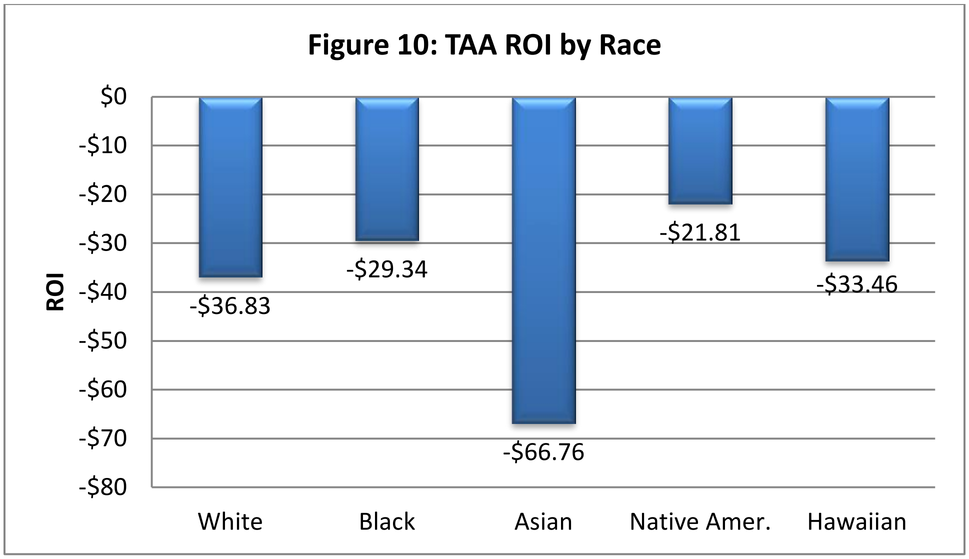


One possible explanation for the differences between programs performance by credential could be because of the nature of the participants in the TAA program. According to national data, 66% of requests for TAA come from manufacturing workers.[19] This may suggest that a greater number of TAA participants already hold the types of occupational licenses and certifications that yielded such tremendous results in the WIA population and hence earning another one may not yield the same returns. Whereas participants with previous manufacturing work experience who gain an Associate's degree or Bachelor's degree may be

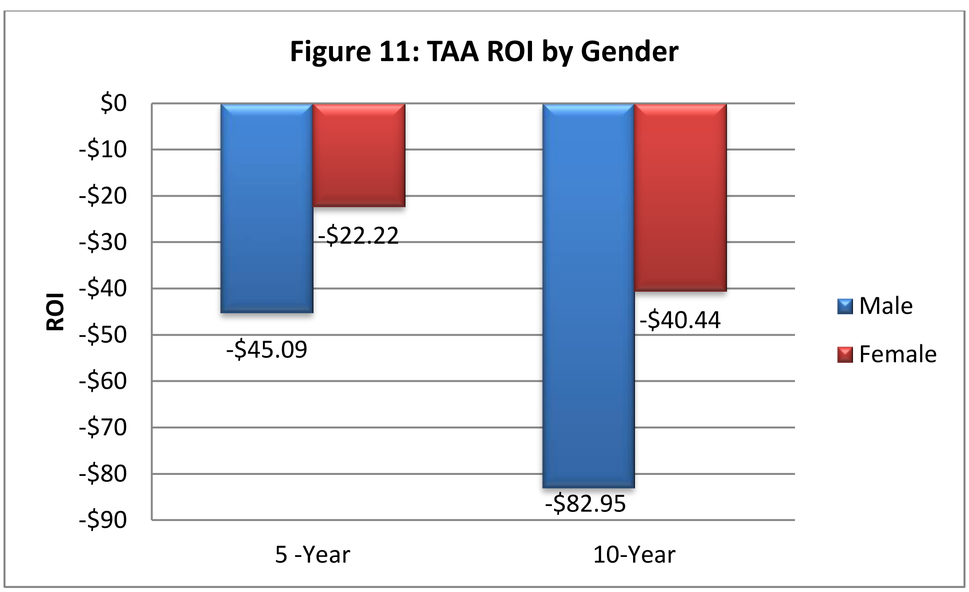
[19] Baker, 2011

able to move up to different types of positions leveraging previous work experience hence yielding higher returns.

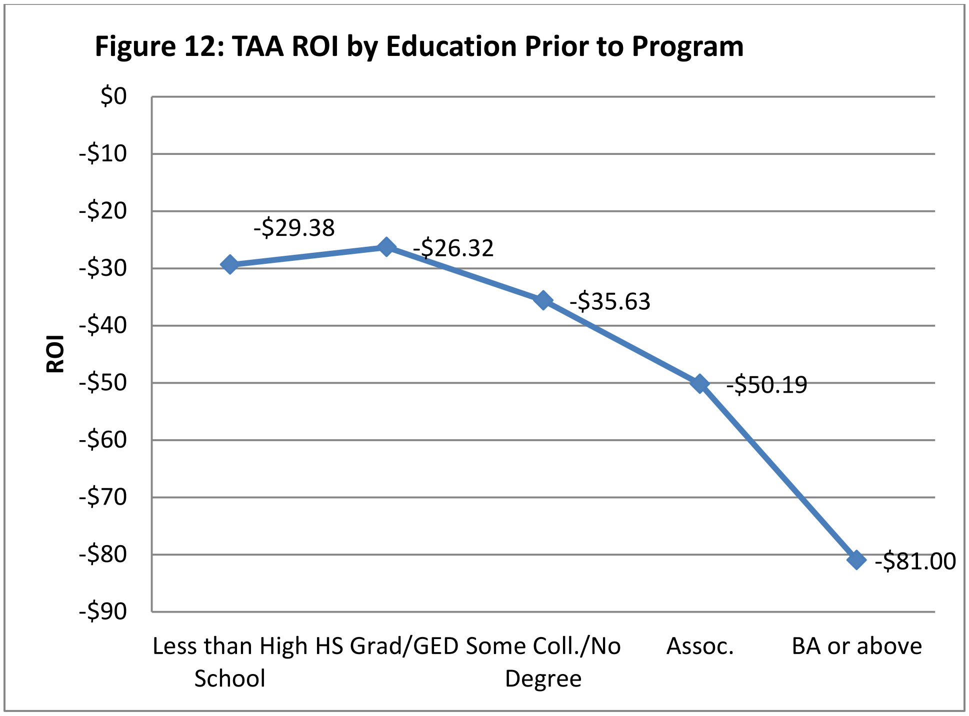
TAA ROIs by Demographics



Consistent with findings for the WIA program, racial groups who are traditionally disadvantaged in the labor market tended to have ROIs that are more favorable (albeit still negative). As Figure 10 shows, Whites and Asians yielded the least favorable ROIs (-$37 and -$67 respectively) while Blacks and Native Americans yielded ROIs that were slightly better (-$29 and -$22 respectively). The same pattern holds for gender where ROIs for women (more often vulnerable in the labor market) are more favorable than those for men (see Figure 11).



TAA also yielded diminishing returns the higher ones education prior to program participation (see Figure 12). Whereas the ROI for a Bachelor's degree or higher was -$81 over 5 years, the ROI for less than a high school diploma was only -$29.



TAA ROI by LWIA

Interestingly TAA shows negative return on investment for every LWIA across both five and ten year time periods except New River/Mt. Rogers. For this LWIA TAA shows a positive ROI for both periods. Further, the ROI for TAA in the New Rivers/Mt Rogers region is very similar to the WIA ROI in this region after year 5 ($12.29 and $11.55 respectively)

In summary TAA participants experienced a tremendous drop in earnings over the study period but still remained in better earnings position than control group members. TAA participants' odds of finding employment improved after the program but remained significantly lower than the control group. Compared to the control group, TAA program participation yielded a positive ROI on 151%. However, compared to their own earnings trajectories program participation yielded a net loss. TAA participants improved their ROIs with training but they remained negative. Like WIA, participation in TAA by demographic groups who are traditionally disadvantaged in the labor market yielded the highest returns.

3. Wagner Peyser Program Outcomes

Wages and Employment

Average wages for WP decreased over the study period by -$6,664 from pre-program average of $18,060 to $11,204 after the program— a drop of 38%. In the second quarter after exit the WP employment rate was much lower than either WIA or WP (48.6%).

WP Return-on-Investment

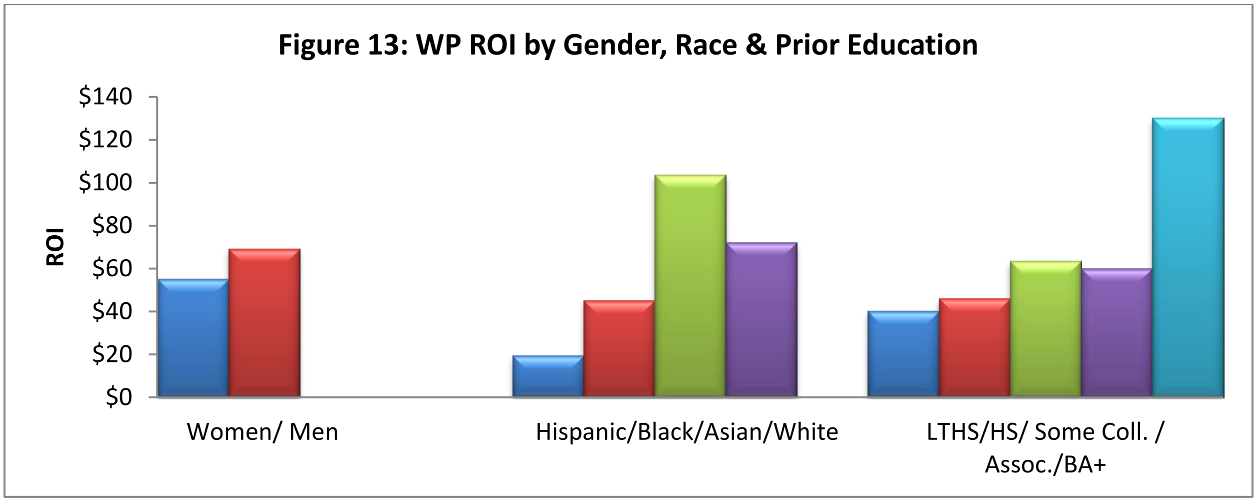
Table 7 displays the key information for the 5-year and 10-year ROIs for WP using the before-and-after method only. Since the WP program acted as the control for the other two, no propensity matching model was calculated for this program. The 5-year and 10-year ROIs are positive for WP. Returns for WP are highest among the three programs primarily because of the very small cost per participants. WP differs from the other two programs in that the services are limited and often offered in the format of self-serve or online. Further, the WP program does not provide training. These factors combine to create what appears to be a large ROI for WP. However WP results must be taken with a great deal of caution. The Virginia workforce system consists of 24 workforce programs in total. Many participants in other workforce programs are jointly enrolled in WP. This means that the results found here may not be fully attributable to the limited services provided by the WP program. Future studies will benefit greatly from being able to identify and control for the joint enrollment systematically.

Table 7: WP ROI Results

	Before-and-After	
	5 Year	Ten Year
Average Cost	$41	
Avg. Net Gain/Loss	$2,150	$3,647
Returns in Dollars	$62.75	$106.74

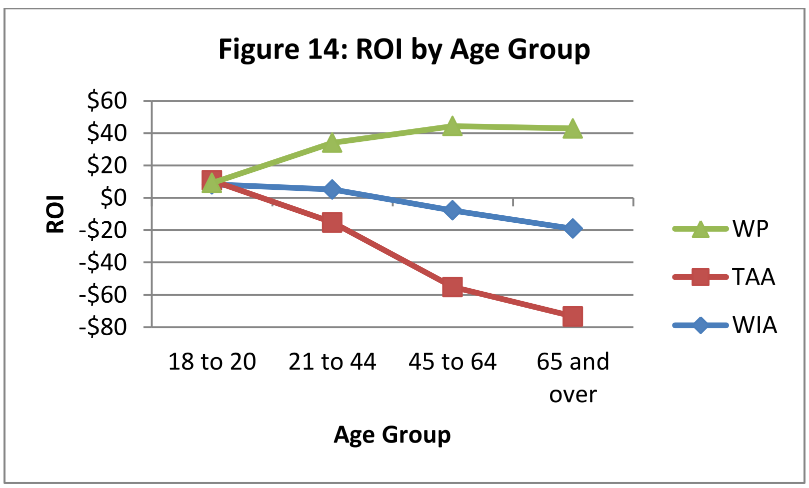
WP ROIs by Demographics

When we examine ROIs by demographic group, patterns for WP results are the reverse of WIA and TAA. ROIs for more advantaged populations are greater than for traditionally disadvantaged populations. Figure 13 shows that ROIs for men are greater than for women; ROIs for Whites and Asians are greater than for Blacks and Hispanics; and ROIs generally rise with prior education levels. These results combined with the previous patterns among WIA and TAA participants suggest that when no training and limited services are provided, disadvantaged populations do not fare as well in terms of ROI as their more employment- ready counterparts.



ROI by Age Group

Consistent with previously discussed demographics, Figure14 illustrates that WP ROI results for age groups are the opposite of the other two programs. While age has an increasingly negative effect on ROI for both the WIA and TAA programs the outcome is increasingly positive with age for WP participants.



In summary, using the before-and-after approach, the WP program shows a positive return on government investment. WP ROI results tended to mirror trends in society as a whole where job-ready participants yielded ROIs that are more favorable whereas WIA results are influenced by demographics and TAA results are influenced by the programs close connection with the manufacturing industry and its decline.

C. To What Extent Do Demographic, Achievement and Service-Related Factors Influence Wages and Employment?

Once we estimated ROI for each program the question remained: What role does each demographic, service and economic factors play in employment and earnings outcomes for workforce program participants? We used two types of regression techniques to address this question. First we use OLS regression to estimate effects on earnings. Next, we used binary logistic regression to estimate the effects of variables on the probability of finding employment two quarters after exit. While propensity matching tries to make the samples as much alike as possible, this technique does not control for multiple variables at once as with regression. Therefore regression results help to assess whether the disaggregated ROI results are supported when multiple variables are controlled.

1. Earnings Models

Model 1 in Table 8 considers the influence of demographic factors on earnings after program exit. The results are consistent with literature on earning influence. [20] Low levels of education (less than high school); disability and gender (female compared to male) all have negative impacts on earnings that are statistically significant across all programs. Higher levels of education all have increasingly large and positive impacts on earnings that are statistically significant across all programs. For example, participants in WIA with some college ($\beta = 598, p < .01$), certificates ($\beta = 1327.13, p < .01$), or bachelor's degree and more ($\beta = 2447.97, p < .01$) can be expected to make \$598, \$1,327 and \$2,447 more per quarter, respectively, than WIA participants with only high school diploma or GED. Results in TAA showed similar trends. The impact of educational gap was generally smaller in WP.

While black group membership has a negative and significant impact on earnings across all programs the other race variables show mixed patterns. For example, being Asian had a negative impact on earnings in WIA and TAA but not in WP, whereas being American Indian has a negative impact in WIA and WP but not TAA. Wages of Hispanic participants suffered a wage penalty of \$351 on average ($p < .05$) for WIA and \$71 for WP.

[20] See for example Moore et al., 2004; Leigh, 2000; Heckman, Heinrich & Smith, 2002

Table 8: OLS Model 1 by Program

	Model 1					
	WIA		WP		TAA	
Demographic Variables						
Age	11.92	**	10.57	**	-73.07	**
Basic Skills	-1251.50	**				
Disability	-1583.85	**	-1121.86	**	-1029.12	
Education						
Less than High School	-1350.21	**	-746.42	**	-1583.07	**
HS Grad/GED						
Some Coll./No Degree	714.70	**	738.71	**	735.25	**
Cert/Deg. LTBA	1700.91	**	472.67	**	1772.88	**
BA or above	2852.43	**	1868.52	**	3205.01	**
Ethnicity	-351.04	*	-71.29	**	179.87	
Gender	-1112.41	**	-622.85	**	-1183.82	**
Limited English Status	-570.19	*			108.87	
Race						
American Indian	-815.05	**	-405.17	**	681.97	
Asian	-113.13		44.67		-1396.56	**
Black	-815.26	**	-603.96	*	-497.34	**
Hawaiian			-155.12	*	-85.65	
White						
Veteran Status	35.55		333.15	**	-132.20	

*Note: *** for .01 and ** for .05*

Interestingly, when we control for demographics but add service and achievement variables (Model 2, Table 9) almost none of the achievement variables show a statistically significant influence on earnings with two exceptions. Although studies emphasize the importance of earned credentials, the kind of contribution that they make in terms of earnings and employment after exit is not clear. In our models, WIA participants who earned occupational skills licensure (β = 590.46, $p < .01$) and other credentials (β = 450.32, $p < .05$) such as diploma and certificate were to earn significantly more in wages than WIA participants who did not earn any credentials. In other words, WIA participants who earned occupational license can expect to earn $590 more than WIA participants without any credentials. Earned credentials, however, were not associated with earnings among TAA participants. These results are consistent with our ROI analysis which shows more favorable ROIs for occupational skills training and licenses among WIA participants.

The highest impact in terms of expected earnings was shown in employment prior to participation. WIA and TAA participants who were employed in the first quarter before participation could be expected to earn $5,717 and $7,473 more after exit, respectively, than WIA and TAA participants who were not employed at the time of registration. Participants in

WP can be expected to make $1,542 more than WP participants who were not employed prior to participation. Participants' previous earnings prior to participation were also positively associated with post-program earnings in WIA (β = .12, p< .01), TAA (β = .21, p < .01), and WP (β = .12, p < .01).

Table 9: OLS Model 2 by Program

	Model 2					
	WIA		**WP**		**TAA**	
Demographic Variables						
Age	10.503	**	-3.676	**	-15.253	
Basic Skills	-178.444					
Disability	-521.631	**	-791.371	**	-746.003	
Education						
Less than High School	-456.353	**	-478.621	**	-434.665	
HS Grad/GED						
Some Coll./No Degree	598.422	**	494.082	**	533.754	**
Cert/Deg. LTBA	1327.133	**	247.937	**	1094.853	**
BA or above	2447.976	**	939.202	**	2201.352	**
Hispanic	-122.047		8.692		541.114	
Gender	-1011.396	**	-429.285	**	-1062.807	**
Limited English Status	-666.292	**			-618.996	
Race						
American Indian	-245.129		-266.603	**	417.978	
Asian	-31.447		6.402		-759.943	
Black	-614.697	**	-342.816	**	-588.160	
Hawaiian			-156.673	*	16.775	
White						
Veteran Status	-85.752		168.645	**	-46.372	
Achievement Variables						
Earned high school diploma	212.756				178.806	
Earned associates degree	229.078				-275.629	
Earned bachelor	-312.071				-794.975	
Earned occupational license	590.467	**			-52.235	
Earned other occupational credential	68.763				-194.237	
Earned other credential	450.322	*			-5352.897	
Service Variables						
Supportive Services	-346.099	**			-837.997	**
Economic Variables						
Prior Employment	5717.220	**	1542.245	**	7473.709	**
Wages	0.122	**	.213	**	.119	**

*Note: *** for .01 and ** for .05*

2. Employment Models

Notable differences were detected in estimating the probability of employment after exit as shown in Table 10. For example, age was negatively associated with the probability of employment after program exit in WIA (*β = -.005, p*< .01), WP (*β = -.01, p* < .01) and TAA (*β = -.03, p* < .01). Whereas age was a positive predictor of earnings, age did not increase the probability of finding employment. This implies that while earnings are likely to increase for those who found employment as they get older, relatively older participants may be at a disadvantage in search of new employment.

Table 10: Logistic Model 1 by Program

	Model 1					
	WIA		**WP**		**TAA**	
Demographic Variables						
Age	-0.006	**	-.013	**	-.041	**
Basic Skills	-0.672	**				
Disability	-0.655	**	-.560	**	-.211	
Education						
Less than High School	-0.553	**	-.338	**	-.513	**
HS Grad/GED						
Some Coll./No Degree	0.007		.042	**	-.059	**
Cert/Deg. LTBA	0.063		.033	**	.072	
BA or above	-0.065		-.021	**	-.011	
Ethnicity	-0.117		-.088	**	-.311	
Gender	0.115	**	.081	**	.171	**
Limited English Status	0.177				.162	
Race						
American Indian	-0.380	**	-.123	**	.238	
Asian	-0.005		-.210	**	-.435	**
Black	-0.092	**	-.063	**	.112	**
Hawaiian	0.019		-.029		-.077	
White						
Veteran Status			-.005		-.078	**

*Note: *** for .01 and ** for .05*

Similar to the results found in the earnings models, disability was also negatively associated with odds of finding employment for WIA participants (*β = -.65, p* < .01) and WP participants (*β = -.56, p < .01)* when controlling for demographic variables. In other words, the odds of finding employment decreased by 56% for WP participants and 65% for WIA participants with disability compared to participants without a disability.

Educational levels were more complicated to decipher in prediction the odds of employment than in the earnings model. For example, as shown in Model 1, some college (*β = .04, p < .01),* associate's degree (*β = .03, p < .01)* or bachelor's degrees (β = -.02, p < .01) were significant predictors of employment among WP participants only. In other words, WP participants who had some college experience or had certificates had a statistically higher chance of finding employment than those only with high school diploma or GED. The difference, however, was slim. For example, the odds of WP participants getting employed increased only by 4% and 3% for those with Some College and Associates' degrees, respectively, compared to those with high school diploma only. However, the odds of finding employment decreased by 3% for WP participants with bachelor's degrees compared to WP participants with high school diploma. The results became more interesting when employment status and wages prior to participation were controlled as those with high school diploma tended to better than all other educational levels. For example, the odds of finding employment decreased by 25% and 18% for those without high school diploma and those with bachelor's degree, respectively, compared to those with high school diploma. Education in general was not a significant predictor of employment in both WIA and TAA. This suggests that a significant factor in whether one finds employment after the WP program is largely influences by prior labor market experience rather than program factors.

Ethnicity (Hispanics) was not significantly related to employment when achievement, service and economic variables were controlled. In terms of gender, females were more likely to find employment than the males in WIA ($\beta = .08, p < .01$) and in WP ($\beta = .09, p < .01$). This implies that although females are put at major disadvantage in terms of earnings compared to males as shown in the multiple linear models, females were generally more successful in finding employment. The odds of finding employment increased for female participants in WIA by 8 percent compared to male participants in WIA and by 10.3% for female participants in WP compared to male participants in WP.

In terms of race, non-whites were generally shown to be at a disadvantage in finding jobs compared to whites. WIA participants who were American Indian ($\beta = -.38, p < .01$) and black (β = -.09, p < .01) were negatively associated finding employment compared to whites, while WP participants who were American Indian ($\beta = -.10, p < .01$), Asian ($\beta = -.20, p < .01$), and black (β = -.01, p < .05) were all negatively associated with employment compared to white WP participants. The odds of finding employment decreased by 9 percent for black participants compared to white participants in WIA.

Being a veteran was negatively associated with employment for participants in WP ($\beta = -.04, p < .01$) and TAA ($\beta = -.36, p < .01$). To put them in context, the odds of finding employment decreased by 5 percent for WP participants with veteran status and by 31 percent for TAA participants with veteran status, compared to non-veterans in WP and TAA, respectively.

Credentials tended to play a bigger role in WIA than in TAA. In WIA, earned high school diploma associates' degree, occupational license, and occupational skills certificate, compared to those with no earned credentials, increased by 25%, 35%, 78% and 48%, respectively. Earned credentials were not as effective in TAA. The only earned credential that was positively associated with employment was associate's degree wherein the odds of employment increased by 89% for TAA participants who earned associates' degrees compared to TAA participants who did not earn any credentials. Another important indicator of employment was employment status prior to participation. WP participants who were employed in the 1st quarter prior to registration were 2.34 times more likely to be successful in finding employment after exit than WP participants who were unemployed at the same period.

IV. Discussion and Conclusions

This analysis estimates Virginia's return-on-investment for WIA, WP and TAA workforce programs using both a propensity matching and before-and-after approaches. Several conclusions drawn from this analysis stand out as important for policy makers. WIA and WP show positive average ROIs across both methods of calculation while TAA results are mixed. ROI results for both WIA and TAA are vastly improved with training compared to not training. Further, earning a credential as a result of training also improves ROIs for both TAA and WIA. Finally, each program has a unique demographic composition which has a significant effect on program outcomes. Participation by demographic groups that have traditionally been disadvantaged in the labor market yielded higher returns than non-disadvantaged groups. However, despite higher ROIs, regression results show that earnings and employment outcomes for participants from certain racial groups, lower education levels, women and disabled people are still less favorable than their counterparts.

The three major factors which help to explain differences in basic ROIs between WIA, WP, and TAA are wage differentials between program participants, program costs, and demographic characteristics of each participant pool. First, benefits for the before-and-after models are calculated based on wage differences between the quarter prior to program participation and the second quarter after. As mentioned earlier, participants in the various programs are starting from very different wage positions. Given the economic realities that make the TAA program necessary (trade related declines), it is important to consider the TAA results (especially the before and after models) in context. While the results were largely negative, this figure is more likely due to shifts in the types of jobs available and pay rates in trade dominant industries than to the quality of program implementation. TAA participants who have come disproportionately from well paying manufacturing jobs started out with wages that were double those of the other program participants[21]. However, TAA participants experienced a more systematic decline because manufacturing was hit hardest by the recent recession. [22] According to the Bureau of Labor statistics, manufacturing lost more than 15% of its workforce between 2007 and 2009.[23] On average TAA participants' wages dropped by nearly half, which negatively impacted ROIs in the form of loss revenues from taxes. Other wage losses and lack of returns compared to control group are consistent with previous studies of TAA outcomes. WP was less affected by the wage loss because their costs were so low to begin with that any gains in benefits savings or tax revenue could easily offset the wage loss.

Another important factor influencing ROI outcomes has to do with the populations served in each program. A portion of the returns calculation is based on potential savings from TANF, SSI and SNAP. While the WIA program has historically partnered with social service

[21] It should be noted that the dislocated worker population is very similar to the TAA population. However since WIA results combine the general adult population with the dislocated workers, the outcomes average out and are positive. Also WIA dislocated workers tend to be concentrated in LWIA impacted by a major work event such as a plant closing. The patterns of closures may explain some of negative WIA outcomes by LWIA.

[22] See D'Amico and Schochet e 2012

[23] http://www.bls.gov/opub/mlr/2011/04/art5full.p

agencies seeking to train clients and help them find work, the TAA program serves individuals who have (recently) lost their jobs or are still employed and are less likely to be utilizing public assistance programs. The potential savings from WIA participants who were previously utilizing public assistance programs but gain employment after the program helps to boost the ROI for the WIA program significantly but not for TAA. This is reflected both in the overall ROIs as well as those disaggregated by race and gender. While TANF, SSI and SNAP data was not available for WP, a significant number of the participants (40%) were UI claimants and therefore savings captured when they entered work helped to boost the WP ROI.

The third, and perhaps most influential, issue is that costs are very different across the programs. While the overall budget for WIA is more than twice that of TAA, the WIA program serves about five times more clients per year (20,159 and 4,236 respectively in 2012). In addition, the cost for training is a particularly influential factor. WP, on the other hand, has the highest budget of the three programs but because it has no training the costs per person are extremely low. The average cost for WIA training is about $435, for TAA the average cost is almost triple at $1,725[24]. To put this into perspective, the average WP cost per participant is less than 1% of the cost for a trained TAA participant and about 10% the cost of one who does not receive training. As ROI is based on wage difference while taking cost into consideration, the higher costs have a large negative impact for TAA ROIs and the reverse is true for WP. General differences in ROI outcomes between TAA and WIA found here are consistent with those reported in Hollenbeck (2009).

Despite the differences in populations served and cost structure, results here suggest that under the right conditions workforce programs can yield positive returns to government investment. Further, some studies suggest that positive returns to workforce investment could potentially create a multiplier effect resulting in an even greater impact on the economy.[25] Even when returns are negative, certain practices can at least improve the ROI. While earnings increase alone are not always enough to compensate for program costs, in some programs savings from public assistance benefits and future tax payments outweigh program costs by year 5. To make the most of Virginia's investment in public workforce development programs, the next section outlines policy recommendations based on our findings.

[24] WIA training costs participant were estimated based on total training costs taken from administrative data and number of participants trained estimated from exit files. TAA training costs, on the other hand, were provided for each participant in the administrative data. Had estimates been derived for TAA as they were for WIA, the differences would have been even greater

[25] EMSI, 2011

V. Policy Recommendations

Public investment in Virginia's workforce development programs is necessary to create a strong workforce, connect job seekers to work opportunities, and provide businesses with the talent necessary to keep them competitive. Under certain circumstances these programs have the capacity to yield future returns on the taxpayers' investment. While each program has a different cost structure and serves a particular demographic, which both play a role in the ROI outcome, under the right circumstances, the likelihood of positive returns can be increased. When economic realities make a positive dollar return not realistic, investment can at least lessen the likelihood of unemployment and loss of tax revenue. ROI analysis can help direct resources to capitalize on proven practices and address inherent challenges in the system.

While our results are exploratory, several key findings deserve consideration by policy makers to move closer toward achieving the goals of the Virginia workforce system and further develop the ROI as a useful policy tool for evaluating workforce development programs. The following is a list of policy recommendations and implications for consideration drawn from our findings.

Capitalize on what is already working.

- **Strategically align workforce training opportunities with credentials and credential pathways.** Results in this study show higher return on investment to certain paths within workforce programs. Not only does training yield more favorable ROIs than not training, but particular types of training lead to the highest ROIs and those who earned a credential as a result of their workforce training also yielded higher ROIs than training without earning a credential. While not all job seekers are ready to pursue a credential at the time of program participation, organizing training modules into credential pathways will create the possibility for job seekers to continue along that pathway at some time in the future and possibly build on the investment started in the workforce program.

- **Ensure that program performance information is both available and understandable to participants by creating easily accessible and user-friendly mechanisms such as social media pages.** Program enrollees may not always have access to the right information on specific program outcomes that would help them make informed decisions about which program paths and options have yielded the most favorable results for past participants. Creating mechanisms for accessing and sharing information on workforce program experiences will help them make well-informed decisions based on past program success.

- **Outreach to traditionally disadvantaged groups.** This research has shown that in both WIA and TAA disadvantaged groups yield the highest return on investment. Their higher ROIs are largely tied to savings from public assistance. Outreach to these groups will further increase the government's return on investment by helping more individuals become employed and self-sufficient. Further, this research has shown that high ROIs may be misleading as disadvantaged groups still have inferior labor market outcomes. Labor market research has shown that one factor contributing to poor outcomes from disadvantaged populations is weak social networks and inadequate labor market information which is often obtained through social connections. Outreach to disadvantaged groups will also ensure that they are well informed of not only the programs available but also the paths within those programs that have led to the greatest returns. This would also include information on an additional support (either within the program or the broader community) that may be necessary for these populations to fully engage in specific program service offerings.

- **Capitalizing on what's working will also entail understanding best practices and finding out why certain types of training programs are yielding poor results.** Understanding whether the issue is a lack of demand for the skills being imparted or poor program implementation. For example, ROIs for entrepreneurship training were negative in the WIA program. Previous research has indicated that most One-Stop staff has limited knowledge about entrepreneurship themselves and is therefore not equipped to determine who this type of training is appropriate for.[26] Collecting data on program implementation would highlight the processes underlying both best practices and underperforming program elements.

Integrate ROI into the broader Virginia workforce performance measurement system.

- **ROI results should be coupled with other types of performance metrics especially ones that place the ROI outcomes in context.** While ROI analysis provides a useful framework for assessing costs and benefits of program investment, this tool should be integrated into a broader system of performance management to contextualize results**.** As this analysis has demonstrated, ROI can vary tremendously based on population being served, cost structure and resources available for each program, economic conditions for a given LWIA or industry trends. ROI results should be used alongside other metrics to fully evaluate program effectiveness from multiple perspectives.

- **Policy makers should strive to create innovative performance metrics including enhanced ROI models to account for economic and demographic context of the programs being assessed**. As with most research on the labor market outcomes, our analysis shows that context matters. Participants who are disadvantaged because they are disabled, have basic skills deficiency and limited English status, minority, and have low levels of education generally face challenges in the labor market regardless of what programs they participate in. ROIs can be misleading for these groups because although they show higher return on investment in WIA and TAA than other groups, regression analysis shows that their actual labor market outcomes (wages and likelihood of

[26] Harper-Anderson & Gooden (2013)

employment) are inferior. Evaluation for all workforce programs should reflect this reality by including innovative performance metrics which value the added challenge of providing services to those who need them most. While this includes demographically disadvantaged populations, it also includes TAA participants whose industry has disadvantaged them in the labor market. While their ROIs may be negative even after program participation, interventions such as training in certain fields can improve their employment and earnings prospects. Measuring and valuing benefits related to challenging contexts removes the disincentive for WIBs avoid populations that need their services most. For this policy to be effective the new measures required for all workforce programs set in 2007 by the Office of Management and Budget (OMB) must move beyond measuring "efficiency" factors only and address the issues of social equity, or lack thereof, and to quantify the value of service to all participants regardless of employment history, demographics and disability.

Improve data collection and data quality for more robust ROI outcomes.

- **We recommend that steps be taken to minimize the number of assumptions underlying ROI (and other performance measures) by utilizing more data points (including both quantitative and qualitative).** We recognize that the chief concern of policy makers regarding employment and training programs is to know how effective the WIA, TAA and WP programs are in helping Virginia residents become more employable and productive. While some of our findings are limited to the available data across the three programs, the current study represents a critical first step in assessing the varying conditions of Virginia's workforce programs and in our efforts toward the larger evaluation goal. However, the current analysis is based on a number of assumptions which were necessary due to missing or limited data.

  Once the VLDS system is fully functional, queries that periodically link data between workforce programs, social service agencies, tax records, and VCCS would greatly improve both the quality of analysis and the depth of analysis possible. For example, use of administrative data for actual amounts of public assistance received and tax paid in place of the averages used here would improve the accuracy of the models.

- **We recommend that VLDS supplement quantitative data on returns on investment with qualitative process data.** Information on participants' personal experiences both in terms of their in-program experience and benefit accrued could help fill in gaps left by administrative records. While we recognize that survey data are not a panacea in addressing the limits of administrative data, because many of the decisions that participants make are behavioral, these additional data will help both policy makers and researchers understand the relationships that cannot be measured by the current metrics which primarily focus only on improving efficiency.

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Appendix A: Data Processing

Data Processing

Each program data set (TAA, WIA, and WP) was originally provided by the Virginia Community College Systems who facilitated the role of central data warehouse with difference data sources (e.g., Virginia Department of Education). Immediately upon receiving the original pull of the data by each corresponding agency, we identified unique cases in each program area using several matches in order to ensure participants are not counted twice in each program by allowing dual enrollment.

The first step in our data processing involved identifying unique cases through randomly given participant identification number. For the purpose of simplicity, our next line of query included only those in each program who are 18 and older with an exit date confirming that they have completed their participation. Finally, using the Wage Record Interchange System (WRIS) indicator, we identified and removed individuals who have participated in workforce investment programs in Virginia but subsequently secured employment in another state. This was a critical part of our data processing as it helps us gauge a more robust picture of the effectiveness of the workforce programs in the state of Virginia. All in all, we were able to identify a total of 9,096 cases in TAA, 1,319,326 cases in WP and 27,626 cases in WIA program.

It is important to note the fact that the figures above are “baseline” estimates which could vary depending on the types of analyses and further analyses involving subcategories. For example, in our linear models regressing earnings in the second quarter after exit on demographic and service factors, we further removed wage records that were deemed to be too extreme and therefore invalid. For example, the value of $999,999.99 was the default value in the data for those who may still be participating in their respective program and was therefore removed for that particular analysis. Unlike the high-end earnings where a cut-off was $999,999.99, we did not set floor values to delete low-end earnings. Although distributions of quarterly earnings were examined exhaustively, we were cautious not to determine a maximum cut-off line to preserve the integrity of the original data as much as possible.

Appendix B: Local Workforce Boards

Table B1: Local Workforce Areas

LWIA #	WIB Name	Service Area
1	Southwestern Virginia	Counties: Buchanan, Dickenson, Lee, Russell, Scott, Tazewell, Wise Cities: Norton
2	New River/Mt. Rogers	Counties: Bland, Bristol, Carroll, Floyd, Giles, Grayson, Montgomery, Pulaski, Smyth, Washington, Wythe Cities: Bristol, Galax, Radford
3	Western Virginia	Counties: Alleghany, Botetourt, Craig, Franklin, Roanoke Cities: Clifton Forge, Covington, Roanoke, Salem
4	Shenandoah Valley	Counties: Augusta, Bath, Clarke, Frederick, Highland, Page, Rockbridge, Rockingham, Shenandoah, Warren Cities: Buena Vista, Harrisonburg, Lexington, Staunton, Waynesboro, Winchester
6	Piedmont Workforce Network	Counties: Albemarle, Culpeper, Fauquier, Fluvanna, Greene, Louisa, Madison, Nelson, Orange, Rappahannock Cities: Charlottesville
7	Region 2000/Central VA	Counties: Amherst, Appomattox, Bedford, Campbell Cities: Bedford, Lynchburg
8	South Central	Counties: Amelia, Brunswick, Buckingham, Charlotte, Cumberland, Halifax, Lunenburg, Mecklenburg, Nottoway, Prince Edward
9	Capital Region Workforce Partnership	Counties: Charles City, Chesterfield, Goochland, Hanover, Henrico, New Kent, Powhatan Cities: Richmond
11	Northern Virginia	Counties: Fairfax, Loudoun, Prince William Cities: Fairfax, Falls Church, Manassas and Manassas Park
12	Alexandria/Arlington	Counties: Arlington Cities: Alexandria
13	Bay Consortium	Counties: Accomack, Caroline, Essex, King and Queen, King George, King William, Lancaster, Mathews, Middlesex, Northampton, Northumberland, Richmond, Spotsylvania, Stafford, Westmoreland Cities: Fredericksburg

14	Greater Peninsula	Counties: Gloucester, James City, York Cities: Hampton, Newport News, Poquoson, Williamsburg
15	Crater Area	Counties: Dinwiddie, Greensville, Prince George, Surry, Sussex Cities: Colonial Heights, Emporia, Hopewell, Petersburg
16	Hampton Roads	Counties: Isle of Wight, Southampton Cities: Chesapeake, Franklin, Norfolk, Portsmouth, Suffolk, and Virginia Beach
17	West Piedmont	Counties: Henry, Patrick, Pittsylvania Cities: Danville, Martinsville, South Boston

Source: Virginia Labor Market Information (LMI) at
https://data.virginialmi.com/gsipub/index.asp?docid=388#WIA

[1]In 2008 Area 9 merged with Area 10 to form the new area 10, and Area 4 merged with Area 5 to form the new Area 4. This explains why Areas 5 and 10 no longer exist.

Table B1: Local Workforce Boards

Local Workforce Investment Board (WIB)	Service Area
Alexandria	Alexandria, Arlington
Bay Consortium	Accomack, Caroline, Essex, Fredericksburg, King George, King William, King and Queen, Lancaster, Mathews, Middlesex, Northampton, Northumberland, Richmond, Spotsylvania, Stafford, Westmoreland
Capital Region Workforce Partners	Charles City, Chesterfield, Colonial Heights, Goochland, Hanover, Henrico, New Kent, Powhatan
Crater Area	Dinwiddie, Emporia, Greensville, Hopewell, Petersburg, Prince George, Surry, Sussex
Greater Peninsula	Gloucester, Hampton, James City, Newport News, Poquoson City, Williamsburg, York
Hampton Roads (Opportunity Inc.)	Chesapeake, Franklin, Isle of Wight Norfolk, Portsmouth, Southampton, Suffolk and Virginia Beach
New River Mt. Rogers	Bland, Bristol, Carroll, Floyd, Galax, Giles, Grayson, Montgomery, Pulaski, Radford, Smyth, Washington, Wythe
Northern Virginia	Fairfax, Falls Church, Loudoun, Manassas City, Prince William
Piedmont Workforce Network	Albemarle, Charlottesville, Culpeper, Fauquier, Fluvanna, Greene, Louisa, Madison, Nelson, Orange, Rappahannock
Region 2000 Central VA	Amherst, Appomattox, Bedford, Campbell, Lynchburg
Shenandoah Valley	Augusta, Bath, Buena Vista, Clarke, Frederick, Harrisonburg, Highland, Lexington, Page, Rockbridge, Rockingham, Shenandoah, Staunton, Warren, Waynesboro, Winchester
South Central	Amelia, Brunswick, Buckingham, Charlotte, Cumberland, Halifax, Lunenburg, Mecklenburg, Nottoway, Prince Edward
Southwestern Virginia	Buchanan, Dickenson, Lee, Norton, Russell, Scott, Tazewell, Wise
West Piedmont	Danville, Henry, Patrick, Pittsylvania
Western Virginia	Alleghany, Botetourt, Clifton Forge, Craig, Franklin, Roanoke, Roanoke City

Appendix C: Measures of Variables

Table C1: Measures of Variables

Dependent Variable	**Description of Coding**
Earnings	Earnings in the second quarter after exit regardless of employment status. (Those unemployed in the quarter is recoded with $0)
Employment	= 1 if participant is employed in the second quarter after exit; 0 if not employed in the same quarter
Explanatory Variables	
Age	Linear term Dummies for the categories: 18 =< age < 21 21 =< age < 45 45 =< age < 65 65 =< age
Basic Skills (Basic Literacy Skills Deficiency)	= 1 if participant has basic literacy skills deficiency, 0 otherwise
Disability	= 1 if participant qualifies to have disability status, 0 otherwise
Less Than High School	Dummy for education categories: coded 1 if participant has not received high school diploma or GED, 0 otherwise
High School Grad/GED	Omitted (reference) category
Some College/No Degree	Dummy for education categories: coded 1 if participant has attended college but has no degree, 0 otherwise
Associates' Degree	Dummy for education categories: coded 1 if participant has associate's degree, 0 otherwise
Bachelor's Degree or Above	Dummy for education categories: coded 1 if participant has bachelor's degree, 0 otherwise
Ethnicity (Hispanic)	Hispanic coded regardless of race if available (missing coded as not Hispanic)
Gender	= 1 if participant is female, 0 otherwise
Limited English	= 1 if participant has limited English language proficiency, 0 otherwise
American Indian	Dummy for race categories: coded 1 if participant is American Indian, 0 otherwise
Asian	Dummy for race categories: coded 1 if participant is Asian, 0 otherwise
Black	Dummy for race categories: coded 1 if participant is black, 0 otherwise
Hawaiian	Dummy for race categories: coded 1 if participant is Hawaiian, 0 otherwise
White	Omitted (reference) category
Earned High School Diploma	Dummy for earned credentials categories: coded 1 if

	participant received high school diploma from the participation, 0 otherwise
Earned Associates Degree	Dummy for earned credentials categories: coded 1 if participant received associate's degree from the participation, 0 otherwise
Earned Bachelor's Degree	Dummy for earned credentials categories: coded 1 if participant received bachelor's degree from the participation, 0 otherwise
Earned Occupational License	Dummy for earned credentials categories: coded 1 if participant received occupational skills licensure from the participation, 0 otherwise
Earned Other Occupational Credential	Dummy for earned credentials categories: coded 1 if participant received occupational skills certificate from the participation, 0 otherwise
Earned Other Credential	Dummy for earned credentials categories: coded 1 if participant received other recognized diploma, degree, or certificate, 0 otherwise
Training	= 1 if participant received training, 0 otherwise
Supportive Services	= 1 if participant received supportive services, which include, but are not limited to, assistance with transportation, child care, dependent care, and housing that are necessary to enable the individual to participate in activities authorized under WIA title IB, 0 otherwise.
Previous Employment	= 1 if participant had employment for the 2nd quarter prior to registration, 0 otherwise
Previous Wages	Continuous; earnings for the 2nd quarter prior to registration

Basic skills deficiency was available only for WIA participants. Age was captured as a linear term in years, as well as up to three dummy variables for ranges of participant age. Also included is the status of disability. Participants are coded 1 for disability as defined in Section 3(2)(a) of the Americans with Disabilities Act of 1990 (42 U.S.C. 12102) which describes it as a physical or mental impairment that substantially limits one or more of the person's major life activities. Participants are coded 0 for otherwise, unless participant did not disclose the information in which case it will be treated as missing.

Race was classified into five categories using white as the reference category. Efforts focused on assuring that the coding was consistent for all three programs in WIA, TAA and WP. Ethnicity was included as an alternative category outside of race so as to distinguish between Hispanics (coded 1) and non-Hispanics (coded 0).

Education is captured as five dummy variables for ranges of schooling. The efforts focused on ranking the level of these categories (e.g., certificates being considered higher than some college/no degree). Limited English Language Proficiency was available as a dummy variable only in WIA and TAA. If the participant has limited ability not only in speaking but also in reading, writing or understanding the English language and whose native language is a language other than English, or who lives in a family or community environment where a language other than English is the dominant language, the participant is coded 1.

Participants were coded 1 if he or she is a person who served in the active U.S. military, naval, or air service for a period of less than or equal to 180 days, and who was discharged or released from such service under conditions other than dishonorable. If the participant is (a) the spouse of any person who died on active duty or of a service-connected disability, (b) the spouse of any member of the Armed Forces serving on active duty who at the time of application for assistance under this part or (c) the spouse of any person who has a total disability permanent in nature resulting from a service-connected disability, for the purpose of clarity and analyses, he or she is coded as 0 (not a veteran). Earned credentials were classified as seven dummy variables with no earned credential as the reference category.

Appendix D: Propensity Score Matching

Propensity Score Matching

While the regression models estimated in the previous section present insight to the earning differentials before and after participation in each of the employment and training program and offer a tool to strengthen causal conclusions, yet decisions to participate in the workforce development program are distinct in that it cannot be randomly assigned and therefore accurate assessments of the causal effects of program participation on outcome (e.g., employment, earnings) are difficult. As a result, key questions remain as to whether different individual propensities toward decision to participate in a workforce program shape the outcomes of individual earnings. While the regression models estimate the benefits that participants receive, such as greater likelihoods of employment and higher wages using a series of instrumental variables in a single program, the current approach adjusts for the effects of program participation by comparing the propensity to participate between those who participated and those who did not participate in the same program.

Propensity score analysis allow investigators to estimate causal treatment effects using observational or nonrandomized data.[27] We used a sample of state workforce development program participants in TAA and WIA to measure their earnings and probability of employment upon two quarters after exiting the program. The exposure of interest was whether one participated in either workforce program prior to their exit, using the Wagner-Peyser as the control group. For instance, individuals who walked into any employment service agencies and left without further signing up for a particular training is so called the "comparison" group or "control" group. The outcomes measured were wage earnings and employment status in two quarters after exiting each program. In observational studies such as this, treatment selection (decision to whether participate or not) is often influenced by subject characteristics. As a result, baseline characteristics of treated subjects often differ systematically from those of untreated subjects. Therefore, one must account for systematic differences in baseline characteristics between treated and untreated subjects when estimating the effect of treatment on outcomes.

Mainly, we used the propensity score analysis to help address the following concern: While proponents of state workforce development programs argue that the benefits from participating in these programs outweigh the costs of the programs, whether the return on investment outcome (e.g., employment status, wage deferential) is strictly a result of the participation is debatable. Would individuals who did not participate in the workforce programs also likely achieve similar results? While the support for these programs to continue has increased, its causal status has been contested[31] and extant research is equivocal. In traditional regression models, identifying the true "treatment effect," and hence the effect of participation, is difficult to measure. The next several paragraphs explain in detail what propensity matching does and the procedures we used in carrying out successful propensity score matching.

[27] Austin, 2011
[31] Austin, 2009

Wagner-Peyser data were merged with Trade-Adjustment data and Workforce Investment Act data separately to create an indicator variable as the binary dependent variable that took on the value of 1 if the observation was from a workforce program and 0 if it was from Wagner-Peyser data only. The explanatory variables included individual characteristics such as age, ethnicity, race, highest education received at the time of enrollment, employment status at the time of enrollment, wages earned in 2^{nd} quarter prior to participation, seasonal farm worker status, disability status, and veteran status. These control variables were used in a logistic regression as independent variables to estimate the propensity score for all, which is then used to match each treatment group with its corresponding comparison group. One weakness in our approach is that in order to ensure that treatment group participants are matched as closely as possible with the corresponding comparison group participants, a large number of confounding variables that far exceed those control variables is needed, which was not available in our data.

The logic behind propensity score methods is that balance on observed covariates is achieved through careful matching on a single score – the estimated propensity of selecting the treatment, or simply the propensity score. The propensity score is defined as the probability of receiving treatment based on measured covariates:

$$e(x) = P(Z=1|X)$$

Where e(x) is the abbreviation for propensity score, P a probability, Z=1 a treatment indicator with values 0 for control and 1 for treatment, the "|" symbol stands for conditional on, and X is a set of observed covariates. In other words, the propensity score expresses how likely a person is to select the treatment condition (participation) given observed covariates, e.g. person characteristics. This matching process creates balances between treated and untreated participants on the propensity score and more importantly is also expected to create balance on the covariates that were used to estimate the propensity score. This balance property is a key aspect of propensity score methods because a balanced pre-test covariate cannot logically be a confounder. The balance that a randomized experiment is expected to create by design is here established through statistical matching.[32]

For the purpose of our analyses, we seek to estimate an individual's propensity to participate in the workforce development programs and then assess the effect of program participation on earnings and employability for individuals with equal likelihoods of participation. As Smith (1997) suggests, this approach is well suited for estimating the counterfactual – ***what would have happened to those who participated has they not participated?***

[32] Austin, 2009

Appendix E: Baseline Characteristics of the TAA Study Samples Before and After Matching

Table E1: Baseline Characteristics of the TAA Study Sample Before Matching

Variable	TAA Participants (Treatment Group, N = 8,644)	Non-TAA Participants (Control Group, N = 816,449)	Overall Sample (N = 825,093)	Standardized Difference of the Mean	p Value
Wages Prior to Participation	8020.14 ± 9083.30	4970.86 ± 7588.58	5002.8 ± 7612	0.336	< .001
Disability	91 (1.1%)	29,310 (3.6%)	29,401 (3.6%)	0.25	< .001
Veteran	762 (8.8%)	69,412 (8.5%)	70,714 (8.5%)	0.011	0.298
Employment Status before Participation	2,184 (25.3%)	125,525 (15.4%)	127,709 (15.5%)	0.224	< .001
Less than High School Diploma	1,094 (12.7%)	99,319 (12.2%)	100,413 (12.2%)	0.016	0.164
Some College	920 (10.6%)	68,803 (8.4%)	69,723 (8.5%)	0.074	< .001
Associate Degree	1,291 (14.9%)	155,977 (19.1%)	157,268 (19.1%)	0.114	< .001
Bachelor's Degree	729 (8.4%)	140,834 (17.2%)	141,563 (17.2%)	0.323	< .001
American Indian	52 (.6%)	12,537 (1.5%)	(12,589 (1.5%)	0.124	< .001
Asian	216 (2.5%)	19,701 (2.4%)	19,917 (2.4%)	0.003	0.605
Black	2,368 (27.4%)	282,808 (34.6%)	285,176 (34.6%)	0.162	< .001
Hawaiian	9 (.1%)	3,268 (.4%)	3,277 (.4%)	0.101	< .001
Female	3,506 (40.6%)	386,192 (47.3%)	389,698 (47.2%)	0.138	< .001
Seasonal Farm Worker	1 (.9%)	5,260 (.6%)	5,261 (.6%)	0.573	< .001
Claimant Referred by WPRS	1,227 (14.2%)	38,889 (4.8%)	40,116 (4.9%)	0.273	< .001

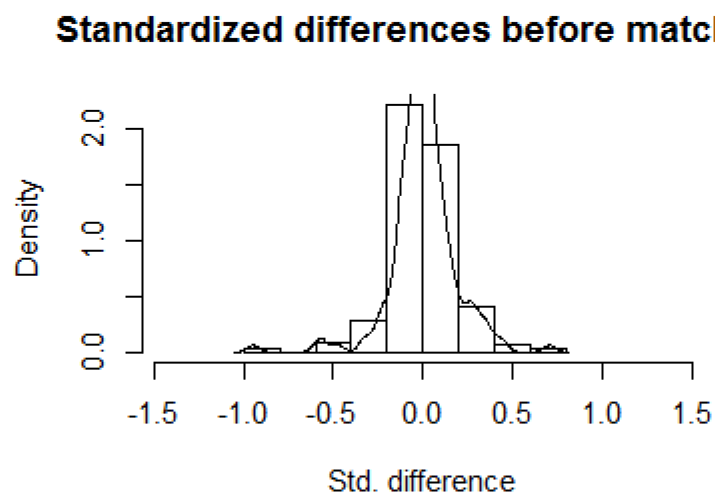
Note: Continuous variables are presented as means ± standard deviation; dichotomous variables are presented as N (%)

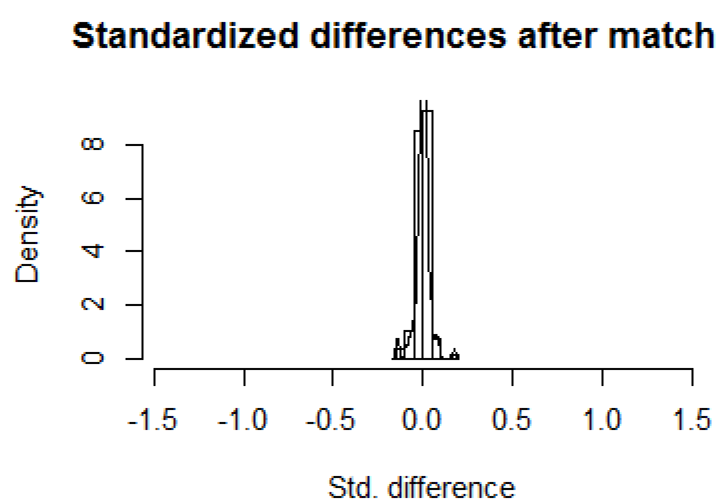
Table E2: Baseline Characteristics of the TAA Study Sample After Matching

Variable	TAA Participants (Treatment Group)	Non-TAA Participants (Control Group)	Overall Sample	Standardized Difference of the Mean	p Value
Wages Prior to Participation	7,998.75 ± 9013.64	7,631.40 ± 10941.22	7,815.07 ± 10025.26	0.04	
Disability	1.10%	1.00%	1.00%	0.006	0.706
Veteran	8.80%	9.10%	9.00%	0.011	0.472
Employment Status before Participation	25.30%	24.40%	24.80%	0.019	0.199
Less than High School Diploma	12.70%	12.50%	12.60%	0.005	0.748
Some College	10.60%	10.70%	10.70%	0	0.98
Associate Degree	14.90%	14.60%	14.80%	0.009	0.563
Bachelor's Degree	8.40%	9.10%	8.70%	0.022	0.153
American Indian	0.60%	0.60%	0.60%	0	1
Asian	2.50%	2.60%	2.50%	0.004	0.772
Black	27.40%	27.20%	27.30%	0.004	0.785
Hawaiian	0.10%	0.10%	0.10%	0.004	0.808
Female	40.60%	40.00%	40.30%	0.012	0.42
Seasonal Farm Worker	5	0%	0%	0.032	0.18
Claimant Referred by WPRS	14.20%	14.40%	14.30%	0.006	0.695

Note: Continuous variables are presented as means ± standard deviation; dichotomous variables are presented as N (%)

Histograms with Overlaid Kernel Density Estimates of Standardized Differences Before and A





Appendix F: Baseline Characteristics of the WIA Study Samples Before and After Matching

Table F1: Baseline Characteristics of the WIA Study Sample Before Matching

Variable	WIA Participants (Treatment Group)	Non-WIA Participants (Control Group)	Overall Sample	Standardized Difference of the Mean	p Value
Wages Prior to Participation	4444 ± 6329.53	4518 ± 6848.40	4515 ± 6825.75	0.152	0.005
Disability	2192 (3.7%)	43129 (3.55)%	45321 (3.5%)	0.05	0.008
Veteran	4944 (8.3%)	111863 (8.9%)	116807 (8.9%)	-0.019	< .001
Employment Status before Participation	11345 (19.0%)	174281 (13.8%)	185626 (14.1%)	0.182	< .001
Less than High School Diploma	6941 (11.6%)	142951 (11.3%)	149892 (11.4%)	-0.014	0.05
Some College	6327 (10.6%)	116587 (9.3%)	122914 (9.3%)	0.052	< .001
Associate Degree	10466 (17.5%)	238290 (18.9%)	248756 (18.9%)	0.155	< .001
Bachelor's Degree	6152 (10.3)%	196246 (15.6%)	202398 (15.3%)	0.105	< .001
American Indian	721 (1.2%)	19302 (1.5%)	20023 (1.5%)	0	< .001
Asian	1079 (1.8%)	25638 (2.0%)	26717 (2.0%)	0.087	< .001
Black	28889 (48.3%)	457414 (36.3%)	486303 (36.9%)	-0.012	< .001
Hawaiian	134 (0.2%)	4492 (0.4%)	4626 (0.4%)	0.014	< .001
Female	32946 (55.1%)	591603 (47%)	624549 (47.3%)	0.191	< .001
Seasonal Farm Worker	91 (0.2%)	7303 (0.6%)	7394 (0.6%)	-0.027	< .001
Claimant Referred by WPRS	3912 (6.5%)	62829 (5.0%)	66741 (5.1%)	0.148	< .001

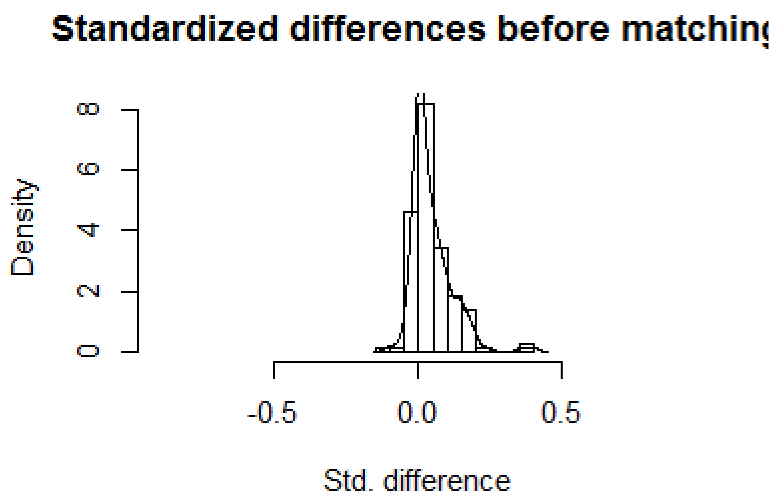
Note. Continuous variables are presented as means ± standard deviation; dichotomous variables are presented as N (%)

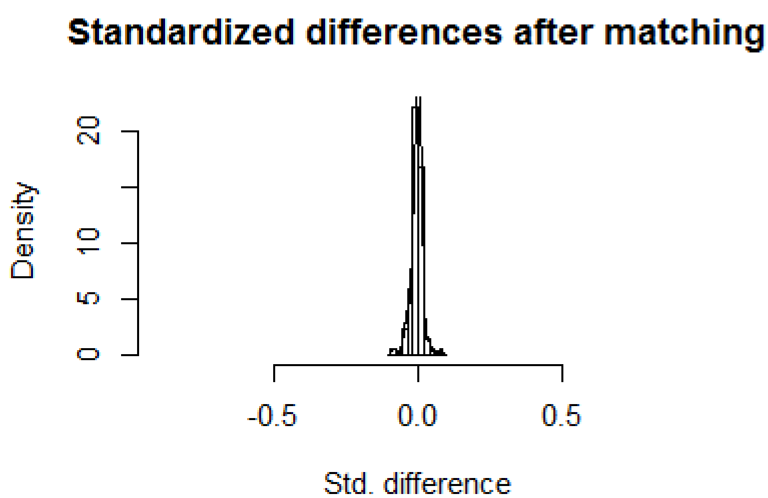
Table F4: Baseline Characteristics of the WIA Study Sample After Matching

Variable	WIA Participants (Treatment Group)	Non-WIA Participants (Control Group)	Overall Sample	Standardized Difference of the Mean	p Value
Wages Prior to Participation	4444.32 ± 6329.53	3481.89 ± 4010.96	3791.67 ± 4899.68	0.001	< .001
Disability	3.70%	2.70%	3.00%	-0.005	< .001
Veteran	8.30%	8.80%	8.60%	0.002	< .001
Employment Status before Participation	19.00%	11.80%	14.10%	0.005	< .001
Less than High School Diploma	11.60%	12.10%	11.90%	0.006	< .001
Some College	10.60%	9.00%	9.50%	-0.004	< .001
Associate Degree	17.50%	11.60%	13.50%	-0.007	< .001
Bachelor's Degree	10.30%	7.10%	8.10%	-0.012	< .001
American Indian	1.20%	1.20%	1.20%	0	1
Asian	1.80%	0.60%	1.00%	-0.017	< .001
Black	48.30%	48.90%	48.70%	0.008	0.013
Hawaiian	0.20%	0.20%	0.20%	0	0.001
Female	55.10%	45.60%	48.70%	-0.02	< .001
Seasonal Farm Worker	0.20%	0%	0%	0	< .001
Claimant Referred by WPRS	6.50%	2.90%	4.10%	-0.016	< .001

Note. Continuous variables are presented as means ± standard deviation; dichotomous variables are presented as N (%)

Histograms with Overlaid Kernel Density Estimates of Standardized Differences Before and After Matching (WIA vs WP).





Appendix G: Propensity Score Matching ROI 5 and 10 Year Calculations

Table G1: Five Year Net Returns on Investment from WIA using Propensity Matching
Taxpayer Perspective (3% Discount Rate)

	Program Year	Year 1	Year 2	Year 3	Year 4	Year 5	**Five Year total Benefits**
Wage diff	$844						
Expenditures/Government							
Average Cost	$901						$901
Returns							
State and local	$82						
Federal Income	$42						
FICA	$65						
Total Additional Tax	$189						
Welfare Savings (TANF. SNAP and SSI)	$531						
	$720	$698	$677	$657	$637	$618	
Total five Year Benefits(PV)							**$3,287**
Net Return							**$2,386**
ROI							**265%**
							$2.65

*All Estimates based on matched dataset

Table G2: Ten Year Net Returns on Investment from WIA using Propensity Matching
Taxpayer Perspective (3% Discount Rate)

	Five Year total Benefits		Year 6	Year 7	Year 8	Year 9	Year 10	10-Year Total
Expenditures/Government								
Average Cost	$901							$901
Returns								
State and local								
Federal Income								
FICA								
Total Additional Tax								
Welfare Savings (TANF. SNAP and SSI)								
			$599	$581	$564	$547	$531	
Total Benefits(PV)		$3,287						**$6,110**
Net Benefits in NPV		$2,386						**$5,209**
ROI		265%						**578%**
		$2.65						**$5.78**

*All estimates based on matched dataset

Table G3: Five Year Net Returns on Investment from TAA using Propensity Matching
Taxpayer Perspective (3% Discount Rate)

	Program Year	Year 1	Year 2	Year 3	Year 4	Year 5	**Five Year total Benefits**
Wage diff	$5,049						
Expenditures/Government							
Average Cost	$2,055						**$2,055**
Returns							
State and local taxes	$490						
Federal Income taxes	$252						
FICA taxes	$386						
Total Additional Tax	$1,128						
Welfare Savings (TANF. SNAP and SSI)*	$12						
Total Benefits(PV)	1131	$1,097	$1,064	$1,032	$1,001	$971	
Five year Total Benefits(PV)							**$5,166**
Net Benefits in							**$3,111**
ROI							**151%**

*All Estimates based on matched dataset
*Out of 9,096 TAA participants in final dataset only 24 indicated any type of public assistance therefore average is very low

Table G4: Ten Year Net Returns on Investment from TAA using Propensity Matching Taxpayer Perspective (3% Discount Rate)

	Five Year Total Benefits		Year 6	Year 7	Year 8	Year 9	Year 10	10-Year Total
Expenditures/Government								
Average Cost								**$2,224**
	$2,055							
Returns								
State and local taxes		$0						
Federal Income taxes		$0						
FICA taxes		$0						
Total Additional Tax		$0						
Welfare Savings (TANF. SNAP and SSI)*		$12						
Total Benefits(PV)		1131	$942	$914	$886	$860	$834	
Five year Total Benefits(PV)								**$9,602**
Net Benefits in	$5,166							**$7,547**
ROI	$3,111							**367%**

Appendix H: ROI by WIB

Table H1: WIA ROI by LWIA		
LWIA	5 Year	10 Year
Alexandria Arlington	$1.44	$3.16
Bay Consortium	$9.79	$17.37
Capital Region Workforce Partnership	-$10.39	-$16.98
Crater Area	$6.24	$11.32
Greater Peninsula	$6.57	$11.88
Hampton Roads	-$6.72	-$10.73
New River Mt Rogers	$12.29	$21.63
Northern Virginia	$9.52	$16.90
Piedmont Workforce Network	$4.40	$8.19
Region 2000 Central Virginia	$10.51	$18.59
Shenandoah Valley	$0.97	$2.35
South Central	$4.86	$8.97
Southwestern Virginia	$6.11	$11.11
West Piedmont	-$1.75	-$2.28

Table H2: TAA ROI by VEC Region[1]		
WIB	5 Year	10 Year
Northern Virginia Workforce Investment Board	-$10.22	-$18.14
Greater Peninsula Workforce Investment Board	-$114.20	-$211.41
Opportunity Inc.	-$111.89	-$207.12
Southwest Virginia Workforce Investment Board	-$9.63	-$17.05
New River/Mt. Rogers WIB	$11.55	$22.32
Piedmont Workforce Network	-$33.03	-$60.53
Bay Consortium Workforce Investment Board, Inc.	-$83.05	-$153.51
Western Virginia Workforce Development Board	-$22.14	-$40.29
Crater Regional Workforce Investment Group	-$52.35	-$96.45
Workforce Investment Board	-$24.79	-$45.22
Region 2000 Workforce Investment Board	-$11.15	-$19.87
Workforce Investment Board (State funds)	-$16.19	-$29.24
Shenandoah Valley Workforce Investment Board	-$33.04	-$60.56
Capital Region Workforce Partnership	-$59.40	-$109.55

[1] While TAA results are reported by LWIA region due to data collection processes, the TAA program is administered locally by the Virginia Employment Commission (state level), not the local WIB.