Workforce Outcomes of WIA On-the-Job Training in Ohio[1]

Kristin Harlow
Lisa Neilson
Josh Hawley
Ohio Education Research Center
The Ohio State University
Columbus, OH

DRAFT – Do Not Cite without Author's Permission

Paper Presented at the Association for Public Policy Analysis & Management Annual Conference,
Albuquerque, New Mexico
November, 2014

---

[1] This workforce solution was funded by a grant awarded to the U.S. Department of Labor's Employment and Training Administration. The solution was created by the Ohio State University's Center for Human Resource Research on behalf of the Ohio Department of Job and Family Services and does not necessarily reflect the official position of the U.S. Department of Labor. The Department of Labor makes no guarantees, warranties, or assurances of any kind, express or implied, with respect to such information, including any information on linked sites and including, but not limited to, accuracy of the information or its completeness, timeliness, usefulness, adequacy, continued availability, or ownership. More information about the Ohio Longitudinal Data Archive can be found at www.ohioanalytics.gov.

Introduction

For the last few decades, the federal government has funded a variety of policy tools to support individuals who struggle to find employment, first through the Job Training Partnership Act, and then through its replacement, the Workforce Investment Act. The impact of these active labor market policies has been the subject of evaluation through improved quasi-experimental design methods (Heckman, Ichimura, & Todd, 1998). However, with an emphasis on job training and job search services, there is still some uncertainty about the impact of government-sponsored on-the-job training, due to the informal nature of the services, and lack of regulation. Is this a good use of public funds, or is it just subsidizing private industry without benefit to employees?

To address this question, we first look at a conceptual model of firm hiring that shows the benefit to the firm of traditional job training and on-the-job training (Neubaumer, 2010). Depending on the expected length of employment, we find that there is incentive for employers to provide high-quality training to employees.

Next, using administrative data from Ohio's Workforce Investment Act Standard Reporting Data and Unemployment Insurance Systems, we create a longitudinal data set to analyze workforce outcomes of individuals participating in WIA-funded on-the-job training. Using Mahalanobis distance matching and propensity score matching techniques, we create a match group for the training participants to minimize selection bias in the analysis of outcomes. We find that over four years, on-the-job training participants see a larger increase in wages than comparisons, and see a smaller decrease in percentage working than comparisons. We find that the proportion of individuals who receive unemployment insurance over time is the same between the two groups.

Literature and Conceptual Framework

Employer-provided training generally increases worker productivity, and strengthens firm performance (Van Horn & Fichtner, 2003). Although human capital is typically thought of in terms of formal education, employer-provided training is just as important in terms of worker productivity (Acemoglu & Pischke, 1999). According to Heckman, "skills acquired in the workplace in the form of . . . workplace education are often neglected in popular discussions because they are not well measured. . . . There is also substantial mistrust of 'unregulated' informal learning whether it is in the workplace or the home" (Heckman, 2000, pp. 5-6).

In addition to firm benefits, there is some evidence that individuals benefit from employer-provided training through improved labor market outcomes (Jaenichen & Stephan, 2011). Gorman et al. suggest that employer-provided training, which varies from traditional training methods by including informal training, results in intangible benefits which may be more valuable over the long term than traditional training methods (2004). In addition, Pindus and Isbell have found evidence that training is more effective when it is sponsored by employers, specifically with regard to wage outcomes (Pindus & Isbell, 1997).

In this study, we focus on a more specific form of employer-provided training, that which is subsidized by government funds. We seek to determine how beneficiaries of employer-provided training fare when it is publicly sponsored as a part of an active labor market policy.

Theoretical Model

Effectiveness of on-the-job training (OJT) can be conceptualized in terms of the calculus an employer uses to make a hiring decision. The hiring employer considers the individual's employment status, as well as training and government assistance (Neubaumer, 2010).

Figure 1: Theoretical Model of the Employment Decision

$$P * \sum_{i=2}^{n} \frac{net\ revenues_i}{(1 + discount\ rate)^i} - cost\ of\ hiring - settling\ in\ costs \geq 0$$

Figure 1 shows the employment decision is based on the present value of a worker, less the cost of hiring the working and the settling in costs (i.e. lower productivity in the first period). The present value of a worker is a function of the worker's net revenues, the expected length of employment (n), and the probability that the employee will stay for the expected length of employment (P) (Neubaumer, 2010). If the total is greater than zero, the employer will choose to hire the employee.

Current unemployment status of a potential employee can impact the model in a number of places. The individual may have a decrease in self-esteem and perhaps human capital, which increases the settling in costs. Further, unemployment may decrease P, or the probability that the individual will maintain employment for the expected duration. To counteract this difficulty in finding an employer, active labor market programs, including formal training and OJT, improve the likelihood that an employer will choose to employ an individual (Neubaumer, 2010).

A formal training program will increase an employer's likelihood of hiring an individual. Effective training will decrease the settling in costs, and increase the net revenues through an increase in the worker's marginal productivity. These potential benefits to the employer, when taken into account given the model in Figure 1, may lead to a decision to hire an individual because of formal training. However, the impact is primarily over the long term, because it is additive through the increased net revenues so the size of the impact depends on n, or the expected length of employment (Neubaumer, 2010).

On the job training (OJT) results in a slightly different impact on the employment decision model. OJT is training, and thus results in an increase in marginal productivity, just like external training. However, the size of the increase is dependent upon the quality of the training (Neubaumer, 2010). This is also true of formal training programs, but there is likely to be less variation and more information about the quality of formal training programs. Employer-provided training isn't regulated in the same way as other formal training programs (Heckman J. , 2000). Further, there is evidence of variation in the quality and type of OJT that exists among firms (Van Horn & Fichtner, 2003). OJT is different than other more formal training because the training is provided directly by the employer, and funding is sent directly to the employer, such that the impact of such funding is not evident through credentialing or similar outputs.

Given that an employer has decided to hire an employee and chosen to accept a subsidy for training in exchange for maintaining the employee for at least some time following the training, we hypothesize that the employer has an incentive to provide high quality training to the employee to maximize the likelihood of a greater benefit through improved human capital and thus higher net revenues. Alternatively, if an employer does not expect to keep the employee for a long period of time (n is small), it might choose to take the subsidized labor and provide inexpensive and less effective training.

Based on the model above and the literature, a quality OJT program should result in positive workforce outcomes for the trainee. Specifically, we expect to see the impact of quality OJT on the trainee's human capital. An increase in human capital should result in higher marginal productivity, higher wages and greater employability for an individual, because human capital is valued in the market and increases firms' profits. As a result, we operationalize high quality OJT as increased wages and rates of employment.

Given the above model, we posit the following hypotheses:

H1: On average, Ohio workers maintain higher rates of employment after OJT participation than a comparison group with similar characteristics who did not receive OJT.

H2: On average, Ohio workers earn higher wages after OJT participation than a comparison group with similar characteristics who did not receive OJT.

Workforce Investment Act On-the-Job Training

We tested the hypotheses using the OJT program funded by the Workforce Investment Act as implemented in Ohio. The Workforce Investment Act of 1998 (WIA) was an amendment and reissuance of the Job Training Partnership Act, reissuing funds to states for local implementation of job training and other workforce development programs. WIA was enacted to be customer-focused, to help Americans access the tools they need to manage their careers through information and high quality services, and to help U.S. companies find skilled workers (U.S. Department of

Labor, 2010). WIA is a source of funding for active labor market policy in the United States. In Ohio, WIA funds are used to fund local One-Stop Centers (currently referred to as OhioMeansJobs Centers), which are county-level offices that provide a centralized location for job search, job training, and other workforce development programs in each county.[2]

Of the various programs and services provided through WIA funding, on-the-job training (OJT) is just one type of training available through the One-Stop Centers. Through OJT, a local Workforce Investment Board may reimburse an employer for costs to train an eligible employee, up to 50% of the salary[3] for a maximum of six months, or $8,000, whichever comes first. The amount and length of reimbursement vary based on the nature of the training. Individuals are evaluated for program eligibility based on the potential position's skill requirements, and how they match with an individual's academic and occupational skill level and prior work experience. Employers must agree to retain successful trainees, must not hire an OJT participant into a position in which the previous employee was laid off, and must not use OJT funds to displace an unsubsidized employee (On-the-Job Training (OJT) Comprehensive Policy, 2014). In the 2012-13 program year, approximately 20% of total WIA trainees received OJT (Ohio Department of Job and Family Services, 2014).

Study Design

To determine for certain that OJT has a positive impact on individual wages or employment, we would need to determine the difference between the wages and employment status of an individual who participated in the program, and the wages and employment of that same individual if he or she did not participate in the program. Because this is an impossible task, the best tool available to determine causal impact of OJT is a randomized experiment in which an individual is

[2] There is one One-Stop Center in every count in Ohio except Cuyahoga County (Cleveland), which has two One-Stop Centers.
[3] Ohio centers have received a waiver that allows a higher reimbursement rate for OJT based on employer size. However, the waiver was not approved until 2010, so will not apply to the OJT participants in the years being studied in this analysis.

just as likely to participate in the treatment as to be in the control group. This eliminates the potential selection bias when evaluating outcomes of program. In quasi-experimental study (where the comparison group is not randomly selected), the individuals participating in the training will likely be meaningfully different from any other individuals used as a comparison, both because of self-selection, as well as because of characteristics that lead program administrators to choose the individual for participation.

Although there was a movement to rely only on randomized experiments for acceptable evidence of causation (LaLonde, 1986; Fraker & Maynard, 1987), Heckman and colleagues published a series of papers showing that by using appropriate methods with appropriate data, quasi-experimental methods can provide meaningful outcomes results (Heckman, Ichimura, & Todd, 1997; Heckman, Ichimura, & Todd, 1998; Mueser, Troske, & Gorislavsky, 2007). Further, there is evidence that among comparable workforce studies, the outcomes using appropriate matching techniques are not significantly different than those using experimental design (Card, Kluve, & Weber, 2010).

Because we are using retrospective administrative data in this study, random selection is not an option. To find evidence of causation, we seek to minimize selection bias that occurs both as a result of characteristics that are measured and observable, as well as characteristics that are unobservable (Heckman & Hotz, 1989). The first step, to minimize selection bias based on observable characteristics, is to create a comparison group that is matched both on propensity score and on an appropriate balance of characteristics to create as close a comparison as possible (Rosenbaum & Rubin, 1983; Heckman & Hotz, 1989; Ho, Imai, King, & Stuart, 2007). The second step, to minimize selection bias due to unobservable characteristics, we will use a difference-in-difference model to measure outcomes (Heckman & Hotz, 1989; Mueser, Troske, & Gorislavsky, 2007).

Data

All data for this study were accessed from the Ohio Longitudinal Data Archive, which houses administrative data from various Ohio state agencies.[4] Data regarding participation in OJT, including dates of participation as well as demographic and geographic variables, are a part of the Workforce Investment Act Standardized Record Data (WIASRD), collected by all WIA offices for federal reporting. Wage, employment, and employer records, as well as unemployment claims and funding, are maintained as part of the Unemployment Insurance (UI) program in Ohio. All individuals in the WIA and UI databases have individual identifiers that allow matching between data sets.

Because the data used in this study are administrative data, we have data for the full population of individuals participating in WIA-funded OJT. Similarly, wage and employer data exists for every individual employed in the state of Ohio with certain specific exceptions. If an individual is at any point self-employed, employed by a federal employer, or employed outside the state of Ohio, that wage and employer information is missing from the study data. We assume, for purposes of this analysis, that these instances of missing wage data will be similar for both the OJT and the comparison group.

We used the WIA data set not only for information about program participants, but also as a pool for identifying a comparison group. The WIA dataset includes not only individuals who received OJT, but also other WIA-funded training, job-placement services, and youth services. In addition, the WIA data includes almost 500,000 records of individuals who have used WIA through self-service job search and other non-intensive WIA-funded services. We used these individuals who received non-intensive services, who have demographic and geographic information available, as a pool from which to identify the comparison group. Individuals with demographic information

[4] Columbus OH: Ohio Longitudinal Data Archive, Ohio Education Research Center, The Ohio State University, 2014.

that was missing or invalid (including gender, age, geographic region) were excluded from the analysis.

OJT participants with a recorded quarterly salary of greater than $60,000 for any of the eight quarters prior to OJT participation were excluded from this analysis as outliers.[5] There is a substantial likelihood that these observations are errors in the data rather than representative of actual earnings of the individuals.

OJT Population

We used OJT participants who began training during calendar years 2006, 2007, and 2008 in this study to allow for analysis of longer-term outcomes.[6] Using the three years of data 2006-08, we are able to look at wage and employment outcomes more than four years after completing OJT. The final population of OJT participants who began within the three year window is 1,188. More details about OJT participants are provided in Table 4 below.

The WIA data in the OLDA provide the date on which an individual starts OJT, but does not have information about the individual's success in the program, or exactly how long training lasts. As a result, the results may be somewhat conservative because they likely include individuals who did not complete OJT as intended. Although we do not have individual-level data of exactly how long WIA-funded OJT lasted, we assume for purposes of this analysis that it was within two calendar quarters because WIA administrative rules limit the time for OJT funding to six months or $8,000, whichever comes first.

Table 1 provides a visual representation of how we defined the quarterly data to aggregate OJT participants who participated in OJT throughout the 2006-08 time period. Each individual was

---

[5] Nine records were dropped from the OJT group as a results of eliminating the outliers, representing less than one percent of the population.

[6] In a meta-analysis of active labor market policy evaluations, Card, Kluve, and Weber (2010) find that training programs generally do not yield benefits until about three years following training.

assigned quarters of participation based on the training start date provided in the WIA data. If the WIA training begin date was within a quarter, that quarter was defined as OJTQ1.

Table 1: Defining Quarters to OJT Participants

	Calendar Quarter									
Quarter begin OJT	2005q4	2006q1	2006q2	2006q3	2006q4	2007q1	2007q2	2007q3	2007q4	2008q1
2006q1	PreQ1	**OJTQ1**	**OJTQ2**	PostQ1	PostQ2	PostQ3	PostQ4	PostQ5	PostQ6	PostQ7
2006q2	PreQ2	PreQ1	**OJTQ1**	**OJTQ2**	PostQ1	PostQ2	PostQ3	PostQ4	PostQ5	PostQ6
2006q3	PreQ3	PreQ2	PreQ1	**OJTQ1**	**OJTQ2**	PostQ1	PostQ2	PostQ3	PostQ4	PostQ5
2006q4	PreQ4	PreQ3	PreQ2	PreQ1	**OJTQ1**	**OJTQ2**	PostQ1	PostQ2	PostQ3	PostQ4
2007q1		PreQ4	PreQ3	PreQ2	PreQ1	**OJTQ1**	**OJTQ2**	PostQ1	PostQ2	PostQ3

Individuals in the comparison group by definition do not have a quarter of participation. In addition, distribution of OJT participation was not equal among the quarters (see Table 2). To account for the uneven participation among the quarters, we randomly assigned the pool of potential comparisons to a quarter of participation in the same proportions as the OJT participants actually began participation to avoid bias caused by temporal effects. For example, since more individuals began OJT during the recession in 2008, it would bias the comparison group to include more individuals from 2006. As a result, the proportion of the comparison group is assigned a "start" quarter at the same rate that OJT participants are found to start in that quarter.

Table 2: OJT Participants Training Start Date by Calendar Quarter

	OJT Participants	Percent
2006q1	78	7%
2006q2	108	9%
2006q3	75	6%
2006q4	22	2%
2007q1	68	6%
2007q2	97	8%
2007q3	157	13%
2007q4	105	9%
2008q1	103	9%
2008q2	118	10%
2008q3	235	20%
2008q4	22	2%
Total	1,188	100%

Literature on labor market outcomes also points to the importance of comparing individuals within the same labor market (Friedlander & Robins, 1995; Mueser, Troske, & Gorislavsky, 2007; Heckman J. , Ichimura, Smith, & Todd, 1998). Because Ohio is a diverse state, we implement exact matching by geographic region. JobsOhio, a nonprofit partner of the Ohio Governor's office, divides Ohio into six geographic regions for economic development purposes.[7] We created the OJT comparison group by matching individuals within each JobsOhio region, to ensure that the comparison to each OJT participant is facing a similar labor market. Because there is such a discrepancy among counties in how prevalently OJT is used, matching was not available in a few counties because there were too few potential matches. However, this geographic variation provides an opportunity for high-quality matches, because the counties surrounding a high-use OJT county have many potential matches without access to OJT, who are likely to be similar to OJT participants.

Creating a Match Group

We took the following steps in creating a match group: estimated the propensity score using relevant variable that might predict OJT participation, chose a matching algorithm, assessed the matching quality, and finally calculated treatment effects (Caliendo & Kopeinig, 2008).

Estimate Propensity Score

The first step in creating a match group using propensity score matching is to build a model that predicts participation in OJT. We use a logit model to predict participation using demographic variables and labor force dynamics prior to program participation (Mueser, Troske, & Gorislavsky, 2007; Heckman & Smith, 1999). Results are provided in Table 3. The variables included in the logit model are used to create the match group.

[7] See jobs-ohio.com.

As mentioned, demographic variables and labor market indicators are key in predicting training participation. In addition, there is a distinct dip in wages prior to OJT in the data, so to ensure that the match group started with a similar salary and experienced a similar dip in wages, we include annual wages two years prior, as well as quarterly wages for the four quarters leading up to OJT (or the equivalent quarter). The remaining labor market variables are included for the quarters in which we found a significant impact on the model.

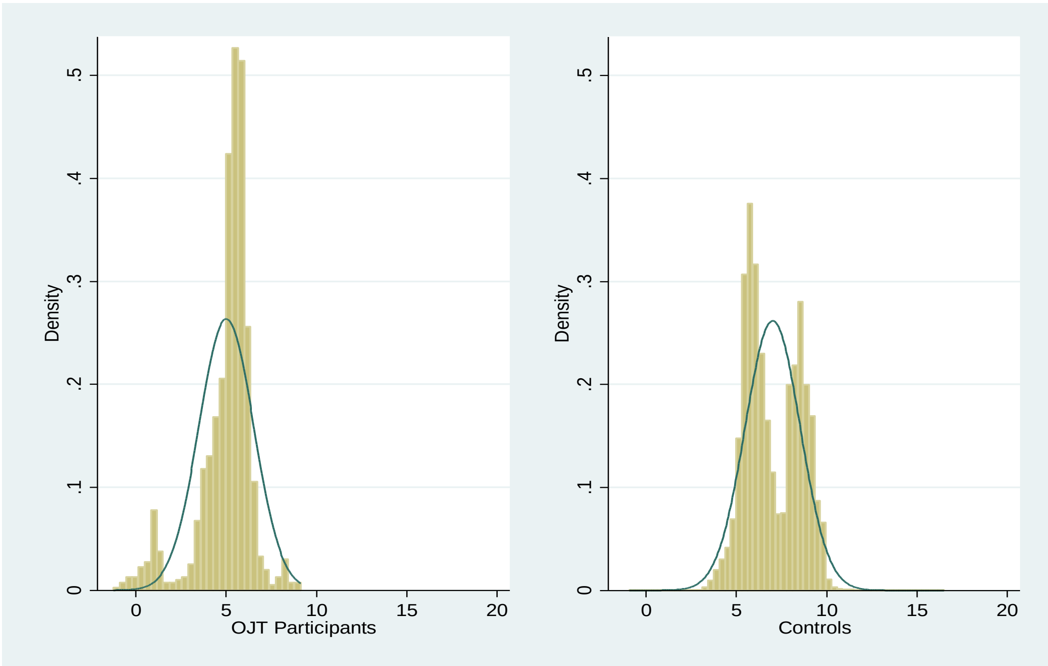
Table 3: Logit Model Predicting Participation in On-the-Job Training

Variable	Time Period	Coefficient	Standard Error	z	P>z
Annual Wages	PreQ5-PreQ8	9.52E-06	2.32E-06	4.1	0
Quarterly Wages	PreQ4	5.85E-06	7.24E-06	0.81	0.419
	PreQ3	-2.67E-06	7.98E-06	-0.34	0.738
	PreQ2	-0.0000201	0.0000108	-1.85	0.064
	PreQ1	-0.0000809	0.0000118	-6.86	0
Employed (dummy)	PreQ2	0.374	0.100	3.75	0
	PreQ1	0.0882	0.0982	0.9	0.369
Multiple Employers (dummy)	PreQ2	0.239	0.0931	2.56	0.01
	PreQ1	0.268	0.0937	2.86	0.004
Unemployment Insurance Claims Funded (dummy)	PreQ4	0.954	0.146	6.53	0
	Preq3	0.864	0.143	6.04	0
	PreQ2	1.304	0.112	11.65	0
	PreQ1	1.104	0.120	9.23	0
Age		0.180	0.0162	11.11	0
Age Squared		-0.00226	0.000214	-10.56	0
Male		0.474	0.0667	7.11	0
Veteran Status		4.423	0.134	32.92	0
Nonwhite*		2.325	0.179	13.01	0
White*		2.622	0.167	15.69	0
Constant		-12.00	0.327	-36.72	0

* Missing Race is the category that is not present to avoid multi-collinearity. Individuals with missing race information were retained in the study, even though those with missing gender and age information were excluded, because there were too many individuals who did not provide their race information, which, if deleted, may have then biased the study population.

Before attempting to create a comparison group, we first determine whether the OJT participants and the pool for comparisons have enough overlap, or in propensity score matching parlance, ensure a region of common support (Caliendo & Kopeinig, 2008). Figure 1 shows histograms of both OJT and the potential pool of comparisons showing sufficient overlap in propensity scores to allow matching. Keep in mind when interpreting the histograms in Figure 2 that there are on the order of 1,000 OJT participants, while there are on the order of 400,000 potential comparison individuals.

Figure 2: Histograms of Estimated Logit Propensity Scores



Matching Algorithm

We created potential match groups using both nearest neighbor match using calipers at 25% of the propensity score standard deviation, and Mahalanobis distance match. In the nearest neighbor match, each participant is matched with a member of the comparison pool who has the propensity score closest to the participant, on a one-to-one basis, so long as their propensity scores are within the caliper limit. When we created this nearest neighbor match group, a quick check of the differences among predictor variables indicated that the groups may still have important differences, based on large discrepancies between the groups on a number of variables.

Next, we tried creating a match group using the Mahalanobis distance match. In this case, matching is done to minimize the distance between each OJT participant and the match as a whole for the group. In this case, the number of matches found for OJT participants decreased somewhat to 931, but there are smaller differences between the groups on each predictor variable (see Table 4). Following Ho et al., we determine that the individual variables on which the groups were matched are sufficiently similar, as the differences are all less than 25% of the standard deviation of the OJT group (2007).

As mentioned above, all matching was done stratified by geographic region. Comparisons were found using the matching process above within each geographic region, then re-aggregated. Regardless of the other similarities and differences between OJT participants and their matches, they all participate in workforce development within the same region.

Assessing Quality of Match

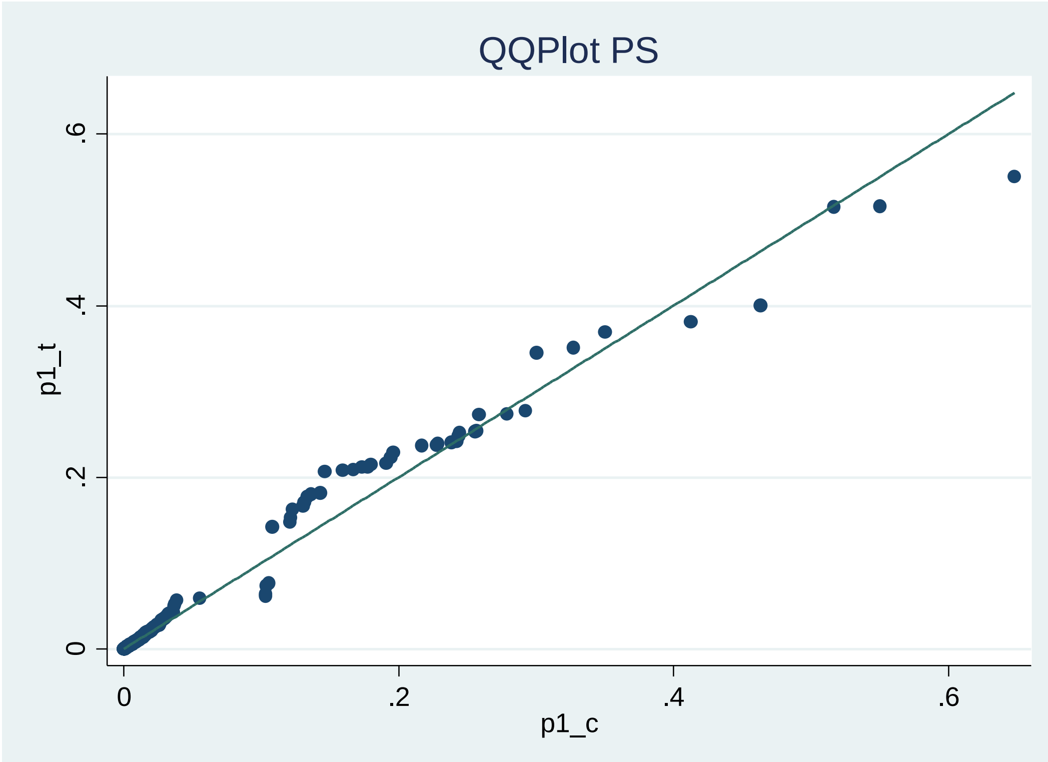
To ensure that our match group is sufficiently similar to the OJT participants, we look at the match in two ways. First, we have determined that each of the matching variables have an average within 25 percent of the OJT standard deviation. Although the comparison group has a systematically lower salary than the OJT participants, they have a similar downward trajectory prior to the quarter of OJT participation. This difference may indicate that there are other unmeasured differences between the groups; the difference in difference outcome analysis will account for any unmeasured fixed differences between the groups. The other characteristics are very similar between the groups.

Table 4: Difference between OJT Participants and Matched Comparison Group

Variable	Time Period	OJT, n=931 Mean	OJT, n=931 SD	Comparison, n=931 Mean	Comparison, n=931 SD	.25*OJT SD	Difference
Annual Wages	Prior Q5-Q8	20,186.35	18,230.41	18,318.59	17,129.52	4,557.603	1,867.76
Quarterly Wages	Prior Q4	4,978.602	5,172.047	4,510.935	4,823.14	1,293.012	467.667
	Prior Q3	4,857.707	4,978.217	4,463.726	4,544.057	1,244.554	393.981
	Prior Q2	4,358.496	4,504.944	4,107.953	4,260.009	1,126.236	250.543
	Prior Q1	3,917.227	4,577.856	3,799.473	4,201.268	1,144.464	117.754
Employed	Prior Q2	0.752	0.432	0.751	0.433	0.108	0.00107
	Prior Q1	0.711	0.454	0.724	0.447	0.113	-0.0129
Multiple Employers	Prior Q2	0.159	0.366	0.151	0.359	0.0915	0.00752
	Prior Q1	0.153	0.360	0.155	0.362	0.0899	-0.00215
Unemployment Claim Funded	Prior Q4	0.0397	0.195	0.0376	0.190	0.0489	0.00215
	Prior Q3	0.0440	0.205	0.0419	0.200	0.0513	0.00215
	Prior Q2	0.0741	0.262	0.0730	0.260	0.0655	0.00107
	Prior Q1	0.0698	0.255	0.0655	0.248	0.0637	0.00430
	Age	37.117	11.545	35.461	11.914	2.886	1.656
	Age Squared	1510.814	897.859	1399.265	896.201	224.465	111.549
	Male	0.678	0.468	0.673	0.469	0.117	0.00430
	Veteran Status	0.0483	0.215	0.0483	0.215	0.0536	0
	Nonwhite	0.146	0.353	0.128	0.334	0.0883	0.0183
	Missing Race	0.0376	0.190	0.0333	0.180	0.0476	0.00430

Second, we plot the propensity scores of the OJT group versus the comparison group (see Figure 3) (Ho, Imai, King, & Stuart, 2007). The plot shows that most matches fall very close to the line along which the propensity scores would be equal. Given the univariate close matches as well as the multi-dimensional propensity score match, we use the group identified through Mahalanobis matching to measure OJT outcomes.

Figure 3: Plot of the Propensity Scores of the OJT and Match Groups



Dependent Variables

We measure OJT outcomes using three measures of labor market success: wages, a proxy for employment, and funded unemployment insurance claims. Wages are as reported in the UI data records, adjusted for inflation to 2010 dollars.

As a proxy for employment, we use found working in Ohio. The employment records available only include those individuals who are employed in Ohio by an employer who reports into the unemployment insurance system. This excludes those employed outside of Ohio, self-employed, and those working for a federal employer, including the military. As a result, employment will not be exactly represented by this outcome variable. However, we assume that the missing employment information will be similar between the OJT and comparison groups.

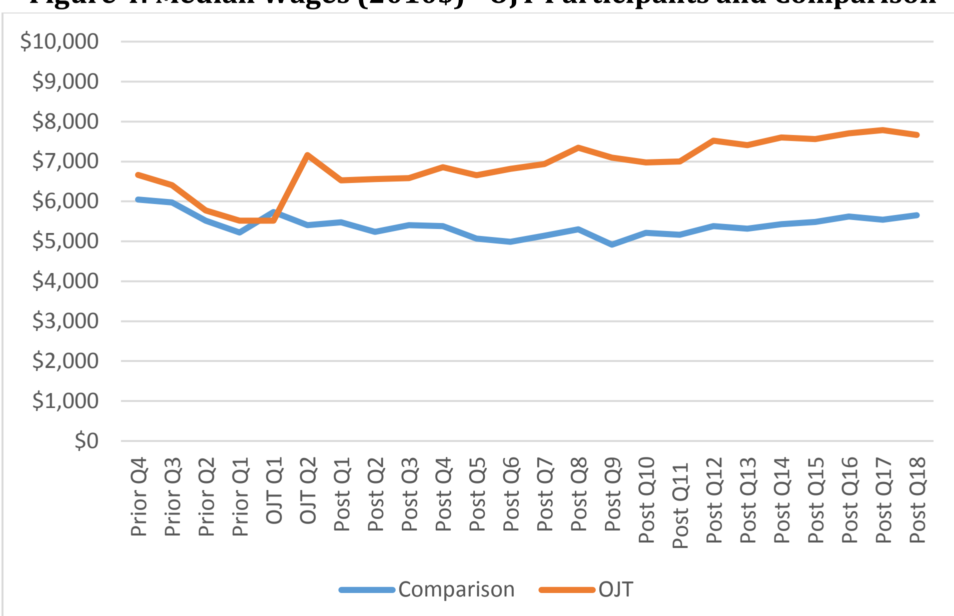
Finally, the funded UI claims is a dummy variable in the quarter in which an individual is approved for unemployment insurance funds. This measure is used as a check on the proxy used for employment.

Results

We calculated OJT impacts on average inflation-adjusted wages, employment and unemployment insurance claims in the 18 quarters following OJT participation. The results provide the average impact for matched OJT participants who entered OJT in calendar years 2006, 2007, or 2008.

Figure 4 shows the median quarterly wages, adjusted to 2010 dollars, for OJT participants and the comparison group. Note that the wages of the OJT group begin about $750 higher four quarters prior to OJT participation. However, once participants gain the benefit of OJT, the wages for OJT participants go up, as a whole, such that by four years after participation OJT participants are making about $2500 more per quarter than the comparison group. This provides strong evidence that OJT participation is a benefit to individuals, especially over the long term.

Figure 4: Median Wages (2010$) - OJT Participants and Comparison



To address the existing difference between comparison and treatment groups even after matching, we use difference-in-difference to measure the average treatment effect of the treated. Following Heinrich et al., Table 5 shows the average quarterly difference in earnings from the eighth quarter prior to OJT to the years following OJT (2009). Using the eighth quarter before OJT participation as a baseline, we find OJT participants see an increase of about $2,000 per quarter in salary, up to an average of $2,300 increase four years following OJT participation. In contrast, those individuals in the matched comparison group saw a consistent salary of about $500 more than the eighth quarter before assigned participation.

Although there is fluctuation in the change in salary over time, there is a consistent difference in salary increase between the OJT participants and the matched comparisons, which trends upward. The average OJT effect by the fourth year after participation is $1,852 per quarter.

Table 5: Average Treatment Effect of the Treated – Average Change in Quarterly Wages[8]

	OJT	Comparison	Difference
Quarters 3-6	1,927	454	1,473
Quarters 7-10	1,815	622	1,193
Quarters 11-14	2,301	582	1,719
Quarters 15-18	2,357	505	1,852

Figure 5 illustrates the percentage of OJT participants and matched comparison group who were found working in Ohio before, during, and after participants were in OJT. As expected the OJT participants have very high employment rate during OJT participation, and although it falls, OJT participants maintain a higher proportion found working even four years after participation.

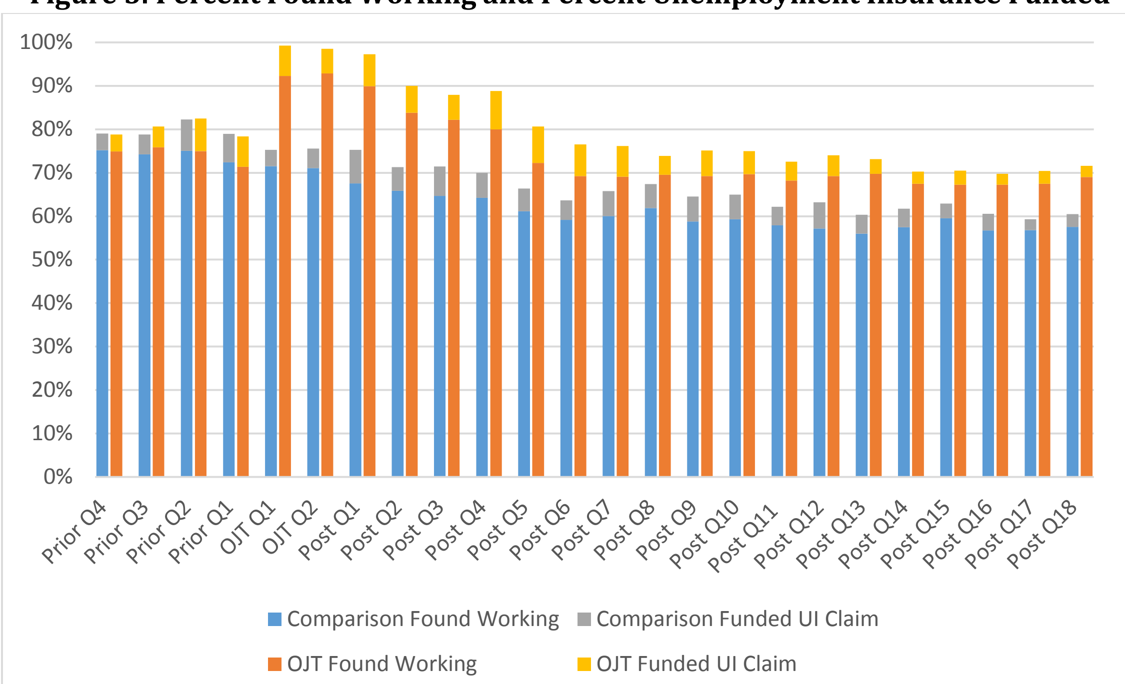
Interestingly, during the quarters that individuals are participating in OJT, there should be 100% employment for OJT participants, but the UI wage data only shows about 92% employed.

[8] We do not report standard errors or p-values with these results. We are measuring the impact of the full population of individuals who participated in OJT in Ohio during 2006-08, and do not have a larger population to which we are generalizing. Further, the standard errors of the ATT for matched group are likely to be biased without adjustment (Abadie & Imbens, 2012).

This discrepancy can be explained by noise in the data, especially given that the quarter in which an individual participated in OJT may not be exactly accurate (Ewald, 2014). This data quality issue is a concern because it may bias our OJT group, if the data inaccuracies are not randomly distributed. However, it is most likely to make our outcomes more conservative. If an individual participates in OJT in a quarter after we had thought, the outcomes for that individual will be smaller. The fact that there are individuals who are receiving unemployment insurance during the quarters in which they are supposed to be participating in OJT indicates that they did not receive training earlier than anticipated. As a result, any outcome findings are likely still consistent with actual outcomes experienced by participants.

Although rates of UI funding are similar between OJT and the comparison group for the four quarters before OJT, the rate for OJT participants grows and stays larger for a number of quarters after OJT participation. However, the proportion of the OJT group found working is also larger over time. This may be a result of individuals who participate in OJT gaining access to social services generally, and gaining assistance with UI processes related to engaging in OJT.

Figure 5: Percent Found Working and Percent Unemployment Insurance Funded



We again use a difference in difference technique to address the fixed, unmeasured differences between the OJT group and the comparison group (see Table 6). Over time, the percent of those who participated in OJT who are found working decreases, but the rate continues to be approximately 10 percentage points higher than the comparison group. The proportion of OJT participants found working four years following participation is about six percentage points lower than the baseline eight quarters before participation. However, we find a 15 percentage point drop in the comparison group. The average OJT effect is nine greater percentage points found working in Ohio after four years.

Table 6: Average Treatment Effect of the Treated – Average Percentage Point Change in Found Working

	OJT	Comparison	Difference
Quarters 3-6	4%	-10%	14%
Quarters 7-10	-3%	-13%	10%
Quarters 11-14	-4%	-15%	11%
Quarters 15-18	-6%	-15%	9%

Because of the nature of the employment data, it is hard to point to a particular cause for the decline in the percent of people found working. Although the individuals may be falling out of the labor market (as perhaps evidenced by the proportion receiving unemployment insurance), individuals may also be moving or finding employment outside of Ohio. Further, the age distribution of OJT is such that some individuals may be retiring. Therefore, the slow downward slope of the proportion of individuals found employed is not necessarily a bad result. The average treatment effect of the treated shows that the change in proportion of individuals found working indicates that those individuals participating in OJT are more likely to remain employed in Ohio than those similar individuals who did not, which is evidence of the effectiveness of OJT at improving employability.

One piece of evidence that may illuminate where employees are going is funded unemployment insurance claims (see Table 7). There is a slight jump in the number of OJT participants who receive funded UI claims in the first year after OJT as compared to the comparison group, but the difference between the growth in UI funding for OJT and the comparison group disappears after two years. As noted above, this jump may be related to receiving WIA services, as the awareness for the availability of social services generally could be higher. In any case, funded UI claims make up a small proportion of the OJT and comparison groups total (ranges from two to eight percent in a given quarter).

Table 7: Average Treatment Effect of the Treated – Average Percentage Point Change in Unemployment Insurance Funded

	OJT	Comparison	Difference
Quarters 3-6	5%	3%	2%
Quarters 7-10	4%	3%	1%
Quarters 11-14	2%	2%	-1%
Quarters 15-18	1%	1%	0%

Implications, Limitations, Future Directions

The analysis in this paper is related to larger active labor market policy, and the impact of subsidizing private firms to provide OJT. Because OJT is less regulated and more inconsistent than traditional training programs, research providing some evidence of the quality of training and the impact on trainees to add to the literature on the merits of OJT is of benefit. Further, there are methodological limitations to studying OJT as compared to traditional training programs. We overcome these limitations to demonstrate that OJT results in improved workforce outcomes.

Our findings show that there is an average treatment effect of the treated on those participating in OJT that grows over four years following participation, both in wages and in the proportion of trainees employed in Ohio. This treatment effect is measured using a well-matched group of similar individuals in the same region of Ohio.

However, these findings have certain limitations. Although the matched group is similar, it still began with average wages below the OJT group. Perhaps there is a better way to match individuals that would provide a more accurate comparison. Further, although the match was by geographic region, it still allows for differences in job prospects localities within the region.

Another limitation leads to a path for future study. Exactly which kinds of jobs are OJT participants successful in? Analysis of successful participants and where they end up over time could lend some evidence to best practices within OJT.

The findings have important implications for the way active labor market policy is structured, and workforce development dollars are spent. On average, funds spent on OJT in Ohio are resulting in improved workforce outcomes, after four years on average an extra more than $7,000 per year. Partnerships with firms that provide quality OJT can be a useful tool in the toolbox of policy makers who seek to address unemployment.

Works Cited

Abadie, A., & Imbens, G. W. (2012). *Matching on the Estimated Propensity Score.* Cambridge, MA: Harvard University and National Bureau of Economic Research. Retrieved from http://www.hks.harvard.edu/fs/aabadie/pscore.pdf

Acemoglu, D., & Pischke, J.-S. (1999). Beyond Becker: Training in Imperfect Labour Markets. *The Economic Journal*, F112-42.

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, 31-72.

Card, D., Kluve, J., & Weber, A. (2010). *Active Labor Market Policy Evaluations: A Meta-Analysis.* Cambridge, MA: National Bureau of Economic Research.

Ewald, K. (2014, October 20). Project Manager. (K. Harlow, Interviewer)

Friedlander, D., & Robins, P. K. (1995). Evaluating Program Evaluations: New Evidence on Commonly Used Nonexperimental Methods. *American Economic Review*, 923-937.

Gorman, P., Moore, R., Blake, D., & Phillips, G. M. (2004). An Empirical Study of the Effectiveness of Publicly-Funded 'Structured On-Site Training': Implications for Policy and Practice. *Journal of Vocational Education and Training*, 387-408.

Heckman, J. (2000). Policies to Foster Human Capital. *Research in Economics*, 3-56.

Heckman, J. J., & Hotz, V. J. (1989). Choosing Among Alternative Nonexperimental Methods for Estimating the Impact of Social Programs: The Case of Manpower Training. *Journal of the American Statistical Association*, 862-74.

Heckman, J. J., & Smith, J. A. (1999). The Pre-Programme Earnings Dip and the Determinants of Participation in a Social Programme. Implications for Simple Programme Evaluation Strategies. *The Economic Journal*, 313-48.

Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an Econometric Evaluation Estimator. *Review of Economic Studies*, 261-94.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an Econometric Evaluatin Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, 605-654.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing Selection Bias Using Experimental Data. *Econometrica*, 1017-98.

Heinrich, C. J., Mueser, P. R., Troske, K. R., Jeon, K.-S., & Kahvecioglu, D. C. (2009). *New Estimates of Public Employment and Training Program Net Impacts: A Nonexperimental Evaluation of the Workforce Investment Act Program.* Bonn, Germany: Institute for the Study of Labor.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as a Nonparametric Preprocessing for Reducing Model Dependence in Paramentric Causal Inference. *Political Analysis*, 199-236.

Jaenichen, U., & Stephan, G. (2011). The Effectiveness of Targeted Wage Subsidies for Hard-to-Place Workers. *Applied Economics*, 1209-25.

Mueser, P. R., Troske, K. R., & Gorislavsky, A. (2007). Using State Administrative Data to Measure Program Performance. *Review of Economics and Statistics*, 761-83.

Neubaumer, R. (2010). *Can Training Programs or Rather Wage Subsidies Bring the Unemployed Back to Work? A Theoretical and Empirical Investigation for Germany.* Bonn, Germany: The Open Access Publication Server of the ZBW - Leibniz Information Centre for Economics.

Ohio Department of Job and Family Services. (2014). *Ohi Workforce Investment Act Program Year 2012 Annual Report.* Columbus, OH. Retrieved from http://www.doleta.gov/performance/results/AnnualReports/PY2012/OHWIAAnnualReport2012.pdf

On-the-Job Training (OJT) Comprehensive Policy. (2014, March 6). *Workforce Investment Act Policy Letter(WIAPL 10-08.2)*.

Pindus, N., & Isbell, K. (1997). *Involving Employers in Training: Literature Review.* U.S. Department of Labor, Employment and Training Administration. Retrieved from http://files.eric.ed.gov/fulltext/ED418293.pdf

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 41-55.

U.S. Department of Labor. (2010 , January 7). *Workforce Investment Act*. Retrieved from United States Deparment of Labor: http://www.doleta.gov/programs/factsht/wialaw.cfm

Van Horn, C. E., & Fichtner, A. R. (2003). An Evaluatin of State-Subsidized, Firm-Based Training. *International Journal of Manpower*, 97-110.