The search for work.

Do worker training programs really lead to employment?

M. Jared McEntaffer

December 26, 2014

Abstract

Many hope that training programs will help the unemployed find new employment opportunities but there is little evidence in support of this. Using administrative data gathered from 2002 to 2011 on unemployed job seekers in South Dakota and neighboring counties in Iowa and Nebraska I estimate how Workforce Investment Act training programs impact observed employment outcomes. The estimation methods are robust to selection bias and provide consistent and efficient estimates of the average treatment effects of both on-the-job and occupational skills training programs. My findings show that both types of training increase the likelihood of employment both one and three quarters after training. The employment effect is initially stronger for men but decrease with time. For women the effects of training increase from the first to the third quarter. On-the-job training provides a greater boost to employment rates for men and women whereas the effects of occupational skills training are inconsistent over time and across gender. The training treatment effects arise from participation in the program itself and are not associated with training in a specific occupation. This indicates that training is a viable employment program for persons with varying backgrounds and skill sets.

JEL Codes: E24, J15, J24, J38, J68

1 Introduction

The United States labor market has seen many ups and downs in its history. Without a doubt the recent past has witnessed a down period like few others. The recent $2007-09$ recession has been the deepest and most protracted recession since the depression. Even more troubling than the historically high unemployment peak of 10.1 percent has been the sclerotic recovery of both national and regional labor markets. In July 2011 the mean duration of unemployment crossed the forty week threshold and remained near that level until October 2012. Before the most recent recession, at no time since 1948, when calculation of this figure began, had the average unemployment spell exceed twenty-five weeks. In contrast, the mean unemployment spell today is almost thirty-seven weeks, and has continuously exceeded twenty-five weeks since July of 2009. The nation is clearly stuck in a so-called "jobless recovery" characterized by the coincident return of robust gdp growth with only tepid employment growth. One contributing factor to slow labor market recovery has been an increase in apparent skills mismatch in the economy. In recent years the unemployment rate has remained stubbornly high at the same time that job vacancies have increased. It seems that the Beveridge curve has once again shifted indicating greater matching inefficiency in the labor market. At the same time policy makers and economists have become increasingly cognizant of stalled real wage growth in the economy. The $2007-09$ financial crisis, housing crash, and subsequent recession severely reduced household wealth for the majority of American wage earners.

This perfect storm of high and extended unemployment, increased skills mismatch, and stalled wage growth has lead to greatly renewed interest in continuing education and worker training programs. Might such programs succeed and help return the labor market and the wider economy to health? Training programs promise to change workers by providing them with new skills and new opportunities that they would not have otherwise. In the current environment characterized by increased mismatch in the labor market and slow economic recovery, such active labor market programs might be much more effective at fostering employment than traditional passive policies.

This paper is the first in a series of papers that provides economists and policy makers with much needed insights into the effects of modern worker training programs. A successful training program must have three qualities. First, it must improve the employment prospects of those who participate. Second, the program should lead to higher earnings for participants. Lastly, training programs should be a net benefit to society. Do today's training programs provide these benefits or do they fall short?

Analysis of training programs is notoriously difficult, and few data exist that allow for even cursory estimation of program effectiveness. There are no publicly available data which provide researchers with detailed micro data on individuals, training programs, and employment outcomes. What limited data do exist come from periodic surveys and do not report detailed and accurate records regarding: the type of training, what occupations persons trained for, the timing of program participation, pre and post training employment status, pre and post training earnings. Additionally, detailed geographic records are often absent leaving the researcher unable to control for idiosyncratic regional labor market characteristics. The administrative data used here come directly from several state agencies and contain the most accurate and detailed records possible. For example, earnings data come from payroll records, use of various welfare programs comes from state records and are not simply self-reported, and the type and

In order to overcome these problem and accurately assess nationally available public worker training programs I use private administrative data gathered on unemployed workers by the State of South Dakota over the period $2002 - 11$. These first of their kind data provide an unique opportunity to study the effects of training programs. More importantly, my findings are broadly applicable to the wider United States, and might be seen as establishing a baseline for the effectiveness of worker training programs in the current economy. Like many other states South Dakota exhibits a great deal of regional variation in both the type and amount of economic activity. Similarly to Pennsylvania, South Dakota has two main population centers separated by a vast stretch of more rural area. Sioux Falls in the east is one of the fastest growing metropolitan areas in the country and has been for more than a decade. Its primary industries are finance and healthcare. In the west, lies Rapid City whose economy is primarily centered around tourism and services. Some of the poorest and most poverty stricken areas in the United States are also found in

South Dakota, particularly on Native American reservations such as Pine Ridge. The rich variation in economic activity, geography, and in the types of occupational training within the data allow me to estimate the effects of training in many ways, and have confidence that my results apply beyond just South Dakota.

In the following sections I discuss the history of job training programs in the United States. I then discuss in detail the programs evaluated in this study and new and unique data employed. This is followed immediately with the empirical estimation of the treatment effects of WIA training programs. I include and discuss the results of several sensitivity tests to ensure the validity of the empirical results. Finally I summarize the conclusions and policy implications of the presented results. As a preview of my results though, I find that both on-the-job and occupational skills training support near to medium term employment. The employment boost provided by on-the-job training is larger for both men and women. However, the benefits to both on-the-job and occupational skills training fall over time for men while increasing for women. Importantly, the benefits of training are not tied to the specific occupations that participants train for. Rather, the benefits appear to derive from participation in general and are available to all job seekers who enroll in training.

2 An Overview of Training Programs in the United States

Perhaps the first nationwide employment programs in the United States grew out of the Roosevelt administration's New Deal programs in the 1930s and 1940s. These Depression era programs, such as the: Civilian Conservation Corps, Civil Works Administration, and Works Progress Administration were a first of their kind. As opposed to more modern employment programs, however, these New Deal programs were relatively narrow in focus. Primarily concerned with providing employment to the greatest number of persons possible, these programs tended to focus on large scale infrastructure and public works projects; the national interstate highway system, for example, was born of such projects.

Passage of the Manpower Development Training Act (MDTA) of 1962 ushered in the modern era of national employment and training programs. O'Leary, Straits, and Wandner

(2004) explains that the MDTA was not a general employment support program in the spirit of previous New Deal era programs, rather, the MDTA was intended as an anti-poverty measure. Congress intended the act to fund training programs targeted towards low income persons and welfare recipients. Funding for training was primarily directed towards on on-the-job training (OJT) and classroom instruction. Funding was controlled at the national level by the Bureau of Labor Statistics (BLS) through twelve regional offices that reviewed grant proposals submitted by the states. The regional system allowed for some flexibility and variation but regional funding decisions were largely controlled from Washington (Bradley, 2013).

Congress allowed the MDTA to expire in 1969, but it soon passed new legislation with similar goals. The 1973 Comprehensive Employment and Training Act (CETA) was an evolution of the MDTA. CETA still targeted low income persons and welfare recipients for training, but expanded the target population to include young persons as well. Training options were also expanded to include employment in public agencies and additional classroom training options (O'Leary, Straits, and Wandner, 2004). CETA also emphasized decentralized decision making and local responsiveness by divesting the BLS of some oversight and decision making powers. States and localities were given more control of funds allocation. In addition to transferring decision authority to state and local governments, CETA called for the creation of local advisory boards representing private and public interests to both guide and shape training programs and evaluation thereof (Bradley, 2013; O'Leary, Straits, and Wandner, 2004).

In 1982 the Reagan administration oversaw the passage of Job Training Partnership Act (JTPA) which replaced CETA. While CETA had introduced the concepts of local control and accountability, JTPA made them a primary feature. With the JTPA, congress increased the representation of private interests in local advisory boards so that training programs would be directed towards the needs of local markets. In a rebuke of CETA, JTPA ended the public sector employment program which had, "[become] a target for national media criticism when careless management of funds and enrollment of program ineligibles were widely reported" O'Leary, Straits, and Wandner (2004). Additionally, JTPA contained provisions requiring that training programs undergo evaluations in order to determine their efficacy, and authorized many evaluation studies that included random assignment of individuals to both training and control groups.

3 Opportunities for Reassessment

As I have shown, the federal government has long provided various programs charged with helping the unemployed and disadvantaged find reemployment. Much of prior program evaluation literature used data from CETA and JTPA training programs. But training in the US is no longer governed by these programs. Might new policies support new findings? Recent training regimes have become much more demand driven by directing training towards the needs of the local labor market and person centered by allowing job seekers to determine the type and direction of their training. Could these changes have altered the effectiveness of job training?

In 1998 congress passed the Workforce Investment Act (WIA) which still provides for public training programs in the United States. The 1998 WIA introduced many innovations that might call previous results into question. First, the new "customer focused" methods of service delivery, especially in relation to training, might mean that training today is more effective than in the past. In the past, training programs were one-size-fits-all. Now participants have the opportunity to complete their training with any number of approved providers. Additionally, the WIA gave states even more control over their workforce development activities when it replaced the local advisory councils with Workforce Investment Boards. The JTPA had required that some local advisory board members came from business, but the Workforce Investment Board (WIB) requirements required that the majority of board members, including board chairs, represent business. By changing the composition of the WIBs congress hoped that states would be able to focus on the programs that were most needed, and thereby increase their impact.

For these reasons it is time to re-evaluate the findings of the past. Is job training more effective today? Has the movement away from public employment and on-the-job training towards occupational skills training benefited job seekers? Answering these questions without the proper data is difficult, and as a result are opportunities for new insights in this area if the proper data are available. Fortunately, the data used here allow me to answer these questions. I expand upon previous research by investigating whether or not the structural changes introduced by the WIA have altered the effectiveness of public training programs relative to the past. I begin with an overview of the institutional frameworks put in place by the 1998 WIA and the types of training available to the unemployed. I close this section with discussion specific to South Dakota and how the administrative data used here are gathered.

3.1 The Local Office System for Employment Services

The Purpose and Organizational Structure of the Local Office System

The WIA governs the provision and administration of most employment programs in the US. Funds are apportioned to the states by the federal government in the form of block grants. States are given much latitude in how these funds are allocated, but the WIA requires that states have certain structures in place to direct how funds are spent[1]. State Workforce Investment Boards that are then responsible for setting labor force development priorities and allocating block grant funds[2]. In addition to forming workforce investment boards, the WIA requires states to maintain and staff at least one physical location where citizens may go to in order access employment services. These office are typically referred to as "One-Stop Career Centers" or simply "One-Stop Centers". In South Dakota these locations are known simply as "Local Offices" and I adopt this naming convention as well going forward[3]. South Dakota, like most states, has a network of Local Offices throughout the state which I refer to broadly as the Local Office System (LOS) or the South Dakota Local Office System (SDLOS). The State of South Dakota staffs eighteen regional LOS locations throughout the state. See Appendix A for full list of these offices and their locations. Local office activities are coordinated and managed from the state capital in Pierre. The LOS is responsible for implementing the development plans of the WIB and for providing additional services as mandated by the Governor and/or state Legislature. The services offered in furtherance of these goals are broadly categorized as either Core, Intensive, or Training. While there may be some policy heterogeneity across the states, the contours of these categories are stipulated by WIA legislation and so the following discussion can be considered generally applicable.

Core Services

Core services are the most basic services offered and are intended simply to provide information regarding local labor market conditions and employment opportunities. Core services are somewhat unique in that the LOS simultaneously serves both job seekers and job creators. In its service to job seekers, the LOS provides information about employment opportunities in order to facilitate job search. Regional offices maintain databases of job openings in the area. Both regional and statewide databases of job openings are accessible at both physical locations and the internet. As part of is core service local offices provide computer access so that job seekers might search job postings or use various software programs in order to prepare resumes or fill out applications. As part of its service to industry the LOS also collects data on economic conditions and labor force characteristics. While such information is typically made to the public at large, the intent is to provide business interests with information so that they can effectively plan for the future. Most core services may be accessed via the internet so that neither individuals nor businesses need ever physically visit a local office.

Intensive Services

The next level of services provided by LOS staff are called Intensive Services. The WIA emphasizes self-help first, and staff do not extend intensive or training services immediately, rather, LOS staff encourage job seekers to take advantage of core services first. Eligibility for intensive and training services generally requires that persons to be at least eighteen years old[4]. Once staff authorize intensive services job seeker will have access to many one-on-one services such as: interview coaching, skills assessments, career counseling, and career planning.

Training Services

Training is the highest level of service authorized under the WIA, and LOS staff only extend access and funding for training programs after several one-on-one meetings with individuals. In each case LOS staff work with the job seeker to develop a career plan and decide if and what type of training might prove beneficial. Once training is authorized, LOS choose the type of training to best suit the individual job seekers career plan.

The WIA provides for two types of training. The first is On-the-Job Training (OJT). Workers who receive OJT are placed with a firm for a trial period stipulated in an employment contract between the firm and the State. Employment contracts may authorize up 1040 hours of OJT employment, but the typical contract is for 480 hours. Upon completion of the contract the State reimburses the firm for up to fifty percent of the employee's wages paid out during the contracted period. At that time the firm has the option to keep the worker as a normal employee should both the business and the trainee desire. Workers develops both occupation and firm specific human capital while working, and these skill hopefully serve them in the future. At the same time the firm gets a chance to evaluate the employee and determine if they would be a good match.

The second type of training available to workers is Occupational Skills Training (OST). With OST workers develop general human capital directed towards specific occupations. Such skills are acquired by attending training seminars, certification programs, or enrolling in either a community college or technical school. The State WIBs certify various providers across the state and individuals are allowed to choose the provider that suits them. OST pays for a portion of tuition costs for the certification or degree program pursued by the trainee. WIA guidelines require that the certification or degree must be completable within four semesters. The WIA OST program focuses on developing specific skill that will facilitate employment. As a result, funding is primarily directed towards programs at technical schools and community colleges. As a general rule, OST will not fund a bachelor's degree.

3.2 The South Dakota Local Office System

The data used in this paper were collected in accordance with the 1998 Workforce Investment Act by the SDLOS on behalf of the South Dakota Department of Labor and Regulation (SDDLR). The data report on all persons who registered with and exited from the SDLOS between January 2002 and December 2012. In order for persons to access various employment services they must register either at a physical LOS location or via the SDDLR website. If registering via the SDDLR website, individuals create a personal account by filling out an online form. If the first contact occurs at a local office, the customer is asked to either use one of the provided computers to register or will be given a paper form. In either case, upon registration a personal profile is created that will follow the registrant until he or she is removed from monitoring. Registrants supply information regarding their employment status, place of residence, age, race, educational attainment, criminal background, and any welfare benefits he or she receive. Staff at local offices then verify and match the provided information with other records from various state agencies. This individual profile assists LOS personnel and the registrant in his or her job search efforts.

Core services are available to all persons either via the internet or local branches. Intensive and training services require one-on-one meetings between staff and job seekers. Once training has been authorized workers at local centers record what occupation the worker is training for. In the case of OJT the workers in the local center record the Standard Occupational Classification (SOC) code for the occupation that a worker is placed in. In the case of OST the staff in the local centers record the SOC code identifying the desired occupation being trained for. After completing training and finding employment LOS staff record whether or not the trainee found employment in a related occupation. For example, suppose someone in OST enrolls in a technical school for the purposes of becoming a radiation technician. Upon completing the program and exiting the system a LOS employee sees that the worker found employment as a registered nurse. In this case even though the worker did not find a job as a radiation technician he or she would be considered to have found employment in a related occupation.

Job seekers are removed from the system once ninety days have passed without the registrant making contact with the LOS – contact in this sense means visiting a physical location, using online services, or speaking with LOS personnel via phone or email. LOS staff maintain contact with trainees while training programs are ongoing ensuring that trainees are not exited for lack of contact. Once ninety days have elapsed, the individual is removed from active monitoring. The individual's exit date is then backdated to the date of last service. Once exited, persons must re-register and create a new profile if they wish to once again access employment services.

4 Exploring the Administrative Sample

The individual data profiles introduced in the prior section are the source of the sample data used in this study. Previous studies have used somewhat similar data, but these studies reported on training programs prior to the WIA and did not contain such rich conditioning variables. As I have discussed earlier, the 1998 WIA introduced several innovations that might make earlier conclusions no longer applicable. The data used here are the first of their kind to analyze employment outcomes of individuals trained in accordance with updated WIA guidelines. As a result, I offer new insights into how the changes in administrative priorities have altered the effectiveness of training

Included in the estimation sample are unemployed persons who registered with the SDLOS between the years of 2002 and 2011 and were aged between twenty and sixty-five at registration. Additionally, I restrict the estimation sample based on geography and educational attainment. The geographic restriction ensures that the sample includes only persons who lived in either South Dakota or in a contiguous border county in Nebraska or Iowa. These border counties are near to the Sioux City MSA which lies at the nexus of South Dakota, Nebraska, and Iowa. Appendix B contains a full list of all South Dakota, Iowa, and Nebraska counties for which data are present[5]. The education restriction excludes persons with educational attainment in excess of a Bachelor's degree. I exclude persons with more than a Bachelor's degree for two reasons. First, such highly educated persons are not part of the target population for WIA training programs. The universal access provisions in WIA legislation do not prohibit such persons from enrolling in training programs, but state WIB funding priorities ensure that persons with lower levels of education are the primary targets for training. Secondly, persons with high income and high educational attainment do not seem to rely on the SDLOS for help in finding employment. I discuss this further in the following section, but the education exclusion restriction provides casual evidence of SDLOS avoidance. After applying the age and geographic exclusion restrictions, only seventy-three persons with a Master's degree and no persons with a Ph.D. appear in the data.

4.1 Characteristics of Job Seekers

One of the strengths of the data employed here is the breadth of information provided on individuals. Contained in the sample are records on $6,322$ unique episodes on joblessness occurring between 2002 and 2011. The data report on racial makeup, family structure, educational attainment, receipt of welfare benefits, and episodes of job training[6]. In addition to simply reporting on whether an individual enrolls in training, the data report on what occupations a person trained for and whether training led to employment in a related occupation. Finally, the data also provide quarterly labor earnings both prior to registration and after exit from LOS monitoring.

Table 1 provides an overview of the individuals who make the sample population. The sample is overwhelmingly white at nearly eighty-five percent. Slightly less than ten percent of the sample is Native American. The remaining group, termed Neither White nor Native American, aggregates several smaller racial and ethnic groups: blacks, Hispanics, Asians, and Pacific Islanders in order of decreasing prevalence. None of these smaller ethnic or racial groups make more than three percent of the sample. The racial makeup of the sample is largely in-line with the State's overall demographics. For example, five year estimates from the American Community Survey between 2008 and 2012 indicate that the overall South Dakota population was 85.9% white, 8.8% Native American, and the remaining 5.3% were from various racial groups, predominantly Hispanic[7].

Of special interest will be how training serves minority populations. In the first part of 2014 the United States Department of Labor (USDOL) announced that it was making fifty

Table 1: Descriptive Statistics: Individual Characteristics [1]

	Mean	Std. Dev.	Count
Individual Characteristics			
Age at Entry	38.698	(11.178)	
Age at Exit	39.699	(11.171)	
Native American	0.098	(0.297)	618
Neither White nor Native American	0.055	(0.228)	348
White	0.847	(0.360)	5356
Male	0.454	(0.498)	2870
Single Parent	0.233	(0.423)	1475
Offender	0.144	(0.351)	909
Veteran	0.072	(0.258)	455
Educational Attainment			
Less than High School	0.111	(0.314)	703
High School Grad	0.566	(0.496)	3579
GED or Equivalent	0.142	(0.349)	897
Associate or License	0.110	(0.313)	698
Bachelor Degree	0.070	(0.254)	440
Literacy Deficiency	0.356	(0.479)	2252
Welfare Related			
Low Income	0.581	(0.493)	3676
Tempory Assistance for Needy Families	0.039	(0.193)	246
Trade Adjustment Assistance	0.077	(0.266)	485
Supplemental Nutritional Assistance	0.205	(0.404)	1294
Observations	6322		

[1] With the exception of age, all variables are categorical.

eight million dollars of additional WIA grant funding available to the states. The grant money was specifically earmarked for training programs targeted at Native Americans. Kuruvilla (2014), in a USDOL press release, quotes US Secretary of Secretary of Labor Thomas E. Perez as having said,

> Increasing access to job-driven education and training opportunities will help more Indians and Native Americans find their path to the middle class.

Clearly worker training is seen as an important tool in the effort to support employment of minorities in general and Native Americans specifically. Preliminary results discussed in a separate paper indicate that training disproportionately benefits Native Americans both in terms of increased employment rates and earnings. These results are not discussed here.

The data also provide insight into individuals' household composition, criminal background, and veteran status. Table 1 reports that 23.3% percent of sample persons are single parents. The data do not separately report on either marital status or the number of children. Traditionally single parents, and especially single mothers, have been afforded targeted status by state and federal employment programs. As such, single parents are often eligible for additional welfare benefits and training services. Under WIA rules and SD WIB guidelines, funding for training services is not specifically earmarked for single parents, but, all else equal, single parents are prioritized when authorizing funds.

The SDLOS also prioritizes services for persons with criminal backgrounds, and Table 1 shows that 14.4 percent of sample sample persons reported having criminal records[8]. OJT employment contracts typically provide for fifty percent wage reimbursement, and only pay out if the employee remains employed for the duration of the contract. This is not the case, however, for OJT workers with a criminal record. The State reimburses one hundred percent of wages paid to OJT workers with criminal histories regardless of whether employment lasts for the duration of the employment contract.

Looking to the educational attainment statistics, it is clear that the population of workers who use SDDLR employment services for job search are less educated. The majority of the sample, nearly fifty-seven percent, have a high school diploma as their highest level of educational attainment. Combining the High School Diploma and GED or Equivalent categories accounts for 70.8 percent of all sample persons. In fact, eighty-two percent of the sample have not earned any form of post-secondary degree. Only seven percent of the sample sample persons have a bachelor's degree and only eleven percent have an Associate's degree or some form of occupational License. Finally, thirty-five percent of the sample are identified as having a literacy deficiency. This sample statistic might under estimate the degree of literacy deficiency, however, because not all persons are tested for literacy competency. Persons who avail themselves of intensive and training services are much more likely to be given these test, but persons who only use core SDLOS services will not be tested. As a result, I present this sample statistic only as evidence of low educational attainment in the sample population which I discuss further in subsequent paragraphs. I do not use this variable in my econometric modeling later on[9].

These sample statistics are greatly misaligned with the South Dakota population as a whole. According to American Community Survey data, the general South Dakota population is slightly more educated than the nation on average. A greater portion of South

Dakotans graduate high school, or achieve a similar certification, than the national average, 31.9 vs. 28.2 percent. More South Dakotans earn Associate's or bachelor's degrees, 28.2 vs. 25.6 percent. In fact, the only category in which South Dakota falls below the national average is in graduate or professional degrees, 7.8 vs. 10.6 percent[10]. This downward deviation in educational attainment is evidence that the type of job search varies with education, at least in South Dakota and surrounding areas. Recall, all job seekers who access the state's employment services are present in the data. The administrative data are not based on survey results designed to oversample any given subpopulation. The composition of the data is purely a result of self-selection in the methods of their job search. More highly educated workers are not relying on the services provided by the state to facilitate job search. These workers are evidently using other methods or services when searching for employment opportunities. This sample population is therefore ideal for identifying the impacts of training on reemployment.

The welfare section of Table 1 provides further evidence that the SDLOS serves a unique population. Local office personnel designated almost sixty percent of the sample as low income according to either the Lower Living Standard Income Level (LLSIL) or the federal poverty line[11]. Additionally, slightly more than twenty percent of the sample receive Supplemental Nutritional Assistance, or food stamps. This is further evidence that the population of workers served by the SDLOS is largely poor and less educated. The data also tell use about cash transfer programs such as Temporary Assistance for Needy Families (TANF) and Trade Adjustment Assistance (TAA)[12]. In the SDLOS sample nearly four percent receive TANF benefits and nearly eight percent receive TAA benefits.

4.2 WIA Training Programs

I turn now to a discussion of the training programs, the central concern of this paper. Table 2 provides a detailed breakdown of training episodes by both the type of training and the occupation category training was directed towards. The data show that during the sample years $2,607$ persons participated in some form of occupational training. There is a clear disparity across training types. Only three hundred and forty-four workers undertook on-the-job training over the ten sample years. On the other hand, $2,263$ persons participated in an occupational skills training program. As a result, OST made up 86.8 percent of all training episodes. Several reasons might account for this disparity. First, on-the-job training requires a coincidence of wants where both an individual is searching for employment and a firm is searching for an employee. Secondly, a company must be willing to enter into an employment contract with the State in order for the OJT placement to occur. While the State will reimburse a firm for a percentage of the wages paid during the training period, the business incurs non-wage costs for providing OJT. Coordination with LOS staff and compliance to WIA rules is not costless. The firm might also believe that better job candidates could be found via other means. Lastly, state employees may be weary of promoting OJT. The public may see OJT as a subsidy to private business and not a job training program. Therefore OJT might be seen as a liability for political stakeholders especially given the additional incentives in place for hiring OJT workers with criminal records. For these reasons one should not be surprised by the large disparity between the two types of training.

Table 2 also breaks down the aggregate training episodes into eleven different major occupation categories based on SOC designations. The data indicate that there is not only a disparity between OST and OJT in the number of training occurrences, but the two different types of training are directed towards different occupation groups. Four major occupation groups accounted for sixty-one percent of all OST services: Office and Administrative Support, Transportation and Material Moving, Healthcare Support, and Healthcare Practitioners and Technical. The picture is slightly different with OJT where the top four major occupation groups: Production,Office and Administrative Support, Installation Maintenance and Repair, and Construction and Extraction, accounted for seventy-two percent of all OJT training. Office and Administrative Support was the only overlap across the two types of training. It was the most popular occupation category for OST training, 23.9 percent, and the second most popular for OJT training, 16.6 percent.

There are some clear patterns that emerge when looking at Table 2. OST is clearly directed towards occupations that require higher levels of education. For example, training directed towards employment in Healthcare is overwhelmingly based on occupational skills training. This is also seen in training for careers in Sciences, Computer and Mathematical

Table 2: Descriptive Statistics: Major Occupation Groups

	OST		OJT	
	Mean	Count	Mean	Count
Management	0.072	162	0.029	10
Business and Financial Operations	0.027	61	0.009	3
Sciences, Computer, and Mathematical [1]	0.051	116	0.015	5
Architecture and Engineering	0.027	62	0.032	11
Community and Social Service	0.006	14	0.003	1
Legal	0.004	10	0.006	2
Education, Training, and Library	0.015	34	0.003	1
Arts, Design, Entertainment, Sports, and Media	0.006	14	0.006	2
Healthcare Practitioners and Technical	0.106	240	0.003	1
Healthcare Support	0.119	270	0.041	14
Protective Service	0.008	17	0.006	2
Service: Food or Personal Care [2]	0.004	8	0.015	5
Building and Grounds Cleaning and Maintenance	0.003	6	0.015	5
Sales and Related	0.008	19	0.047	16
Office and Administrative Support	0.239	540	0.166	57
Construction and Extraction	0.032	72	0.113	39
Installation, Maintenance, and Repair	0.024	55	0.116	40
Production	0.092	209	0.326	112
Transportation and Material Moving	0.156	354	0.052	18
Total for Training Type		2263		344
Training Related Employment after one Quarter	0.495	1121	0.782	269
Received Training		2607		2607
Did not Receive Training		3715		3715
Observations		6395		6395

[1] Combines occupation categories: Computer and Mathematical with Life, Physical, and Social Sciences

[2] Combines occupation categories: Food Preparation and Service with Personal Care Services

occupations. It is unclear at this time what is driving the large OST enrollment for occupations in Transportation and Material Moving. Similarly, the data show that OJT is directed towards occupations that do not necessarily require high levels of formal education – e.g. Production, Office and Administrative Support.

Immediately one must consider whether the concentration of training in specific occupations is what might drive the employment effects of training. I do find large and significant employment effects resulting from training which I discuss in Section 8. But could it be that these results are not driven by participation in a training program, but rather by the occupation towards which training is directed? This is an important question to answer from a policy perspective. If the benefits of training accrue only to those who train in a specific occupation, then should policy makers stop funding training for other occupations? Wouldn't this leave some workers out in the cold if their backgrounds prevented them from finding employment in the targeted occupations. Moreover, does this mean that training programs must be tailored so as to service the unique labor markets peculiar to each state? Each city? This would inevitably lead to bureaucratic log jams as state WIBs attempt to set priorities for numerous localities. It would be much better if training benefits all participants regardless of the direction of their training. If the benefits flow from program participation rather than the exact type of program, then all persons stand to benefit from participation. In Section 9.3 I perform just such a robustness check by establishing whether it is the occupation towards which training is directed or simply the participation in a training program that is driving the observed employment effects. Luckily for states and potential participants, I find that the latter seems to be driving the results in this case.

4.3 Regional Considerations in the Data

Finally, Table 3 provides insights into the regional characteristics and time trends within the data. As previously stated, the local office data reports on registrants from all South Dakota counties as well as many persons in many other states across the country. The geographic exclusion restrictions limits the sample to persons in South Dakota and from four counties in Iowa and four counties in Nebraska. Appendix B provides a list of counties included in this study and which geographic regions they are located in. Iowa and Nebraska residents total three hundred ninety-six persons within the overall sample, 6.2 percent. The majority of these non-residents, roughly 75 percent, resided in the Iowa county of Woodbury which is part of the Sioux City MSA. In Table 3 I also show the number of persons living in reservation counties. Reservations do not conform neatly to county boundaries, and are found in all three larger geographic regions. For illustrative purposes, however, I identify a county as a reservation county if the majority of the land area in the county is located on reservation land. Less then twenty percent of Native Americans in the sample reside in reservation counties. Therefore, when applying regional controls in my econometric modeling I do not separate reservation counties from the larger regional categories of east, central, or west.

Table 3: Descriptive Statistics: Regional Characteristics

	Mean	Std. Dev.	Count
Unemployment Rate[1]	3.934	(1.148)	
Region of Residence			
East	0.449	(0.497)	2840
Central	0.042	(0.201)	267
West	0.042	(0.201)	268
Sioux Falls	0.245	(0.430)	1547
Rapid City	0.140	(0.347)	887
Reservation	0.017	(0.129)	107
Iowa	0.054	(0.227)	343
Nebraska	0.010	(0.099)	63
Year of Registration			
2002	0.045	(0.207)	283
2003	0.176	(0.380)	1110
2004	0.109	(0.312)	690
2005	0.068	(0.252)	432
2006	0.092	(0.289)	583
2007	0.103	(0.304)	652
2008	0.095	(0.293)	601
2009	0.210	(0.407)	1325
2010	0.059	(0.237)	376
2011	0.043	(0.202)	270
Observations	6322		

[1] Unemployment rate is specific to county and year of exit

South Dakota is the 17th largest state in the United States in terms of land area, but ranks 46th in terms of population. The state is predominantly rural and is home to only three designated metropolitan areas: the Sioux City MSA in the southeast, the Sioux Falls MSA in the east, and the Rapid City MSA in the west. South Dakota is roughly three hundred eighty miles across from east to west, and nearly three hundred and twenty five miles separate Sioux Falls and Rapid City. The state splits itself into three regions, east, central, and west. These regional divisions are largely based on differences in population and economic activity. Farming is the dominant industry in the eastern region, but economic activity in this region is surprisingly diverse. Sioux Falls is home to large and quickly growing Healthcare and Finance industries. South Dakota's two main state universities are also located in the eastern region. As one moves west the population and economic activity falls rapidly. The state capital Pierre is the largest population center in the central region and boasts a population of roughly thirteen thousand. Tourism and ranching are some of the largest economic drivers in the central region. The western region of South Dakota is also very sparsely populated outside Rapid City and surrounding areas. Tourism is by far the most important economic driver in the western region as it is home to several national parks and monuments such as Mount Rushmore.

The vast majority of the South Dakota population lives in the eastern region and this holds true in the LOS sample as well. Nearly seventy percent of sample persons resided in either the eastern region or in the Sioux Falls MSA. Fourteen percent of the sample reside in the Rapid City MSA. The remaining 16.6 percent live in one of the remaining South Dakota regions or else in one of the Nebraska or Iowa counties. Western and Central South Dakota are very sparsely populated and this is reflected in the data. As detailed in Appendix B, there are sixteen counties in Central SD and ten counties in Western SD regions, but more sample persons reside in four Iowa counties than in either of these regions.

The average unemployment rate in the South Dakota sample was 3.9 percent. This is not the statewide average unemployment rate but rather the weighted average of county specific unemployment rates. The statewide and regional averages for each sample year can be found in Appendix B. South Dakota continually has one of the lowest unemployment rates in the nation. Table 12 in Appendix B shows that over the sample period the unemployment ranged from a statewide low of 2.9 percent in 2007 to a statewide high of 5.2 in 2009. This low average unemployment rate masks some regional variations, however. Unemployment in reservation counties is consistently above the state average by several percentage points. In 2011 unemployment in reservation counties averaged 8.94 percent, the highest average regional rate during the 2002-11 period.

The number of persons entering the administrative sample set is relatively stable over time. The fewest registrants occurred in 2003 while the greatest number occurred in 2004. The small number of registrants in 2003 is partly due to changes in the way that the state administered its WIA program relative to prior years. In fact 2003 is the first year that data were aggregated into a centralized database. The following year the Gateway computer company closed a large manufacturing plant in North Sioux City and closed a technical support branch in Sioux Falls. This singular incidence was primarily responsible for the large spike in enrollment in 2003.

5 Introductory Remarks Regarding Program Evaluation

Both economists and policy makers have long been interested in program evaluation. Will participation in a job training program increase employment rates and earnings? Will attending a financial literacy seminar improve participants' credit rating? Does union membership increase wages? These are all examples of situations where the policy maker or researcher is interested in quantifying how participation influences individual outcomes. For training programs in particular the social value of the program is directly related to the degree in which participation increases positive outcomes. If job training programs do not result in higher employment rates and earnings, what benefit does society gain from the public provision of these programs?

Program evaluation can prove problematic though. For ethical and/or political reasons it is often not feasible for such programs to take place in laboratory like conditions. The modern economy is exceedingly complex and it is impossible to control all of the factors that might influence individuals' outcomes. Moreover, the hallmark of rigorous program, or treatment, evaluation is randomization of treatment, but this is often not possible in social experiments. Randomized assignment to either a treatment or control group implies that assignment is uncorrelated with potential outcomes. But in the case of a job training program, for example, administrators might select individuals for treatment exactly because they believe the training will prove beneficial. If only the most able are given training how can the treatment effect be disentangled from the effect of unobserved ability? Additionally, the data available to economists are often decidedly non-experimental.

Lalonde (1986) demonstrated the difficulties and pitfalls of using standard econometric techniques to evaluate program outcomes especially in the face of non-experimental data. In this important work, LaLonde compared estimates of treatment effects of a job training program where individuals were randomly assigned to either treatment or control groups. He found that econometric estimation of the programs effectiveness did not coincide with non-parametric difference in means estimator. This work has long served as a cautionary tale for researchers wishing to establish the efficacy of job training programs using non-experimental data.

In response to Lalonde's critique, economists and others have developed new parametric and semi-parametric methods that allow for unbiased program evaluation even in the face of non-experimental data. Such efforts began with Rosenbaum and Rubin (1983) even before Lalonde's seminal article was published. Many additional authors through out the years have worked to further the state of the art in this area. Imbens and Angrist (1994) and Angrist, Imbens, and Rubin (1996) are two examples of such works. Heckman, Lalonde, and Smith (1999) provides an excellent, and thorough, survey of this literature and discusses how newer techniques stand up to the Lalonde critique. However, the authors are quick to note that,

> [t]he best solution to the evaluation problem lies in improving the quality of the data on which evaluations are conducted and not in the development of formal econometric methods to circumvent inadequate data. (Heckman, Lalonde, and Smith, 1999)

The administrative data used here are just such data. The data do not come from surveys and are not subject to recall bias. Additionally, all variables, with the exception of post treatment outcomes of interest, employment status and earnings, are measured prior to treatment. This is crucial for proper identification of treatment effects (Cameron and Trivedi, 2005; Heckman, Lalonde, and Smith, 1999; Jacobson, Lalonde, and Sullivan, 2005).

In the next sections I establish how WIA job training programs influence post training employment rates. I begin by discussing the estimation framework and the necessary assumptions for identification of the training treatment effect. I then describe my estimation methodology and results. Finally I discuss my conclusions and the possible policy implications of my results.

6 Quantifying the Treatment Effect of Program Participation

6.1 Defining the Problem and the Treatment Effect

I estimate the influence of worker training on employment outcomes at two points in time. First I look at employment in the first quarter following an individual's exit from the local office system, and secondly at employment in the third quarter following exit. Jacobson, Lalonde, and Sullivan (2005) found evidence that training such as OST leads to only modest benefits for participants and that these rewards typically take years to appear. This study shows that significant short term dynamics exist as well. Following the notation of Heckman, Lalonde, and Smith (1999) and Cameron and Trivedi (2005) I define the treatment indicator for individual i as $D_i = j$, for $j = 0, 1, 2$ and $i = 1 \ldots n$. The possible treatment states are $j = 0$ for the control group which does not receive training, $j = 1$ indicates OST, and $j = 2$ indicates OJT. Further, I define the binary outcome variable y_{ij} where $y_{ij} = 1$ if individual i with treatment status j is employed and zero otherwise. Of course individuals cannot exist in multiple states. Individuals cannot be in both the control and one of the treated groups at the same time. Likewise, a persons cannot receive both OST and OJT. This is similar to the issue of missing data because y_j and y_{-j} cannot be observed at the same time and therefore the quantity of interest, the change in the likelihood of employment, $E(\Delta_{j0}) = E(y_j - y_0)$ is not explicitly identified within the data.

Analysis is still possible, however, even though the effect of interest is unknown. The potential-outcome model developed by Rubin (1974) using counterfactuals provides a framework that allows for identification. Proceeding *as if* individuals could exist in multiples states, there are two measure of program evaluation that are common in the literature. The first, called the Average Treatment Effect (ATE) is the expected benefit arising from training that would accrue to a random individual in the population. The ATE is defined as

$$E(\Delta_{j0}) = E(y_j - y_0) \quad j = 1, 2. \tag{1}$$

Note in Equation (1) that the benefit is not conditional upon selection for training. This has led some to consider it a poor estimator of program effectiveness because it does not provide an estimate of how treatment benefited the treated individuals. It is however the quantity of interest to policy makers who wish to know how participation would benefit any individual unemployed worker.

The Average Treatment Effect on the Treated (ATET), shown below in Equation (2),

$$E(\Delta_{j0}) = E(y_j - y_0 | D = j) \quad j = 1, 2 \tag{2}$$

does condition upon treatment and represents the change in the outcome variable as a result of treatment for those who participated. Cameron and Trivedi (2005); Greene (2012) and Heckman, Lalonde, and Smith (1999) caution however that the ATET is a partial equilibrium estimate and should not be used as an assessment tool if the treatment program is large enough to have have significant general equilibrium effects. This is likely not a problem in the case of the program studied here, but, as previously stated, the ATET is not the policy relevant result.

6.2 Identification Assumptions

Rubin's causal model provides the framework for estimating the ATE and ATET as presented in Equations (1) and (2). These effects are easily estimated by using the difference in sample means in experimental situations where assignment is randomized. Randomization of treatment ensures that outcomes are independent of selection such that

$$y_0, y_1, y_2 \perp\!\!\!\perp D.$$

But, as touched on earlier, most economic treatments are observational rather than experimental. When individuals choose treatment the possibility for selection bias exists. In the case of job training programs, persons might choose training specifically because they think that it will benefit them. Additionally, program administrators might assign the most gifted and motivated persons to training. These persons might have positive labor market outcomes after training, possibly making the training seem effective, but such talented individuals might have achieved similarly without additional training. The Conditional Independence Assumption (CIA), given by Equation (3) states that, conditional upon $\boldsymbol{X}$, outcomes are independent of treatment.

$$y_0, y_1, y_2 \perp\!\!\!\perp D \,|\boldsymbol{X} \tag{3}$$

Importantly, the vector of conditioning variables can be related to treatment but should not be a result of treatment (Cameron and Trivedi, 2005; Heckman, Lalonde, and Smith, 1999; Jacobson, Lalonde, and Sullivan, 2005). As a result, any conditioning covariates that might change with time such as: age, educational attainment, earnings, or geographic location should be measured prior to treatment[13].

The second important assumption for identification of treatment effects is known as the Overlap Assumption. The overlap assumption shown in Equation (4) requires that no persons can either be excluded from or guaranteed treatment.

$$0 < P(D = j|\boldsymbol{x}) < 1 \tag{4}$$

More specifically, the overlap assumption requires that all sample persons have a positive probability of assignment to each treatment state. In this case, all persons must have a positive probability of being in either the control, OST, or OJT groups. The universal access requirements of WIA legislation stipulates that all persons eighteen and older can receive training, subject to the availability of funds. But the reality in practice might be different there. In the current context there is a possibility that both the conditional independence and the overlap assumptions are violated. In Section 9 I present the results of several sensitivity tests which establish the validity of these necessary assumptions.

7 Estimation Methodology

There is a large literature surrounding the estimation of treatment effects when treatment is binary. Binary treatment describes situations where treatment is either administered or not. An example from the field of medicine would be a drug trial where some participants are given an experimental drug and others do not. The treatment group is the cohort to whom the drug is administered while the control group contains the persons who did not receive the drug. Another example of binary treatment might be where persons may enroll and participate in a financial literacy course. Researches might then wish to study how the the savings decisions of treatment group differ from those of the control group. Heckman and Robb (1985); Heckman, Lalonde, and Smith (1999) and Imbens (2000) discuss numerous ways in which researchers might estimate the effectiveness of binary treatment even when the underlying data are non-experimental. A recent review of this literature can be found in Imbens and Wooldridge (2009).

The current analysis however does not concern itself with a binary worker training program. Unlike previous studies I estimate the treatment effects of two different training programs, and therefore must use techniques suitable for multivalued treatment. Cases of multivalued treatment occur when participants might find themselves in one of many possible treatment states. For example, in modern drug trials a participant might be administered: no treatment, a placebo, or the actual drug. Of interest in this case would then be the relative differences in observed outcomes between the three different cohorts. The worker training programs studied here are similar because persons might not participate at all or could enroll in either OJT or OST. Non-experimental methods for identifying the treatment effects of multivalued treatments are less developed, but Imbens (2000) demonstrates that the Rubin causal framework remains valid in situations of multivalued treatment.

I estimate the treatment effects of the OST and OJT programs using the "doubly-robust" Efficient Influence Function (EIF) method developed by Cattaneo (2010). Initially developed by Robins and Rotnitzky (1995) and Robins, Rotnitzky, and Zhoa (1995), doubly-robust estimators, of which there are several, are examples of multi-stage estimators that allow the researcher to control for potential biases including self-selection bias which is the primary cause for concern in non-experimental program evaluation. Doubly-robust treatment effect estimators typically require the researcher to specify estimation equations for both the selection into treatment and the outcome of interest before finally estimating the treatment effect of interest. The benefit of such doubly-robust methods is that they allow for consistent and efficient estimation of both the ATE and ATET as long as either the selection or outcome models are correctly specified (Kang and Schafer, 2007).

In this paper I estimate the ATE of training on observed employment outcomes according to Equation (1). I use the Cattaneo (2010) EIF method which defines a multistage flexible parametric procedure to estimate the mean employment rate for each of the control, OST, and OJT cohorts. In the first stage I specify the treatment equation and estimate the likelihood an individual exists in each of the possible treatment states. Following Imbens (2000) I refer to this individual treatment probability, $\widehat{p}_j(\boldsymbol{x_i}) = P[D = j|\boldsymbol{x}_i]$, as the Generalized Propensity Score (GPS). These generalized propensity scores are later used as inverse probability weights in the final estimation stage. The second stage yields a bias correction parameter and requires specifying the outcome equation. Hereafter I refer to the first stage as either the treatment or selection stage, and the second stage as the employment or outcome stage. Finally, I solve a series of inverse probability weighted moment conditions for the EIF estimators, $\widehat{\mu}_j$ $j = 0, 1, 2$, which are the estimated conditional mean employment rates for each treatment state. I then calculate the average treatment effect of the training programs according to Equation (1)

The EIF method identifies the mean employment rates as the solutions to the series of population moment conditions depicted in Equation (5)

$$E\left[\frac{D_i(j)(y_i - \mu_j)}{p_j(\boldsymbol{x_i})} - \frac{e_j(\boldsymbol{x_i}; \mu_j)}{p_j(\boldsymbol{x_i})}[D_i(j) - p_j(\boldsymbol{x_i})]\right] = 0 \tag{5}$$

where $D_i(j)$ for $j = 0, 1, 2$ is the treatment state indicator, $p_j(\boldsymbol{x_i}) = P(D = j|\boldsymbol{x_i})$ is the generalized propensity score, and $e_j(\boldsymbol{x_i}; \mu_j)$ is a bias correction term. For estimation, the population moment conditions are replaced with the sample moment conditions given in Equation (6)

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{D_i(j)(y_i - \widehat{\mu}_j)}{\widehat{p}_j(\boldsymbol{x_i})} - \frac{\widehat{e}_j(\boldsymbol{x_i}; \widehat{\mu}_j)}{\widehat{p}_j(\boldsymbol{x_i})}[D_i(j) - \widehat{p}_j(\boldsymbol{x_i})]\right] = 0 \tag{6}$$

which identify the EIF estimators, $\widehat{\mu}_j$ for $j = 0, 1, 2$. Before solving the sample moment conditions it is first necessary to estimate the general propensity scores, $\widehat{p}_j(\boldsymbol{x_i})$, and the correction parameter, $\widehat{e}_j(\boldsymbol{x}_i; \widehat{\mu}_j)$.

I estimate the generalized propensity scores using a multinomial logit. The dependent variable in the multinomial logit model is the individual's treatment state, D_i, such that

$$D_i = \begin{cases} 0 & \text{if individual } i \text{ receives no training.} \\ 1 & \text{if individual } i \text{ enrolls in OST.} \\ 2 & \text{if individual } i \text{ enrolls in OJT.} \end{cases} \tag{7}$$

I approximate the unknown population function $p_j(\boldsymbol{x_i}) = P(D = j|\boldsymbol{x_i})$ using various first order polynomials in $\boldsymbol{x}$ which include both interactions and quadratic terms for continuous variables. In total, I estimate ninety-four potential treatment stage multinomial regression specifications. These regression models are ranked according to Akaike Information Criterion (AIC), and I choose the model that minimizes the AIC in order to generate the propensity score weights [14]. See Appendix C for a more detailed discussion regarding how I select the proper model specification including a description of all covariates used and the final model selected to calculate the propensity scores.

First the parameter estimates for the selection, or treatment, equation are found by maximizing the likelihood function according to

$$\widehat{\boldsymbol{\beta}}_j = \arg\max_{\beta} \sum_{i=1}^{n} \sum_{j=0}^{2} D_i(j) \ln \left[\frac{\exp(\boldsymbol{x}_i \boldsymbol{\beta}_j)}{\sum_{j=0}^{2} \exp(\boldsymbol{x}_i \boldsymbol{\beta}_j)} \right], \quad j = 0, 1, 2 \tag{8}$$

with the standard normalization of $\beta_0 = 0$. Once the correct model and coefficients are estimated, I calculate the generalized propensity scores which are simply the predicted values from the multinomial logistic regression. These general propensity scores

$$\widehat{p}_j(\boldsymbol{x_i}) = P[D = j|\boldsymbol{x}_i] = \frac{\exp(\mathbf{x}_i \boldsymbol{\beta}_j)}{1 + \sum_{j=1}^{2} \exp(\mathbf{x}_i \boldsymbol{\beta}_j)}, \quad j = 0, 1, 2 \tag{9}$$

then serve as inverse probability weights in ultimate estimation of the sample moment conditions.

In the second stage I estimate the remaining bias correction parameter which Cattaneo

(2010) defines as $e_j(\boldsymbol{x};\mu_j) = E(y - \mu_j \mid \boldsymbol{x}, D = j)$. The sample equivalent is given by

$$\widehat{e}_j(\boldsymbol{x};\mu_j) = \boldsymbol{z}_e(\boldsymbol{x})'\widehat{\boldsymbol{\delta}}_j(\mu_j). \tag{10}$$

In order to estimate the correction term, $\widehat{e}_j(\boldsymbol{x};\mu_j)$, I first specify the outcome, or employment, equation, $y_i = \boldsymbol{z(x_i)\gamma}$. I again approximate the unknown population function using first order polynomials in $\boldsymbol{x}$. In order to choose the proper specification I estimate 203 models I include both interactions and quadratic terms for the continuous variables. Model performance is again compared using the AIC. The vector of covariates which minimizes the AIC defines $\boldsymbol{z}_e(\boldsymbol{x})$ which is used to estimate the bias correction parameter.

Now that the proper covariate vector is identified I estimate $\widehat{\boldsymbol{\delta}}_j(\mu_j)$ for each training state using a linear sieve according to

$$\widehat{\boldsymbol{\delta}}_j(\mu_j) = \arg\max_{\delta_j} \sum_{i=1, D_i=j}^{n} \left[y_i - \mu_j - \boldsymbol{z}_e(\boldsymbol{x})'\widehat{\boldsymbol{\delta}}_j(\mu_j) \right]^2. \tag{11}$$

This concludes the second estimation stage. Importantly, while the second stage has several sub stages, the specification of the covariate vector $\boldsymbol{z}_e(\boldsymbol{x})$ requires only the flexible parametric modeling of the outcome model.

With all parameters in the sample moment conditions in Equation (6) defined, the moment conditions are solved for the EIF estimator $\widehat{\mu}_j = E(y_i|\boldsymbol{x}_i, D = j)$ which provides a consistent and efficient estimate of the conditional mean outcome of person i in treatment state j. With estimates of the conditional means in hand it is now possible to calculate the ATE of training within the sample population as the difference in the conditional mean employment rates such that

$$ATE_{OST} = E(y_1 - y_0|X, D = 1) = \widehat{\mu}_1 - \widehat{\mu}_0 \tag{12}$$

and

$$ATE_{OJT} = E(y_2 - y_0|X, D = 2) = \widehat{\mu}_2 - \widehat{\mu}_0. \tag{13}$$

8 The Effects of Training on Post Training Employment

I find that the employment effects of training are positive but somewhat inconsistent. I find that both types of training increase the likelihood of employment in the first and third quarters after exit, but the magnitude of the effect does not remain constant over time. Moreover, the effects of training are not equal for men and women. For men the effects of training decrease with time, but for women the effects of training grow with time. This pattern holds for both OST and OJT. The estimated effects of OJT are sensitive to the specification of the treatment equation and varying the regressors in this stage of estimation has large impacts on the ultimate statistical significance of the estimated ATE. This sensitivity could result from a violation of the underlying conditional independence or overlap assumptions, and in Section 9 discuss tests of these assumptions.

Table 4 contains the primary results regarding employment in the first quarter after exit from the local office system. The table shows both the estimated employment probabilities for the control, OST, and OJT groups as well as the estimated treatment effects of training. I present the results for the whole sample and also separately for men and women. The estimates of the conditional mean employment probabilities are doubly robust and control for potential selection bias. Standard errors are robust to heteroskedasticity.

My results show that the job seekers in the control group have, on average, an 80.3 percent chance of being employed during the first quarter after ending contact with the LOS. Stated otherwise, job seekers had a roughly twenty percent chance of either remaining unemployed or leaving the labor force by the end of the first quarter following exit. The mean employment rate for OST enrolled persons was 83.1 percent, and the mean employment rate for OJT participants was 88.9 percent. These employment rates remain largely unchanged when the sample is divided into males and females, but men had slightly higher employment rates than women in the OST and OJT groups but not in the control group.

The lower portion of Table 4 shows the ATE for each treatment level. As defined in Equation (1) the treatment effect of OST is the difference in the estimated conditional mean employment rates between the OST group and the control group. Likewise the

Table 4: Effect of Training on One Quarter Post Exit Employment Rates

Employment Probability	Combined		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Control	0.803	(0.006)	0.797	(0.010)	0.810	(0.009)
OST	0.830	(0.009)	0.832	(0.013)	0.825	(0.013)
OJT	0.889	(0.017)	0.911	(0.017)	0.878	(0.026)
Avg. Treatment Effects	**Combined**		**Male**		**Female**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
OST vs. Control	0.026**	(0.011)	0.035**	(0.016)	0.015	(0.016)
OJT vs. Control	0.085***	(0.019)	0.114***	(0.020)	0.068***	(0.027)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ATE of OJT is the difference in the conditional mean employment rates of the OJT and control groups. Both types of training have a positive and statistically significant affect on employment rates in the first quarter after exit. However, the effect of on-the-job training is roughly three times greater than the effect of occupational skills training. OJT increases a given individual's employment probability by 8.6 percentage points, and reduces the probability of remaining unemployed from 19.7 percent to 11.1 percent, a reduction of 44 percent. The effect of occupational skills training is also positive but noticeably smaller in absolute magnitude. OST increases the likelihood of employment by 2.7 percentage points.

Interestingly, these sample wide effects mask some heterogeneity across gender. In the first quarter following exit from LOS tracking I find that both types of training are more effective for men than they are for women. The ATE of OJT increases by more than one standard deviation from 8.6 to 11.4 percentage points. The effect for women is smaller where OJT increases the probability of employment by 6.8 percentage points. Likewise, the ATE of OST is larger for males than for females. The data show that OST has no statistically significant effect on employment for women.

From these results it seems that OJT should be the preferred training program. However, there is reason to suppose that these results should be expected and are not overly informative. First, OJT presupposes employment. Persons enrolled in an OJT program are placed with a firm at the outset of training. Therefore, one should expect high rates of employment for these persons. As a result one might expect that OJT would have a larger

Table 5: Effect of Training on Three Quarters Post Exit Employment Rates

Employment Probability	Combined		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Control	0.776	(0.007)	0.768	(0.010)	0.784	(0.009)
OST	0.803	(0.010)	0.791	(0.015)	0.817	(0.013)
OJT	0.851	(0.029)	0.828	(0.021)	0.875	(0.033)
Avg. Treatment Effects	Combined		Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
OST vs. Control	0.027**	(0.012)	0.023	(0.018)	0.032**	(0.016)
OJT vs. Control	0.074**	(0.030)	0.060***	(0.023)	0.091***	(0.034)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

impact on employment in the near term after completing training. Therefore it will be important to establish whether or not the effects of OJT persist over time. If the effects of OJT persist it might indicate quality matching between firms and trainees. On the other hand, if the effects of OJT dissipate as time passes it could be an indication of mismatch or that firms see the OJT program as a way to find low cost temporary workers. OST on the other hand does not directly lead to employment, and individuals enrolled in OST much search for employment after completing their training. In this case the effects occupational skills training might take longer to develop.

I show in Table 5 how training influences employment rates in the third quarter after exit from the SD LOS. The findings are intriguing. First, the data indicate that overall employment rates fall with time for LOS users. Table 5 shows that the mean employment rates for the control group fell to 77.6 percent, and the employment rates of OST and OJT enrollees fell to 80.3 and 85.2 percent. This could be sign of job mismatch, or that the population of workers studied here are only weekly attached to the labor force. Why employment rates fall across the board is an interesting question that demands further inquiry, but cannot wholly be answered here. Employment rates of women enrolled in a training program remained mostly unchanged but fell across the board for men.

The data indicate that the sample wide employment benefits from training attenuate with time. However, when looking at males and females separately I find that the effects of training increase with time for women while simultaneously falling for men. For men, after only three quarters the average treatment effect of OST is no longer statistically different from zero and the average treatment effect of OJT is cut in half, falling from 11.4 to 5.9 percentage points. For women the movement is in the opposite direction. The ATE of occupational skill training in the first quarter was not statistically different from zero but by the third quarter the effect is statistically significant and reduces the probability of unemployment by 3.3 percentage points. Table 5 also shows that the treatment effects of OJT increase for women, rising from 6.8 to 8.9. It appears that the benefits of training are short lived for men at least in so far that training leads to rapid reemployment. Before, attempting to draw

It remains to be seen whether the estimated increases in employment rates justify program expenditures. I address this issue in a separate paper where I estimate the ATE of training on earnings and perform a cost benefit analysis of the OST and OJT training programs.

9 Sensitivity Tests and Robustness Checks

As I discussed earlier, identification of the average treatment effect of training is only possible given the conditional independence and overlap assumptions. If these assumptions are invalid then the estimated treatment effects do not provide consistent estimates of the true impact of program participation. It is therefore critical to demonstrate that the assumptions hold in the SDLOS administrative data. Establishing that the overlap condition holds is straight forward, but there is no direct test for the conditional independence assumption because individuals cannot exist in multiple treatment states simultaneously. An indirect test of this assumption does exist, however, and I report the results of this test below.

9.1 Testing the Overlap Assumption

Defined in Equation (4), the overlap assumption requires that no person is either guaranteed or excluded from treatment. Testing this assumption is relatively straight forward and I evidence from two test of this assumption. In the first test I present summary statis-

Table 6: Overlap Test: Estimated Propensity Scores

Conditional probability of assignment to control group

	Mean	Std. Dev.	p(5)	p(50)	p(95)
$\mathrm{P}(D = 0 \,\vert\, D = 0)$	0.609	(0.200)	0.298	0.609	0.921
$\mathrm{P}(D = 0 \,\vert\, D = 1)$	0.587	(0.208)	0.263	0.587	0.911
$\mathrm{P}(D = 0 \,\vert\, D = 2)$	0.602	(0.176)	0.328	0.602	0.877

Conditional probability of assignment to OST group

	Mean	Std. Dev.	p(5)	p(50)	p(95)
$\mathrm{P}(D = 1 \,\vert\, D = 0)$	0.382	(0.203)	0.066	0.382	0.699
$\mathrm{P}(D = 1 \,\vert\, D = 1)$	0.397	(0.213)	0.065	0.397	0.729
$\mathrm{P}(D = 1 \,\vert\, D = 2)$	0.356	(0.177)	0.081	0.356	0.632

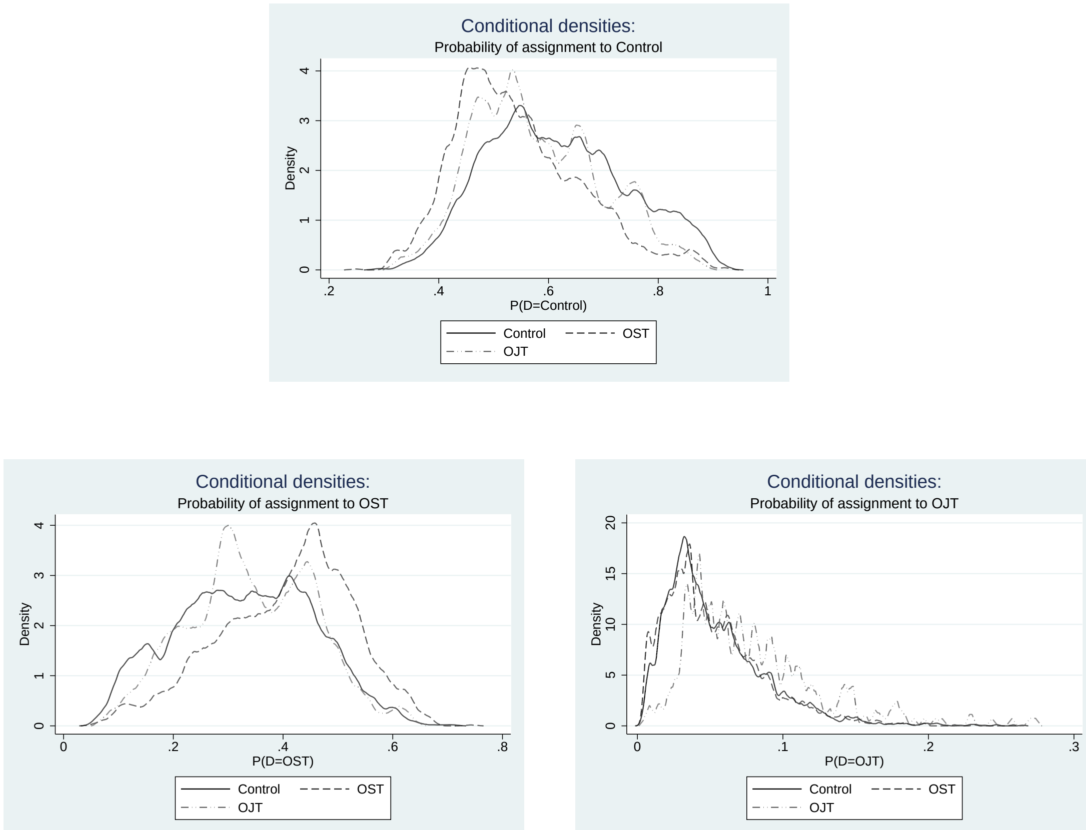
Conditional probability of assignment to OJT group

	Mean	Std. Dev.	p(5)	p(50)	p(95)
$\mathrm{P}(D = 2 \,\vert\, D = 0)$	0.133	(0.078)	0.012	0.133	0.255
$\mathrm{P}(D = 2 \,\vert\, D = 1)$	0.131	(0.076)	0.012	0.131	0.249
$\mathrm{P}(D = 2 \,\vert\, D = 2)$	0.139	(0.080)	0.015	0.139	0.264

tics relating to the estimated propensity scores. I estimate the propensity scores using a multinomial logit following Equation (9). The conditional propensity scores show the probability an individual will be assigned to treatment state j given that the person is already in state k according to $P(D_{jk}) = P(D = j|D = k) \quad \text{for } j = 0, 1, 2;\ k = 0, 1, 2$. These summary statistics are presented in Table 6. As shown in the table, the distributions of propensity scores are highly similar and there is a great deal of overlap across all treatment groups.

Figure 1 also presents the results of graphical test of the overlap assumption. I use a kernel density estimator and the raw propensity scores summarized in Table 6 to produce a smoothed density function depicting the conditional probability an individual is assigned to a given treatment state. I use the triangle kernel in all cases due to its but adjust the bandwidth across cases (Imbens and Wooldridge, 2009). When calculating the conditional propensity scores for the control and OST groups I use a bandwidth of $h = .032$. However, in the case of OJT the distribution of conditional probabilities is highly skewed and a smaller bandwidth is necessary to prevent over smoothing of the kernel density (Cattaneo, Drukker, and Holland, 2013). I therefore use a choose a bandwidth of $h = .004$

Figure 1: Overlap Test: Graphical summary of propensity scores



which prevents issues with over smoothing near the zero lower bound. The visual test again indicates a high degree of overlap between the various propensity scores. For the Control and OST groups the propensity scores are well behaved without significant mass near either zero or one. However, for the OJT group many of the propensity scores are near zero due to the small number of OJT training events in the sample. This could lead to potential issues in estimating the treatment effects using weighting methods (Busso, DiNardo, and McCrary, 2014; Cattaneo, Drukker, and Holland, 2013). As mentioned earlier the estimated OJT treatment effects are sensitive to the specification of the treatment equation. Slight changes in the specification of the treatment model will cause changes in the significance of ATE results in the combined sample, but the results in the Male and Female subsamples are more robust to changes in specification. I also estimated treatment effects using Regression Adjustment methods that do not use inverse probability weighting. Because propensity scores are not used as weights, Regression Adjustment methods are not influenced by very small propensity scores. My results from these estimations were qualitatively and quantitatively similar to the results presented in Tables 4 and 5. This leads me to believe that the low probabilities of assignment to OJT are not biasing my results and that the Overlap Assumption is satisfied by the data.

9.2 Testing the Conditional Independence Assumption

The central assumption necessary for identification of treatment effects is the conditional independence assumption given in Equation (3). As previously mentioned, there is not direct test of this assumption. Following the recommendation of Imbens (2004) and Imbens and Wooldridge (2009) I estimate the ATE of training on employment status prior to registration with the SDLOS using the same methodology describe in Section 7. The data report on labor earnings both one and two quarters prior to registration which I use to identify employment status in the relevant quarter. I present the results of these tests in Table 7.

Table 7: Effect of Training on Employment Rates Both One and Two Quarters Prior to Registration

	1 Qtr Prior		2 Qtrs Prior	
Employment Rate				
Treatment Status	Mean	Std. Dev.	Mean	Std. Dev.
Control	0.465	(0.007)	0.715	(0.007)
OST	0.442	(0.009)	0.724	(0.008)
OJT	0.494	(0.021)	0.756	(0.021)
Average Treatment Effect				
Treatment Status	ATE	Std. Dev.	ATE	Std. Dev.
OST vs Control	–0.023**	(0.010)	0.011	(0.011)
OJT vs Control	0.029	(0.022)	0.042*	(0.022)

The results of the conditional independence test accord with economic theory and also provide evidence that the conditional independence assumption is likely not violated. First, Table 7 shows that there is a small yet statistically significant, at the five percent level, relationship between OST and employment one quarter prior to registering with the LOS. This could be taken as evidence that selection and outcomes are not independent which would call the previous estimates of the ATE of training in question. On the other hand, it is well known that extended unemployment lowers the opportunity cost returning to school as opposed to continuing job search. By design the OST program promotes skill acquisition by allowing persons to community colleges or technical schools etc. As such, this small relationship found one quarter before registration is likely explained by an increased willingness to delay search and pursue schooling. Additionally, this potentially troubling result is not present when estimating the ATE of training on employment two quarters prior to registration. The results in Table 7 show that the relationship between OST and prior employment is no longer present, but in its place we now find a relationship between OJT and prior employment. This inconsistency of significant relationships between training and prior employment leads me to believe that my results are valid and not biased due to a violation of the conditional independence assumption. I do not present the results here, but additional tests estimating the ATE of training on pre-enrollment earnings produce similar results. In fact, training is found to have no predictive power for earnings in either the first or second quarter prior to enrollment. I therefore conclude that selection bias is not driving my results.

9.3 Treatment Effect of Training in Specific Occupations

While selection bias might not be driving the results, perhaps there is heterogeneity in the effects of training surrounding which occupations persons trained for. It could be that the increase in observed employment rates previously attributed to enrollment in a training program is better owed to training directed at a specific occupation category, such as healthcare. As shown in Table 2, much of the OJT training was directed at occupation groups such as Production, or Office and Administrative Staff. It is possible then that the larger observed benefit to OJT training is not due to on-the-job training per se, but rather attributable to training in these occupations. It is therefore necessary to estimate the ATE of training towards a given occupation rather than simple the ATE of a specific type of training program.

Table 8: Aggregate Occupation Training Groups[1]

	Mean	Count
No Training	0.588	3715
Management, Professional, and Related	0.118	749
Service Occupations	0.052	327
Sales and Office Occupations	0.100	632
Natural Resources, Construction, and Maintenance	0.033	206
Production, Transportation, and Material Moving	0.110	693

[1] Combines the SOC categories given in Table 2 according to BLS definitions. See Endnote [15] for details on which SOC occupation categories are included in each category.

Table 8 provides a summary of the number of training episodes in each of several aggregate occupation groups. It is not possible to estimate the treatment effects for all eleven major occupation categories presented in Table 2. However, the BLS does define several higher level occupation groups which aggregate the more narrowly defined categories presented earlier[15].These are the categories depicted in Table 8. Using the same techniques and methods given in Section 7, I estimate the average treatment effect of training towards each of the five occupation groups. If there is a large employment effect associated with certain occupation groups it could be evidence that the type of occupation trained for, as opposed to the training program, is driving the results discussed above. This does not appear to be the case, however.

Table 9 show that training towards the third, fourth, and fifth occupation groups does have a positive influence on employment in the first quarter following exit. Persons who trained towards occupations in the areas of Natural Resources, Construction, and Maintenance had a 92.6 percent probability of being employed within one quarter of exiting the South Dakota LOS. This represents an ATE of 12.1 percentage points. Training towards Production, Transportation, and Material Moving occupations also had a large, positive, and statistically significant impact on persons employment prospects. Interestingly, the estimated ATE of training towards Management, Professional, and Related occupations was negative. Little weight should be placed on this result however given both the extremely small magnitude of the effect and the lack of significance.

The effects of occupation directed training do not persist into the third quarter tough.

Table 9: Effect of Training on One Quarter Post Exit Employment Rates

Employment Probability	Mean	Std. Dev.
Control	0.805	(0.006)
Management, Professional, and Related	0.792	(0.032)
Service Occupations	0.883	(0.059)
Sales and Office Occupations	0.836	(0.017)
Natural Resources, Construction, and Maintenance	0.930	(0.042)
Production, Transportation, and Material Moving	0.874	(0.029)
Avg. Treatment Effects	**Mean**	**Std. Dev.**
Management, Professional, and Related	–0.013	(0.033)
Service Occupations	0.079	(0.059)
Sales and Office Occupations	0.031*	(0.018)
Natural Resources, Construction, and Maintenance	0.125***	(0.043)
Production, Transportation, and Material Moving	0.070**	(0.029)

In fact, my results presented in Table 10 show that the occupation towards which one trains has no significant impact on employment in the third quarter after exit from the LOS. The same general drop off in employment is again observed and training now has no noticeable effect on employment. I take this as evidence that the training programs themselves are driving the employment effects observed in the data, as opposed to the occupation towards which they are directed. Perhaps participation in training contains some signaling value two which employers respond. It is difficult to draw had conclusions at this stage of the analysis but it is clear that the training programs themselves are associated with significant and longer lived employment effects, but I find no such relationship between employment and the specific occupational training categories.

10 Conclusions and Policy Implications

In the preceding analysis I have presented new evidence regarding the effectiveness of worker training programs in the United States. Central to this effort was the South Dakota administrative data. Unlike any publicly available data, the administrative data used here provide detailed records on individual characteristics, labor market histories, and participation in training program. These data paint a rich and accurate picture of persons before, during, and after accessing freely available employment services provided by the State of South Dakota. Crucially, the data report on persons who enroll in training and

Table 10: Effect of Training on Third Quarter Post Exit Employment Rates

Employment Probability	Mean	Std. Dev.
Control	0.777	(0.007)
Management, Professional, and Related	0.788	(0.028)
Service Occupations	0.800	(0.078)
Sales and Office Occupations	0.806	(0.021)
Natural Resources, Construction, and Maintenance	0.836	(0.074)
Production, Transportation, and Material Moving	0.792	(0.036)
Avg. Treatment Effects	**Mean**	**Std. Dev.**
Management, Professional, and Related	0.011	(0.029)
Service Occupations	–0.023	(0.079)
Sales and Office Occupations	0.029	(0.022)
Natural Resources, Construction, and Maintenance	0.060	(0.075)
Production, Transportation, and Material Moving	0.015	(0.037)

persons who do not. Therefore, the data report all variables of interest for both treatment and control groups. Using this uniquely suited data I estimated the average treatment effect (ATE) of national Work Force Investment Act (WIA) training programs on post training employment rates by comparing the outcomes of persons who enrolled in training programs with the outcomes of persons who did not. The WIA provides states with funding that they may direct towards two types of training, on-the-job training (OJT) and occupational skills training (OST). This study advances the literature by estimating the treatment effects of both types of training individually. Additionally, to the author's knowledge, this paper is the first to differentiate between the effects of training programs in general and the effects of training towards a specific occupation. No publicly available data allow such a comparison. The administrative data used here are unique in this aspect.

I find that both OJT and OST increase the likelihood of employment in the period shortly after training. OJT greatly increases the likelihood of employment one quarter after training from 80.3 to 88.9 percent, an increase of 8.6 percentage points. The employment effects of OJT are nearly sixty percent larger for men than they are for women, 11.4 versus 6.8 percentage points. Additionally, the effects of OJT persist over time in the sample at large so that in the by the third quarter after exiting the LOS on-the-job training still increases average employment rates by 7.6 percentage points. Interestingly, the average treatment effect of OJT falls for men but increases for women. The ATE falls for men by fifty percent to 5.9 percentage points, whereas, in the case of women, the ATE increases by thirty percent, from 6.8 to 8.9 percentage points.

Similar dynamics, if slightly smaller effects, are found for occupational skills training. The employment boost provided by OST in the combined sample remains constant at 2.7 percentage in both the first and third quarters following exit. In both time periods the effects of OST are statistically significant but small in absolute magnitude. But again the sample average hides some dynamics regarding the effectiveness of the training programs for men and women. OST has a larger impact on male employment in the first quarter and no statistically significant impact on female employment in the same period. However, by the third quarter after exit the effects are reversed, and there is no significant effect for men but there is for women. This follows the pattern established by OJT where the effects of training attenuate with time for men but increase over time for women.

I find that the above results are not driven by selection bias. Nor are my results driven by the choice of which occupations an individual trains towards. I find that participation in a training program provides benefits to trainees beyond those associated with training for a specific occupation. So what conclusions can be drawn from these results and what are the potential policy implications for going forward? First, I must reinforce that this study does not look at the impact of training on earnings. My results indicate that OJT has stronger and more persistent impacts on employment than OST. This does not mean, however, that the same effects would hold when looking at the treatment effect of training on earnings. In a separate paper I show that OST has a larger impact on earnings for men, and for both men and women the effects of OST on earnings grow with time while the effects of OJT fall over time.

It seems that both OJT and OST are effective programs but that on-the-job training is more effective at encouraging short term employment. So why then might policy makers and program administrators in South Dakota appear to avoid such programs. Only 346 of the $2,637$ training episodes recorded between 2002 and 2011, roughly thirteen percent, were OJT. Perhaps this is due to the monitoring difficulties or the political pitfalls surrounding the state subsidizing wages in private companies. It would be interesting to see if other states similarly favor occupational skills training over on-the-job training. Given some of the historical and political issues surrounding OJT it is likely that the pattern persists across many states. This is perhaps unwarranted though. My results indicate that OJT might be a powerful tool for administrators in all states.

Further analysis is warranted before definitive conclusions can be made. Therefore, in subsequent papers I have estimated the impacts of training on earnings and will conduct a cost benefit analysis. However, while the picture in not yet complete, this study does find compelling evidence that WIA training programs provide significant benefits to participants. More importantly, these benefits are not limited to training in certain occupations. My results indicate that participation in training programs provides a benefit that cannot wholly be attributed to the occupation an individual trained. As a result WIA training programs benefit job seekers from diverse backgrounds and with differing skill sets. In this author's opinion, training programs are a viable and valuable tool for promoting the reemployment of the unemployed.

Notes

[1] For a comprehensive explanation of WIA programs, funding mechanisms, and rules, especially as they relate to Title I which authorizes training services see Bradley (2013).

[2] WIA regulations set some limits on how funds can be allocated. A potion of the state's block grant is controlled directly by the Governor. Additionally, There are broad guidelines dictating that a minimum percentage of the block grant must be directed towards training.

[3] In South Dakota the decision was made to change the naming of the local employment services offices from One-Stop Centers to Local Offices in order to avoid confusion. In South Dakota a large number of convenience stores and gas stations use the phrase "One-Stop" in their branding. Apparently a sufficient number of persons expressed confusion regarding the similar naming of these very different entities that the State decided to rename its One-Stop Career Centers as simply Local Offices.

[4] Intensive and training services are generally only extended to WIA Adult and WIA Dislocated workers in accordance with WIA rules. WIA Adult workers include job seekers at least eighteen years old who qualify for or have exhausted their unemployment insurance benefits. WIA Dislocated workers must meet the same criteria as WIA Adult workers, but, additionally, their job loss must stem from business closure or layoffs due to economic conditions. The WIA also identifies WIA Youth workers as job seekers who are under the age of eighteen at the time of registration. These persons are generally not eligible for intensive and training services, but states have great latitude in how they allocate workforce development funds. Decisions are made on a case by case basis but the general rule is that intensive and training services are only awarded to WIA Adult and Dislocated workers.

[5] All US states have agreements in place regarding information sharing for WIA purposes. The states of Nebraska and Iowa share earnings and welfare use information with the SDDLR when residents of those states register with the SDLOS.

[6] Pursuant to SDDLR WIA guidelines, the SDLOS registration questionnaire does not ask after an individual's marital status, or number of children. However, the data report when a job seeker is a single parent because these persons are potentially eligible for additional services. The data also do not report whether or not an individual receives UI benefits, but all persons in the final estimation sample were either eligible for, or had exhausted, their unemployment insurance benefits at the time of their registration.

[7] Data on the racial and ethnic makeup of South Dakota is found at the "Demographic and Housing Estimates" link in the American Community Survey Section at this website http://quickfacts.census.gov/qfd/states/46000lk.html.

[8] This variable is self reported and not verified by staff, at the time of registration, but the state conducts a criminal background check if training is later authorized. Registrants

are instructed to answer in the affirmative if they have been subject of criminal proceedings as a result of misdemeanor or felonious crimes. The exact wording of the question is given below.

> I have been subject to any stage of the criminal justice process or require additional assistance in overcoming barriers to employment resulting from a record of arrest or conviction for committing delinquent acts, such as crimes against a person, property, status offenses or other crimes.

[9] Literacy deficiency is established based on an individual's test results from Tests of Adult Basic Education (TABE). These are national standardized states that measure basic ability in reading, language, math and spelling.

[10] Data on relative educational attainment of South Dakota vs. the United States as a whole can be found at the "Social Characteristics" link in the American Community Survey Section at this website http://quickfacts.census.gov/qfd/states/46000lk.html.

[11] Both states and the federal government use the poverty line and the Lower Living Standard Income Level (LLSIL) to identify persons and household with low income so that they may be targeted for various welfare programs. Pursuant to federal guidelines local office employees designate individuals as Low Income if their income over the six month period prior to registration was below either the federal poverty line or seventy percent of the LLSIL, which ever is higher. The LLSIL is adjusted yearly to account for regional and metropolitan income variations. For more information on the LLSIL see http://www.doleta.gov/llsil/2014/.

[12] TANF is a welfare program that provides temporary supplemental income to qualifying individuals. The federal government provides block grants to the state which they administer. Qualifying individuals must have children under the age of nineteen in the home, and TANF benefits are tied to the number of qualifying children. Recipients are generally required to find and maintain employment while receiving benefits. For specific information on TANF in South Dakota see http://dss.sd.gov/tanf/. For information on federal legislation regarding TANF see http://www.acf.hhs.gov/programs/ofa/programs/tanf.

[13] This weaker assumption is referred to by many names in the literature. The term *conditional independence* is used by Cameron and Trivedi (2005); Lechner and Wunsch (2009). Other authors use phrases such as: *ignorability* Rubin (1974), *unconfoundedness* or *weak unconfoundedness* (Imbens and Wooldridge, 2009; Imbens, 2000), or *exogeneity* (Heckman and Robb, 1985; Heckman et al., 1998). While the terminology varies across the literature the underlying assumption is the same. In each case the authors assume that the conditional mean of the outcome variable is independent of selection.

$$E(y_j|\boldsymbol{X}, D) = E(y_j|\boldsymbol{X}) = \mu_j$$

[14] The AICc is calculated according to the formula below where n is the number of sample observations and k is the number of model covariates

$$AICc = -2\ln(\mathcal{L}) + \frac{2kn}{n-k-1}.$$

[15] Information on the SOC classification system and these aggregate categories in particular can be found at http://www.bls.gov/soc/soc_2010_user_guide.pdf. The categories used here combine SOC major groups at the two digit level according to the following rules:

- Management, Professional, and Related Occupations includes major groups 11-29.
  - Management
  - Business and Financial Operations
  - Computer and Mathematical
  - Architecture and Engineering
  - Life, Physical, and Social Science
  - Community and Social Service
  - Legal
  - Education, Training, and Library
  - Arts, Design, Entertainment, Sports, and Media
  - Healthcare Practitioners and Technical
- Service Occupations combines major groups 31-39.
  - Healthcare Support
  - Protective Service
  - Food Preparation and Serving Related
  - Building and Grounds Cleaning and Maintenance
  - Personal Care and Service
- Sales and Office Occupations combines major groups 41-43.
  - Sales and Related
  - Office and Administrative Support
- Natural Resources, Construction, and Maintenance Occupations combines major groups 45-49.
  - Farming, Fishing, and Forestry
  - Construction and Extraction
  - Installation, Maintenance, and Repair
- Production, Transportation, and Material Moving Occupations combines major groups 51-53.
  - Production
  - Transportation and Material Moving

Appendix A Local Office Locations

The State of South Dakota staffs eighteen Local Offices across the state. Each office is responsible for overseeing programs in its area. The top panel of Table 9 below provides a list of the cities and counties in which the official offices reside. The bottom panel of Table 9 Lists the center name and location of unofficial local offices that are maintained by third parties but are approved by the WIB to provide core, intensive, and training services. The Star Academy located outside Custer is a juvenile detention facility and primarily works with youths. No persons in the estimation sample registered for services through the Star Academy.

Table 11: Official and Unofficial Local Office Locations

Region	Location	County
Central	Pierre	Hughes
	Winner	Tripp
East	Mitchell	Sanborn
	Watertown	Codington
	Huron	Beadle
	Yankton	Yankton
	Madison	Brookings
	Aberdeen	Brown
	Sioux Falls	Yankton
	Brookings	Brookings
	Vermillion	Plymouth
Rapid City	Rapid City	Meade
reservation	Pine Ridge	Shannon
West	Spearfish	Lawrence
	Hot Springs	Fall River
Location	**Center Name**	**County**
Rapid City	Career Learning Center Of The Black Hills	Pennington
Custer	Star Academy	Charles Mix
Sioux Falls	Volunteers Of America	Minnehaha

Appendix B Regional Data Summary

South Dakota Regions and their Composite Counties

South Dakota counties designated as "East"

- Beadle, Bon Homme, Brookings, Brown, Clark, Clay, Codington, Davison, Day, Deuel, Grant, Hamlin, Hanson, Hutchinson, Kingsbury, Lake, Marshall, Miner, Moody, Sanborn, Spink, Union, Yankton

South Dakota counties designated as "Central"

- Aurora, Brule, Campbell, Douglas, Edmunds, Faulk, Gregory, Hand, Hughes, Hyde, Jerauld, Mcpherson, Potter, Sully, Tripp, Walworth

South Dakota counties designated as "West"

- Butte, Custer, Fall River, Haakon, Harding, Jones, Lawrence, Mellette, Perkins, Stanley

South Dakota counties designated as "Reservation" by parent region

- Roberts (East); Buffalo, Charles Mix, Lyman (Central); Corson, Dewey, Jackson, Shannon, Todd, Ziebach (West)

South Dakota counties in the Sioux Falls MSA

- Lincoln, McCook, Minnehaha, Turner

South Dakota counties in the Rapid City MSA

- Meade, Pennington

Nebraska counties

- Cedar, Dakota, Dixon, Knox

Iowa counties

- Lyon, Monana, Plymouth, Woodbury

Summary of Historical South Dakota Labor Market and Population Data

Table 12: Historical Unemployment Rates by Region.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
State Wide	3.50	3.70	3.70	3.10	2.90	3.00	5.20	5.10	4.70	4.20
East	3.96	3.98	3.93	3.38	3.22	3.27	5.30	5.24	4.83	4.23
Central	3.39	3.47	3.55	3.12	2.99	2.91	4.04	4.09	4.03	3.58
West	3.39	3.65	3.77	3.13	2.98	2.98	4.71	4.48	4.51	4.27
Reservation	6.25	6.78	7.55	6.69	6.38	6.23	8.54	8.48	8.94	8.71
Sioux Falls	3.05	3.38	3.25	2.88	2.67	2.97	5.22	4.98	4.38	3.85
Rapid City	3.35	3.50	3.55	3.10	2.80	3.00	5.15	5.45	4.90	4.40

Table 13: Historical Population: in thousands

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
State Wide	764	770	775	783	792	799	807	816	824	834
East	459	458	455	456	457	458	460	469	471	472
Central	66	65	65	64	63	63	63	64	65	65
West	62	62	62	63	63	63	63	65	66	66
Reservation	63	64	64	64	64	64	64	64	65	65
Sioux Falls	203	209	214	221	227	232	237	229	232	237
Rapid City	115	117	118	119	120	122	124	127	128	130

Table 14: Historical Employment Growth by Region.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
State Wide	0.01	0.01	0.01	0.02	0.01	0.01	–0.02	–0.00	0.01	0.01
East	0.68	0.05	0.09	0.86	0.40	0.34	–2.18	–0.10	0.31	0.83
Central	1.59	–0.85	–2.07	–0.58	–2.10	0.83	0.24	1.53	–0.91	0.24
West	2.10	–0.77	–0.91	1.63	–3.15	0.27	0.12	1.39	–1.70	–0.44
Reservation	2.61	0.41	–1.63	2.39	–5.94	–0.07	1.69	2.99	–0.75	–0.54
Sioux Falls	1.37	1.73	0.86	2.19	–0.73	0.34	–3.84	4.70	1.27	1.32
Rapid City	1.08	1.07	0.09	0.72	0.19	0.13	–3.09	1.23	1.34	0.52

Appendix C Technical Appendix

C.1 Treatment Stage Model Selection

In order to select the proper model specification for the treatment stage regression I use the Stata command `bfit` developed by Cattaneo, Drukker, and Holland (2013). The command estimates multiple model specifications and then ranks the models according to fit. I rank the models and select the specification that provides the best fit for the data according to the AIC. Table 15 full list of potential regressors as well as short descriptions. The omitted education category is high school graduate and the omitted region control is the eastern region. See Appendix B for an exact description of the South Dakota regions.

Table 15: Treatment stage variable descriptions

`male`	Male
`native`	Native American
`nonwnat`	Neither white nor Native American
`sngleprnt`	Single parent (self-reported)
`taa`	Trade Adjustment Assistance
`lowincome`	Low-Income (income below federal poverty line or LLISL)
`offender`	Criminal Record (self-reported misdemeanor or felony)
`lths`	No high school diploma or equivalent
`ged`	GED certificate
`assoc`	Associate's degree
`bach`	Bachelor's degree
`reg20**`	Year of registration with SD LOS
`regctrl1`	Regional control - Sioux Falls
`regctrl2`	Regional control - Rapid City
`regctrl3`	Regional control - Central region
`regctrl4`	Regional control - Western region
`startage`	Age are registration with SD LOS
`startage2`	Squared age at registration

Table 3 in Section 4 presents additional regions that exist within the data. For estimation I follow LOS regional groupings and include the Nebraska and Iowa regions with the eastern region South Dakota. The Vermillion office in southeast South Dakota works with these persons and coordinates any training authorized for persons living in Nebraska or Iowa. Additionally, due to a paucity of observations in reservation counties, I group reservation counties with their larger regional designations when determining the proper model specification for the training and outcome equations.

The following code excerpt depicts the estimation command used to fit and rank the various treatment selection specifications.

```
/*  Defining groups of variables to be used in model selection. The TREATMENT
    global variable contains the potential regressors for the treatment
    specifications. The selected model is used to estimate the generalized
    propensity scores.
*/

global treatment ///
        male native nonwnat sngleprnt taa lowincome lths ged assoc bach  ///
        reg2004 reg2005 reg2006 reg2007 reg2008 reg2009 reg2010 reg2011  ///
        regctrl1 regctrl2 regctrl3 regctrl4 startage startage2

*   Treatment Stage used in all models
bfit logit trained2 $treatment , corder(1) base(0) sort(aic)
    qui mlogit trained2 r(bvlist)
    disp e(cmdline)
```

The following code excerpt demonstrates the output created by the preceding commands. As shown, the many estimated models are estimated and then ranked according to the AIC. The covariates and model specification is then captured and displayed for use later.

```
*       Treatment State

bfit logit results sorted by aic
-----------------------------------------------------------------------------
       Model |     Obs    ll(null)   ll(model)      df          AIC         BIC
-------------+---------------------------------------------------------------
    _bfit_24 |    6322   -5301.421   -4984.945      50     10069.89    10407.48
    _bfit_23 |    6322   -5301.421   -4987.443      48     10070.89    10394.97
    _bfit_93 |    6322   -5301.421   -4897.664     138     10071.33    11003.08
    _bfit_71 |    6322   -5301.421   -4984.676      52     10073.35    10424.45

                               [ ...  Intentionally Omitted   ...]

     _bfit_2 |    6322   -5301.421   -5273.503       6     10559.01    10599.52
    _bfit_47 |    6322   -5301.421   -5272.362       8     10560.72    10614.74
     _bfit_1 |    6322   -5301.421   -5299.167       4     10606.33    10633.34
    _bfit_46 |    6322   -5301.421   -5298.066       6     10608.13    10648.64
-----------------------------------------------------------------------------
.          qui mlogit trained2 r(bvlist)

.          disp e(cmdline)

mlogit trained2 i.(male native nonwnat sngleprnt taa lowincome lths ged assoc
                bach reg2004 reg2005 reg2006 reg2007 reg2008 reg2009 reg2010
                reg2011 regctrl1 regctrl2 regctrl3 regctrl4 offender) c.(startage)
```

C.2 Employment Stage Model Selection

In order to determine the proper specification for the employment, or outcome, equation I follow a similar procedure to the one described above. The set of potential covariates for this stage is a superset of the potential treatment stage covariates. I include several other potential regressors in addition to those detailed above in Table 15: `tanf` (Temporary Assistance for Needy Families), `wia_dislocated` (WIA Dislocated worker – see Endnote [4] for additional information), `urate` (unemployment rate if county of residence), `urate2` (squared unemployment rate).

While selection into treatment is only measured at one point in time, I observe individual employment outcomes at two points in time after a person exits the LOS system. It is therefore necessary to estimate two outcome specifications; one for the employment status in the first quarter and one for the employment status in the third quarter following exit.

The following code excerpt depicts the estimation commands used to fit and rank the various employment status specifications. In the logistic regressions below the dependent variable is the binary employment status in the first quarter (`q1emp`) and in the third quarter (`q3emp`) after exit.

```
/*  Defining variables to be used in model selection. The OUTCOME
    global variable contains the potential regressors for the outcome
    specifications. The selected model is used to estimate the bias correction
    term.
*/

global outcome ///
        male native nonwnat sngleprnt taa lowincome lths ged assoc bach ///
        reg2004 reg2005 reg2006 reg2007 reg2008 reg2009 reg2010 reg2011 ///
        regctrl1 regctrl2 regctrl3 regctrl4 startage startage2          ///
        wia_dislocated tanf urate urate2

*   Q1 Employment
bfit logit q1emp $outcome , corder(1) base(0) sort(aic)
    qui logit q1emp r(bvlist)
    disp e(cmdline)

*   Q3 Employment
bfit logit q3emp $outcome , corder(1) base(0) sort(aic)
    qui logit q3emp r(bvlist)
    disp e(cmdline)
```

The following code excerpt demonstrates the output created by the preceding commands. As shown, the potential models are estimated and then ranked according to the

AIC. In total, two-hundred and four models are estimated. Note the slight difference between the two outcome specifications. The Q3 employment specification includes two regional controls not found in the Q1 specification.

```
*       Q1 Employment

bfit logit results sorted by aic
-----------------------------------------------------------------------------
       Model |     Obs     ll(null)    ll(model)      df           AIC          BIC
-------------+---------------------------------------------------------------
    _bfit_177 |    6322    -3013.311    -2859.246      28      5774.493     5963.543
    _bfit_179 |    6322    -3013.311    -2857.663      30      5775.326      5977.88
    _bfit_176 |    6322    -3013.311    -2860.823      27      5775.645     5957.943
    _bfit_175 |    6322    -3013.311    -2861.922      26      5775.843      5951.39

                               [ ...  Intentionally Omitted   ...]

    _bfit_2   |    6322    -3013.311    -3011.145       3       6028.29     6048.545
    _bfit_53  |    6322    -3013.311    -3010.661       4      6029.322     6056.329
    _bfit_27  |    6322    -3013.311    -3010.949       4      6029.898     6056.906
    _bfit_78  |    6322    -3013.311    -3010.492       6      6032.984     6073.495
-----------------------------------------------------------------------------

.          qui logit q1emp r(bvlist)

.          disp e(cmdline)
logit q1emp i.(male native nonwnat sngleprnt taa tanf veteran offender lths ged
            assoc bach wia_dislocated reg2004 reg2005 reg2006 reg2007 reg2008
            reg2009 reg2010 reg2011 regctrl1 regctrl2) c.(urate urate2 startage
            startage2)
```

```
*       Q3 Employment

bfit logit results sorted by aic
-----------------------------------------------------------------------------
       Model |     Obs     ll(null)    ll(model)      df           AIC          BIC
-------------+---------------------------------------------------------------
   _bfit_179 |    6322    -3247.086     -3043.12      30      6146.241     6348.794
   _bfit_128 |    6322    -3247.086    -3046.724      29      6151.449     6347.251
   _bfit_175 |    6322    -3247.086    -3051.827      26      6155.654       6331.2
   _bfit_178 |    6322    -3247.086    -3049.591      29      6157.183     6352.985

                               [ ...  Intentionally Omitted   ...]

   _bfit_103 |    6322    -3247.086    -3237.171       4      6482.342     6509.349
    _bfit_27 |    6322    -3247.086     -3239.09       4       6486.18     6513.187
     _bfit_2 |    6322    -3247.086    -3240.813       3      6487.626     6507.881
     _bfit_1 |    6322    -3247.086    -3243.785       2      6491.571     6505.074
-----------------------------------------------------------------------------

.          qui logit q3emp r(bvlist)

.          disp e(cmdline)
logit q3emp i.(male native nonwnat sngleprnt taa tanf veteran offender lths ged
            assoc bach wia_displaced reg2004 reg2005 reg2006 reg2007 reg2008
            reg2009 reg2010 reg2011 regctrl1 regctrl2 regctrl3 regctrl4)
            c.(urate urate2 startage startage2)
```

References

Angrist, Joshua D, Guido W Imbens, and Donald B Rubin. 1996. "Identification of Causal Effects Using Instrumental Variables." *Journal of the American Statistical Association* 91 (434):444–455.

Bradley, David H. 2013. "The Workforce Investment Act and the One-Stop Delivery System." Tech. rep., Congressional Research Service, Washington D.C.

Busso, Matias, John DiNardo, and Justin McCrary. 2014. "New Evidence on the Finite Sample Properties of Propensity Score Reweighting and Matching Estimators." *Review of Economics and Statistics* Forthcomin.

Cameron, Adrian Colin and Pravin K Trivedi. 2005. *Microeconometrics: Methods and Applications*, *Cambridge Books*, vol. 100. Cambridge MA: Cambridge University Press.

Cattaneo, Matias D. 2010. "Efficient semiparametric estimation of multi-valued treatment effects under ignorability." *Journal of Econometrics* 155 (2):138–154.

Cattaneo, Matias D, David M Drukker, and Ashley D Holland. 2013. "Estimation of multi-valued treatment effects under conditional independence." *Stata Journal* 13 (3):407–450.

Greene, William. 2012. *Econometric analysis*. Boston: Prentice Hall.

Heckman, James J, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd. 1998. "Characterizing Selection Bias Using Experimental Data." *Econometrica* 66 (5):1017–1098.

Heckman, James J, Robert J Lalonde, and Jeffrey A Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." In *Handbook of Labor Economics*, vol. 3A, edited by Orley Ashenfelter and David Card, chap. 31. Amsterdam, North Holland, 1865–2097.

Heckman, James J and Richard Robb. 1985. "Alternative methods for evaluating the impact of interventions." *Journal of Econometrics* 30 (1-2):239–267.

Imbens, Guido W. 2000. "The role of the propensity score in estimating dose-response functions." *Biometrika* 87 (3).

———. 2004. "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review." *The Review of Economics and Statistics* 86 (1):4–29.

Imbens, Guido W and Joshua D Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62 (2):467–475.

Imbens, Guido W and Jeffrey M Wooldridge. 2009. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47 (1):5–86.

Jacobson, Louis, Robert J Lalonde, and Daniel G Sullivan. 2005. "Estimating the returns to community college schooling for displaced workers." *Journal of Econometrics* 125 (1-2):271–304.

Kang, Joseph D. Y. and Joseph L. Schafer. 2007. "Demystifying Double Robustness: A Comparison of Alternative Strategies for Estimating a Population Mean from Incomplete Data." *Statistical Science* 22 (4):523–539.

Kuruvilla, Jason. 2014. "Approximately $58M in grants available to support Indian and Native American employment and training programs."

Lalonde, Robert J. 1986. "Evaluating the Econometric Evaluations of Training Programs with Experimental Data." *The American Economic Review* 76 (4):604–620.

Lechner, Michael and Conny Wunsch. 2009. "Are Training Programs More Effective When Unemployment Is High?" *Journal of Labor Economics* 27 (4):653–692.

O'Leary, Christopher J, Robert A Straits, and Stephen A Wandner. 2004. "U.S. Job Training: Types, Participants and History." Kalamazoo MI: W.E. Upjohn Institute for Employment Research, 1–20.

Robins, James M and Andrea Rotnitzky. 1995. "Semiparametric Efficiency in Multivariate Regression Models with Missing Data." *Journal of the American Statistical Association* 90 (429):122–129.

Robins, James M, Andrea Rotnitzky, and Lue Ping Zhoa. 1995. "Analysis of Semiparametric Regression Models for Repeated Outcomes in the Presence of Missing Data." *Journal of the American Statistical Association* 90 (429):106–121.

Rosenbaum, Paul R and Donald B Rubin. 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika* 70 (1):41–55.

Rubin, Donald. 1974. "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies." *Journal of Educational Psychology* 66 (5):688–701.