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Earnings Progression Among Workforce Development Participants: Evidence from Washington State

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1 Introduction

The United States government has funded workforce development programs since the passage of the Wagner-Peyser Act in 1933. The broad goal of workforce development and job training is to provide individuals with skills to enable them to obtain and maintain employment (O'Leary et al., 2004). Publicly funded workforce training encompasses a range of activities, complementing and, at times, including employer-provided job training and training through the public community and technical college system.

The most recent major federal workforce policy innovation was the Workforce Investment Act (WIA) of 1998. It mandated the local availability of One-Stop Career Centers across the United States, which are open to all individuals, regardless of prior work experience or education. WIA includes programs for adults, dislocated workers, and youth. The Department of Labor required states to implement most provisions of WIA by July 1, 2000 (U.S. Government Accountability Office, 2005).

This research is a case study of selected workforce development programs in the state of Washington. Washington has a highly developed workforce policy system, clear strategic goals, and a commitment to research and evaluation. Although workforce programs are implemented differently from state to state, the essential elements of the programs in this evaluation are the same across all states.

In Washington, One-Stop Career Centers are known as WorkSource centers. The centers provide services within the following categories: core, intensive, training, follow-up, and support. Core services include skill assessment, labor market information, and job search and placement assistance. Intensive services are available to individuals who are unable to obtain a job solely through the use of core services, and include specialized assessments and counseling. Training services, available only to individuals who have also received core and intensive services, attempt to enhance skills with the goal of preparing individuals for local job opportunities. For individuals who have obtained employment, follow-up services are available for at least 12 months and may include additional career counseling, contact with employers, and peer support groups. Finally, support services may include assistance with child care, transportation, or work-related expenses.

State and local Workforce Investment Boards (WIBs) oversee the implementation of WIA. The WIBs include representatives of business, labor and government. By law, the majority of WIB members are business representatives, who are charged with ensuring that workforce development programs respond to the needs

of local employers. In Washington, the statewide WIB is called the Workforce Training and Education Coordinating Board. The state has twelve local WIBs, which are called Workforce Development Councils (WDCs). Except in the most populated counties such as King County, which includes Seattle, each WDC covers several counties.

Approximately 3,700 individuals exited WIA Title I-B Adult staff-assisted programs in Washington during the 2006 calendar year (Workforce Training and Education Coordinating Board, 2008). Thousands more adults each year receive WorkSource services that are either not funded by the Title I-B program or are not assisted by Title I-B staff members (but may be assisted by non-Title I-B staff). This group is called Labor Exchange, Employment Service, or Wagner-Peyser. Labor Exchange services include self-assisted services, facilitated self-assisted services, and staff-assisted services. Substantial overlap occurs between Labor Exchange services and WIA core and intensive services (Eberts & Holzer, 2004). One distinction is that state employees directly provide Labor Exchange services, while private companies or community-based organizations provide WIA services under contract at many One-Stop Career Centers.

For purposes of this research, Labor Exchange clients are those who did not receive a WIA Adult service but did receive a service coded as Labor Exchange, Wagner-Peyser, or Claimant Placement Program.¹ Individuals who received only a self-service through Washington's Go2WorkSource website are not part of either the treatment or comparison group for this analysis. In addition, WIA training services are not included in Labor Exchange programs here, as they are in federal reporting. Approximately half of WIA participants in Washington have received training services, according to data used in this analysis.

Although WIA services are available to individuals of all income and education levels, participants are more disadvantaged than state residents as a whole. The median annual earnings of adult program participants who exited in 2005-06 and worked in the third quarter after the program was \$20,373² (Workforce Training and Education Coordinating Board, 2008). The statewide median earnings among workers in 2007 was \$30,535 (U.S. Census Bureau, 2009).

Given the relatively low earnings associated with participants' initial job placements, wage and earnings progression among training recipients are of substantial concern to workforce investment practitioners,

¹The Claimant Placement Program serves recipients of Unemployment Insurance in the state of Washington.

²For comparison, the poverty threshold for a family of three in 2007 was \$17,170 (U.S. Department of Health and Human Services, 2007).

policy makers, and antipoverty scholars. This research measures earnings progression among workforce development participants by comparing earnings progression among individuals served by WIA Title I-B to earnings progression among individuals served by the Labor Exchange program. The chapter uses propensity score methods for purposes of equating observable characteristics across the two groups.

The structure of the chapter is as follows. First, I review the existing literature on earnings progression among disadvantaged workers. Then I describe the specific research questions, data, and methods before presenting descriptive statistics, analytical results, and a discussion of their implications.

2 Background

State officials in Washington are keenly interested in preparing workers for jobs that have demonstrated career ladders and lead to earnings increases over time. The premise is that publicly funded training, first, provides the foundation for connecting workers with jobs, and, second, enhances the ability of individuals to advance to positions with greater compensation as they add work experience and obtain additional, often privately-provided, training.³ Of course, individuals might not achieve earnings gains even with publicly funded job training, for reasons such as training ineffectiveness, labor competition, layoffs, weak labor markets, or insurmountable personal barriers. Other potential reasons include a lack of additional employer-provided training or a lack of returns to work experience. In these cases, we would expect to observe stagnant wages over time.

Similar concerns arise in research on Temporary Assistance for Needy Families (TANF) and the economic safety net in general. A central debate among welfare researchers is whether low-income parents are better served by “work first” programs that promote immediate entry into the labor market or by education and training prior to job application (Brown, 1997). Advocates of education argue that workers can become stuck in “dead-end” jobs without it, while others suggest that simply being employed is a major advancement for disadvantaged individuals (Mead, 1993). Ultimately, assessment of whether immediate or deferred placement is more appropriate economically depends upon earnings levels and earnings growth among individuals who follow each strategy.

³This view is related to the larger theory of human capital, which suggests that investments in knowledge, skills, health and values enable individuals to receive financial returns in the labor market that would not have been available without such investments (Becker, 1993).

Previous research on wage and earnings progression can be categorized by the population under study: 1) less skilled workers in general, 2) recipients of TANF or the Earned Income Tax Credit (EITC), and 3) participants in workforce development programs. Research on less skilled workers⁴ has generally found relatively modest rates of earnings growth that are similar to those of other workers in the population. Current Population Survey data indicate comparable rates of wage growth across educational groups, with a possible exception for young high school dropouts who have relatively lower and more volatile wage growth, especially during recessions (French et al., 2006). In general, wage growth varies over time in accordance with economic conditions, and tends to be highest during the early years of a worker's career.

Data from the National Longitudinal Survey of Youth (NLSY) 1979 panel suggests that wage growth among less skilled workers no longer attending school would be approximately 4 to 6 percent per year of full-time work, and that this rate is similar to that for medium-skilled workers (Gladden & Taber, 2000).⁵ The finding that wage growth of high school dropouts in the NLSY as a function of work experience is approximately comparable to that of high school graduates suggests that neither the theory of "dead-end" jobs nor of rapid advancement with human capital is fully accurate (Gladden & Taber, 2000).

Despite similar returns to experience, there still may be differences in observed earnings growth if high school dropouts work more sporadically than high school graduates. In the CPS data presented by French et al. (2006)⁶, observed growth is contingent on labor market conditions as well as educational attainment. While wage growth as a function of year and experience are both important to less skilled workers, the results from the NLSY—that wage growth in response to experience is approximately equal for high school graduates and dropouts—are more relevant for this study.

Several experimental studies have tested the effects of special programs on wage growth. The Employment Retention and Advancement (ERA) project was implemented in 16 locations across the United States between 1999 and 2009 to promote career advancement among low-wage workers. Evaluations by MDRC indicate that the program's effectiveness varied by site. In Cleveland, the program was not well integrated into participants' lives and had minimal effects (Miller et al., 2008). In Riverside County, California, the program appeared to

⁴Less skilled workers are usually defined as having an educational credential no greater than a high school diploma.

⁵Unless otherwise specified, all research on this topic uses the logarithm of wages as the dependent variable rather than direct wages, in order to correct for skewness in the wage distribution.

⁶Growth is defined as the percentage increase in the hourly wage among individuals in the survey wave who were working both then and during the previous year's outgoing rotation group.

contribute to increased earnings in the initial job as well as a greater probability of obtaining subsequent jobs that provided for earnings increases (Navarro et al., 2007). Overall, relatively little is known about effective strategies for promoting advancement among less skilled workers.

TANF recipients, who are predominately female, generally fare much worse in the labor market than women in the population at large. Only 25 percent of women ages 26-27 who had previously enrolled in welfare had ever worked at least 35 hours per week in a job that paid at least \$8 per hour, compared to 73 percent of women who had not received welfare, according to data from the NLSY (Pavetti & Acs, 1997). Among former TANF recipients, data from the Survey of Income and Program Participation indicate that increases in the logarithm of median annual earnings were 3.8 percent during 1996-1997, 2.8 percent during 2001-2002 and -1.4 percent during 2002-2003 (Chrisinger et al., 2008).

The Earned Income Tax Credit attempts to encourage low-income individuals such as former TANF recipients to engage in paid work. While some observers have worried that the EITC subsidizes low-quality jobs, Dahl et al. (2009) find that earnings growth rates were as high or higher among single mothers who had received the EITC than among those who hadn't.

Research specifically on workforce development addresses the impacts of program participation on earnings and employment, both in the short term and long term. Some studies measure rates of earnings growth as well. A large, multi-state nonexperimental WIA impact study by Heinrich et al. (2008) finds that benefits to recipients of core or intensive services during 2003-2005 were \$100-200 per quarter above what non-participants (UI recipients or Labor Exchange participants) experienced, and that training participants received up to \$400 more per quarter than they otherwise would have. The researchers use propensity score matching methods to account for different characteristics among the treatment and comparison groups.

Similarly, an analysis of Washington administrative data from 2001 through 2004 suggests that WIA Title I-B Adult programs added approximately \$403 to participants' long-term average quarterly earnings and were associated with a 6.6 percent increase in the long-term number of quarters employed, relative to a Labor Exchange comparison group (Hollenbeck & Huang, 2006). In this case, the researchers define long-term as 9-12 quarters after exit. Regression-adjusted difference-in-difference methods account for self-selection in to the program. Overall, the impact of WIA on earnings and employment outcomes appears to be positive, but modest, in most states.

Researchers have also extensively evaluated the predecessor programs to WIA: the Job Training Partnership Act (JTPA) of 1984-1999, the Comprehensive Employment and Training Act (CETA) of 1974-1984, and the Manpower Development Training Act (MDTA) of 1962-1973. In general, the results suggest that training programs are associated with modest increases in earnings that are greater for women than men and that fade out over time (Holzer, 2009). A common interpretation is that “wage gains from these programs tend to be quite modest (although the costs are often also small)” (Gladden & Taber, 2000, p. 160). Indeed, federal spending on employment and training programs totals approximately 0.1 percent of GDP, and has decreased substantially since the late 1970s (Holzer, 2009). An additional challenge is that training funds are used to support a diverse set of activities, so that pinpointing successful elements through a national evaluation becomes difficult. Previous research has, in general, also not addressed adequately the rates of earnings growth on the job or through changing jobs in order to understand whether particular programs or career paths are more promising than others.

In the most closely related previous study of earnings growth rates, Mueser & Stevens (2003) use data from six states (Florida, Georgia, Illinois, Maryland, Missouri and Texas) and calculate that quarterly earnings rose faster for adult WIA clients who received training than those receiving core or intensive services, especially in the period immediately surrounding the clients’ exit from the program. The earnings increase in the year after participation was 69 percent in the training group compared to 22 percent in the core group. In the subsequent year, the rates were equal. The follow-up period in the study was only two years.

In summary, there is some evidence that federally funded training is associated with earnings growth in the short term. Research on wage growth and skills in general implies that long-term earnings gains, above those experienced by other groups, might be more difficult to achieve. Overall, however, there have been very few studies of long-term earnings progression among WIA participants.

3 Research Questions and Hypotheses

The primary research question addressed in this analysis is: what is the difference in earnings progression between individuals who received any WIA Title I-B Adult service (core, intensive, and training) and those who received only Labor Exchange services?

Underlying the central question are two hypotheses:

(H1) Achieving a Steeper Path: General Human Capital

Generalized investments in knowledge, skills, and values, such as that provided in training course attendance, enable WIA enrollees to achieve higher earnings growth rates than non-enrollees with the same educational background.

(H2) Achieving a Steeper Path: Specific Human Capital

Specific components of WIA, such as personalized training and service recommendations, position participants to climb the earnings ladder within a firm or sector at a faster rate than their comparable counterparts who do not receive specialized services.

4 Data

The data for this research come from two types of statewide administrative records maintained by the State of Washington. Data on WIA program participation and participant demographic information come from the Services, Knowledge and Information Exchange System (SKIES), which is the statewide workforce investment case management system that was first implemented in 2002. Data on earnings and employment come from Unemployment Insurance (UI) records. The Washington Employment Security Department matched these datasets on Social Security number (SSN) and provided the combined dataset with an alternative individual identification number in lieu of the SSN for protection of participants' privacy.

SKIES contains detailed information on the characteristics of job seekers and the services they receive. The participant characteristics are available for a single point in time and include gender, race, primary language spoken, zip code of residence, TANF reciprocity status, schedule availability for work, date of birth, veteran status, Unemployment Insurance status (whether currently or formerly receiving UI), and highest degree completed. Employees of WorkSource Washington enter this information into SKIES at the point of contact with participants in One-Stop Career Centers. SKIES also contains records of the services provided to job seekers. SKIES includes the start and end dates of participation, and whether the participant completed the relevant course, program, or degree. The name of the service provider is included in many cases, but the details of training programs, such as the skill and industry focus of the training, are not available.

Quarterly earnings, hours worked, and industry codes from the North American Industry Classification System (NAICS) come from the UI dataset. Employers that are covered by the UI system must report quarterly wages of all employees for purposes of administration of the UI program. Coverage includes most state and local government employees, employees of private firms employing any workers for a minimum of 20 weeks per calendar year, and employees of agricultural firms that pay at least \$20,000 cash annually to agricultural laborers (Bureau of Labor Statistics, 2008). UI does not cover domestic workers, self-employed farmers, railroad workers, and self-employed nonagricultural workers.

This research uses SKIES and UI data from 2001 through the first quarter of 2009. The data include earnings for the entire study period to allow comparison of earnings before, during and after program participation. Table 1 shows the dates of coverage. The total number of individuals in the analysis is 39,981. Of these, 13,261 received a WIA Adult service.

Table 1: Coverage Dates in the Analysis

Data Type	Dates Included
Program Records	January 1, 2002 - June 30, 2008
Earnings Records	January 1, 2001 - March 31, 2009

Individuals may begin service at any point within the dataset. For example, someone might have his or her first contact with the workforce development system in 2005 and would only be in program records after that date. Once an individual ever receives a WIA Adult service, that individual is always in the treatment group for all future quarters, whether or not a Labor Exchange service follows a WIA service. The data include complete earnings records for all individuals from 2001 forward.

The SKIES/UI administrative dataset is a unique resource that provides rich and up-to-date information on labor market experiences and workforce development program participation for the entire state of Washington. Compared to data from surveys, administrative data have the advantage of complete coverage of participating individuals, some of whom might be difficult to reach for a survey for reasons such as lacking a stable residence or a telephone. Administrative data are also better sources of precise dates of program participation, whereas survey respondents may have difficulty recalling exact dates and wage information over time. In addition, the processing time required for data from surveys, sometimes even if administered on the Internet, implies that very recent data often are not available.

Nevertheless, administrative data appear to undercount certain types of earnings relative to survey data. Specifically, individuals who have earned tips, who work for UI-exempt employers, who work outside of their state of residence, or whose employer did not report earnings correctly, often have lower UI-reported than survey-reported earnings (Wallace & Haveman, 2007). Another disadvantage of administrative data is that they were originally collected for a purpose other than research. Data fields that are important to researchers might be less important to program administrators and, as a consequence, contain a high proportion of ambiguities, errors, or missing values. As an example, the hours field in the UI data does not allow researchers to distinguish between individuals who work part time for an entire quarter and those who work full time for only a month.

Despite these limitations, the SKIES/UI dataset provides a superior resource over survey data for the purposes of addressing the proposed research question. The data allow for a complete enumeration of all program participants in the state and a comprehensive reporting of quarterly wages from all covered employment. Other researchers have successfully used workforce administrative data after engaging in data cleaning and the creation of standard definitions to bring consistency to their analysis (Heinrich et al., 2008; Hollenbeck & Huang, 2006).

The results of this research are not strictly generalizable to other states in the United States. In Washington, WIA Adult participants had 12.4 mean years of education and were on average 36.7 years old at registration (Hollenbeck & Huang, 2006). Approximately 57 percent were female. In the twelve states analyzed by Heinrich et al. (2008), the mean years of education were 12.3 and the average age was 32.7. Approximately 58 percent of participants were female. Nearly 45 percent of the sampled individuals in the multi-state study were black and 3 percent were Hispanic, while only 31.7 percent of the Washington participants were members of a minority group.⁷ Average quarterly earnings in the year prior to participation (in 2008 dollars) were \$2,970 in Washington, compared to only \$2,162 in the multi-state study. In addition to these differences in participant composition, industry types differ in Washington from other states, as do the specific training programs and support services provided by the workforce development agencies. For example, Washington has a higher concentration of employment in the aerospace and aluminum industries than the U.S. as a whole (Sommers, 2001).

⁷SKIES does not include Hispanic as a separate racial category, and an ethnicity variable was not part of the dataset.

5 Research Design and Methods

The goal of this research is to measure the association of participant exposure to federally funded workforce development programs with earnings progression. The estimate of interest is the effect of the workforce program treatment on the treated individuals, although I do not assume causal relationships. The research uses a nonexperimental, ex post evaluation design. Most prior evaluations of workforce development have used similar approaches (Hollenbeck & Huang, 2006; Heinrich et al., 2008; Sianesi, 2004).

An alternative to the current nonexperimental design is an experimental evaluation. The advantage of an experimental design is that researchers randomly assign individuals either to participate or not participate in the program. This randomization ensures that, given a sufficient sample size, the treatment and control groups have a similar composition, and that estimates of the program's effects are not subject to selection bias. With a nonrandomized evaluation, the primary concern is that people who participate are different from those who do not. In that case, the observed effects could be due to differences in treatment and comparison group composition rather than the program itself. Offsetting these advantages is that randomized experiments are costly and time-consuming to conduct. Randomized trials also are subject to concerns about applicability of findings outside of the experimental setting, for reasons such as randomization bias and contamination. Econometric methods can sometimes approximate the results of an experiment, but nonexperimental estimates generally still suffer from some degree of selection bias (Pirog et al., 2009). If an imperfect estimate of program impact is still desirable to policy makers, as it often is, one of the main research tasks is to minimize selection bias.

Bearing in mind concerns about selection, I use several models to estimate the relationship of interest. The outcome variable, E_{it} , is the quarterly earnings of individual i in quarter t .⁸ I include earnings from all UI-covered jobs worked in Washington during the quarter. All dollar amounts are expressed in 2008 prices.

To achieve comparability with U.S. Department of Labor performance measures and Hollenbeck & Huang (2006), I define individuals as members of the treatment group if they last received services from a selected program during the relevant fiscal year. Consistent with DOL protocol, the exit date is measured as

⁸This response variable was chosen rather than the earnings growth rate because, with the inclusion of quarters in which earnings are zero, the value of the earnings growth rate can range from -1 to nearly infinity. Due to the greater number of quarters in which the WIA Adult population is unemployed prior to participation, their earnings growth rate after program exit is higher for the treatment than the comparison group virtually by construction.

90 days after the end of the most recent service. Several other studies instead use the program entry date because of concerns that the program exit event is not independent of program outcomes, and that any low earnings during program participation are also relevant to consider. These concerns are valid. I chose the exit rather than entry date as the identifying point because of my interest in post-program earnings progression, which would be representative of a long-term outcome in the absence of a continuing intervention. In the analysis, I drop earnings observations in the exit quarter and two quarters on either side of the exit date, in part to address the “Ashenfelter dip”⁹ and in part to minimize the influence of short-term differences between the treatment and comparison groups associated with nonrandom exit dates.

The models estimate quarterly earnings as a function of several covariates. The variable Q_t is the time difference between the current quarter and the quarter of program exit. It ranges from -29 to 29. For example, the count would be 2 in the third quarter of 2006 for someone who exited in the first quarter of 2006. It would be -29 during the first quarter of 2001 if an individual exited during the second quarter of 2008.

The variable $PostWIA_{it}$ takes the value of 1 in quarters after WIA Adult program exit. It is 0 otherwise, and always 0 for individuals who have never participated in WIA Adult programs. A similar variable exists for the comparison group. $PostLE_{it}$ is 1 after Labor Exchange exit and 0 otherwise. If a Labor Exchange participant subsequently exits from WIA Adult, that person is counted only as a WIA Adult participant in order to maintain mutually exclusive treatment and comparison groups, under the assumption that WIA provides additional and more intensive services than Labor Exchange. The quarterly county non-seasonally adjusted unemployment rate is included as U_{it} to account for macroeconomic influences.

The primary model is a series of individual-level ordinary least squares (OLS) regressions whose coefficients are later weighted and averaged. The model takes the following form for each person.

$$E_{it} = \beta_{0i} + \beta_{1i}Q_t + \beta_{2i}PostWIA_{it} + \beta_{3i}PostWIA_{it}Q_t + \beta_{4i}U_{it} + \beta_{5i}PostWIA_{it}U_{it} + \epsilon_{it} \quad (1)$$

Similarly for Labor Exchange participants, the individual specification is as follows.

⁹A concern throughout research on training programs is that earnings usually are lower in the years immediately before and during program participation relative to earnings in the years on either side of program participation (Ashenfelter, 1978).

$$E_{it} = \gamma_{0i} + \gamma_{1i}Q_t + \gamma_{2i}PostLE_{it} + \gamma_{3i}PostLE_{it}Q_t + \gamma_{4i}U_{it} + \gamma_{5i}PostLE_{it}U_{it} + \epsilon_{it} \quad (2)$$

The coefficient of most interest is on the interaction of post-participation with time. This enables a comparison of post-participation earnings slopes. The coefficient on Q_t captures the overall trend in earnings prior to program participation. The coefficient on the post-participation dummy allows for a one-time shift in earnings coincident with participation. Controlling for county unemployment permits a measurement of the reduction in earnings that might be associated with working in a high-unemployment county. The interaction of the unemployment rate and participation indicates the additional association with earnings of the county unemployment rate after participation. If positive, the coefficient on this interaction could suggest that WIA participants might not be as strongly harmed by high unemployment as non-participants, or that training might be more effective during recessions (Lechner & Wunsch, 2009).

I use individual-level regression because it allows all of the coefficients to vary by individual. The analysis estimates regressions separately for each individual, and then averages coefficients across individuals for each variable. I average the β_{3i} and compare them to the averaged γ_{3i} . A function of each individual's propensity score, which will be described below, serves as a weight to account for selection.

An individual approach accounts for heterogeneity across people who receive workforce services and may differ from the results of a pooled regression. The individual approach does not permit inclusion of time-invariant personal characteristics, so the constant and other coefficients in the model subsume these effects.

For comparison, I also present a pooled model. In this approach, clustered standard errors account for the repeated observations by person. The vector Z_{it} includes demographic controls for age, gender, race, educational attainment, single parenthood, veteran status, geographic location (Workforce Development Council region), unemployment insurance receipt at baseline, primary language, and disability status. The mutually exclusive categories for educational attainment are less than high school, high school diploma or GED, some college, associate's degree, bachelor's degree, or graduate degree. The specification follows.

$$\begin{aligned}
E_{it} = & \beta_0 + \beta_1 Q_t + \beta_2 PostWIA_{it} + \gamma_2 PostLE_{it} + \beta_3 PostWIA_{it} Q_t + \gamma_3 PostLE_{it} Q_t + \\
& \beta_4 U_{it} + \beta_5 PostWIA_{it} U_{it} + \gamma_5 PostLE_{it} U_{it} + \beta_6 Z_{it} + \epsilon_{it}
\end{aligned} \tag{3}$$

Again, none of the estimates include the five quarters immediately surrounding program exit.

5.1 Addressing Selection Bias

The primary approach this study takes to reduce selection bias is propensity score weighting. In general, propensity score methods first use a logit or probit regression to estimate the probability of program participation on the basis of observed characteristics for each individual in the sample, whether he or she participated or not. Researchers then use this conditional probability, or propensity score, in a variety of ways to reduce bias due to observed covariates (Rosenbaum & Rubin, 1983). The propensity score is denoted $p(X_i)$ for individual i with observed characteristics X_i . If D is a binary indicator of membership in the treatment group, $p(X_i) = Pr(D_i = 1 | X_i)$.

In propensity score weighting, the propensity score weights take the value of 1 if the individual is in the treatment group and $p(X_i)/(1 - p(X_i))$ if the individual is in the comparison group, in order to form a comparison group that is observationally similar to the treatment group. These weights permit computation of the average treatment effect on the treated (ATT), rather than the overall average treatment effect (ATE) that might be observed were any individual from the population at large to participate in the programs (Gelman & Hill, 2007). The weights account for differential probability of treatment by weighting individuals from the comparison group who have similar observable characteristics as treatment group members more heavily than comparison group members who are dissimilar. For more details on these weights, also known as the Horvitz-Thompson estimator, see, for example, Rosenbaum (1987), Imbens (2000), Frolich (2004), and Guo & Fraser (2010).

An important component of generating propensity scores is to perform balancing tests. These tests verify that characteristics of treatment and comparison group members are similar for each region of the propensity score distribution, and that program group membership is independent of observed characteristics,

so that $D \perp X \mid p(X)$. If conditional distributions of characteristics are approximately equal, the propensity score balances the covariates in expectation (Smith & Zhang, 2009). Although Smith & Zhang (2009) recommend the regression test, they note that it is difficult to satisfy. Less stringent tests, used here, require only approximately equal means across the program groups (Dehejia & Wahba, 1999). These tests include a univariate t test for differences in means, a multivariate analog, the Hotelling T -squared test, and a standardized differences test. The standardized differences test computes the following statistic, where $\overline{x_{k,D=1}}$ is the mean of the variable x_k for the treated group and $\overline{x_{k,D=0}}$ is the mean for the weighted comparison group.

$$SD = \frac{100(\overline{x_{k,D=1}} - \overline{x_{k,D=0}})}{\sqrt{(var(x_{k,D=1}) + var(x_{k,D=0}))/2}} \quad (4)$$

The value of SD should be less than 20 (Rosenbaum & Rubin, 1985). For the t tests, the t statistic should be less than 1.96. If none of these were to hold, the propensity score prediction model would have to be adjusted to include additional terms (Becker & Ichino, 2002), but that is not the case here.

The assumptions of propensity score approaches include the following: program selection is only on the basis of observable characteristics (called ignorability), unobservables do not determine selection or the program outcome, there is some positive probability of participation for all values of the predictors, and the treatment does not influence the outcome for people who didn't receive it (Rubin, 1978; Cameron & Trivedi, 2005). Further, propensity score methods work best when treated and control group members are in geographic proximity to each other, when the propensity score is based on a large number of predictors, and when program definitions and data quality are similar for the treated and control groups (Heckman et al., 1997). Many of these assumptions appear to hold in this study, with the possible exception of the influence of unobservable characteristics.

Propensity scores for each group are shown in the results section. In addition, I show demographic characteristics with and without adjustment for propensity scores. The propensity scores account for differences in observable characteristics in the propensity function of treatment and comparison groups.

6 Results

The total number of individuals in the analysis is 39,981, including 13,261 WIA Adult participants and 26,720 Labor Exchange participants. Table 2 provides details of the time period in which individuals in the dataset first joined the treatment group. Since the data cover 33 quarters (January 2001 to March 2009), the analysis includes up to 1,319,373 person-quarters. To focus on the traditional working-age population, the results include only individuals who are between the ages of 18 and 64 during the entire time period. The sample size for analysis shrinks to 5,677 WIA participants and 12,360 Labor Exchange participants after missing data are considered. One reason is that historical information, such as earnings in the 10th quarter prior to exit, which I use to balance the treatment and comparison groups, is not available for all individuals, since it excludes those who exited early in the analysis period. I also rely on industry of employment for balancing, excluding individuals who were never employed during the study period. As a result, this sample is potentially more advantaged than the entire workforce development participant population.

Table 2: Participant Counts by Cohort of First Exit in Data

Cohort	WIA Adult	Labor Ex.	Total
Jan. 2002 - June 2002	525	2,065	2,590
July 2002 - June 2003	2,242	6,876	9,118
July 2003 - June 2004	2,439	5,450	7,889
July 2004 - June 2005	2,151	3,982	6,133
July 2005 - June 2006	2,166	3,358	5,524
July 2006 - June 2007	1,938	2,591	4,529
July 2007 - June 2008	1,800	2,398	4,198
Total	13,261	26,720	39,981

Table 3 shows characteristics of the treatment and comparison groups prior to adjustment for the probability of participation. Almost all averages were significantly different across the treatment and comparison groups. The individuals who received a WIA Adult service had average quarterly earnings during the 10th quarter prior to exit of \$5,643 in 2008 dollars, compared to \$10,169 for Labor Exchange. These amounts include individuals with no covered work during that quarter. On average, individuals who participated in WIA Adult were employed (had earnings of at least \$100) during approximately 9.9 of the quarters in the data prior to their first exit, while Labor Exchange participants were employed during 10.8 of the quarters in the data prior to their first exit. WIA participants were younger than Labor Exchange

Table 3: Demographic Composition of Sample, Unweighted

	WIA Adult		Labor Ex.	
	Mean/N_1	Std. Err.	Mean/N_2	Std. Err.
Quarters Employed Prior to Exit	9.9***	(0.1)	10.8***	(0.1)
Earnings in 10th Quarter Before Exit	5643.5***	(74.0)	10169.1***	(69.4)
Earnings in 7th Quarter Before Exit	6231.8***	(72.1)	10763.8***	(63.8)
Earnings in 5th Quarter Before Exit	5276.7***	(83.2)	10027.5***	(67.1)
Age	36.1***	(0.1)	39.5***	(0.1)
County Unemp. Rate in 2nd Qtr. Before Exit	6.0***	(0.0)	6.2***	(0.0)
Employed in 6th Qtr Before Exit	87.4***	(0.4)	94.1***	(0.2)
Less than HS	10.3***	(0.4)	5.6***	(0.2)
HS or GED	40.2	(0.7)	39.2	(0.4)
Some College	28.2	(0.6)	27.5	(0.4)
Associate's Degree	9.4**	(0.4)	10.8**	(0.3)
Bachelor's Degree	9.2***	(0.4)	13.5***	(0.3)
Graduate Degree	2.7*	(0.2)	3.4*	(0.2)
Nonwhite	27.8***	(0.6)	22.8***	(0.4)
Female	58.4***	(0.7)	46.5***	(0.4)
Veteran	29.8***	(0.6)	25.6***	(0.4)
UI Claimant	23.5***	(0.6)	30.8***	(0.4)
Single Parent	25.1***	(0.6)	11.4***	(0.3)
Primary Language Not English	8.4***	(0.4)	4.6***	(0.2)
Has a Disability	3.5**	(0.2)	2.6**	(0.1)
Accommodation and Food Services	8.5***	(0.4)	2.8***	(0.1)
Admin. and Support and Waste Management	11.9***	(0.4)	7.3***	(0.2)
Agriculture, Forestry, Fishing and Hunt	2.7*	(0.2)	2.1*	(0.1)
Arts, Entertainment, and Recreation	1.9***	(0.2)	1.0***	(0.1)
Construction	4.0	(0.3)	3.5	(0.2)
Educational Services	3.3**	(0.2)	2.5**	(0.1)
Finance and Insurance	3.2***	(0.2)	5.4***	(0.2)
Health Care and Social Assistance	16.3***	(0.5)	6.7***	(0.2)
Information	1.9***	(0.2)	4.1***	(0.2)
Management of Companies and Enterprises	0.1	(0.0)	0.2	(0.0)
Manufacturing	13.9***	(0.5)	35.2***	(0.4)
Mining	0.1***	(0.0)	0.9***	(0.1)
Other Services (except Public Admin.)	5.4***	(0.3)	3.1***	(0.2)
Professional, Scientific, and Technical	3.6***	(0.2)	5.0***	(0.2)
Public Administration	2.8	(0.2)	2.4	(0.1)
Real Estate and Rental and Leasing	2.0**	(0.2)	1.4**	(0.1)
Retail Trade	12.0***	(0.4)	7.9***	(0.2)
Transportation and Warehousing	3.0***	(0.2)	4.2***	(0.2)
Utilities	0.5	(0.1)	0.4	(0.1)
Wholesale Trade	3.0**	(0.2)	3.9**	(0.2)
	5677		12360	

Numbers are percentages except for quarters employed, earnings, and age

Asterisks indicate significant differences from other group using a two-tailed *t* test

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

participants and more likely to be nonwhite, female, veterans, single parents, disabled, or not to speak English as a primary language, compared to Labor Exchange clients. Educational attainment was less for WIA than for the Labor Exchange group, as measured by the percentage of the group members who had earned a college degree.

The industry in which individuals worked during the 7th quarter prior to exit, if employed, varied substantially across the groups. Compared to Labor Exchange, WIA participants were more frequently working in accommodation and food services, administration, arts, education, health care and social assistance, retail, and other services. They were less frequently represented in finance, information, manufacturing, professional occupations, transportation, and wholesale trade.

Figure 1: Estimated Probabilities of Participation (Propensity Scores)

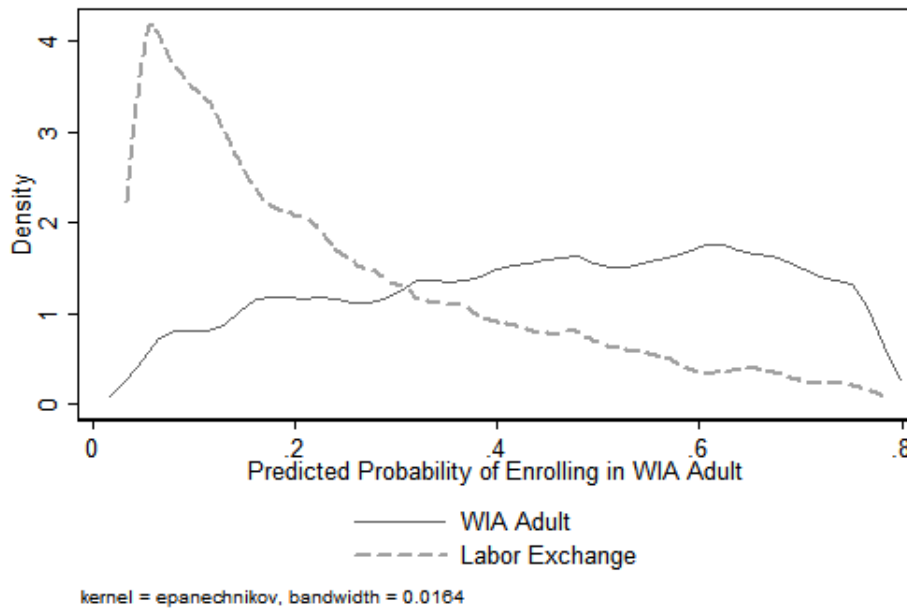


Table 5 shows the factors that were used to predict participation in the WIA Adult program. These include age, gender, race, number of hours worked during the in seventh quarter prior to exit, educational attainment, earnings in the fifth and tenth quarters prior to program exit, single parent status, Unemployment Insurance status at first program entry, the number of total quarters employed prior to program exit, primary language, geographic location (Workforce Development Council area), veteran status, disability status, the county-level unemployment rate, and industry of employment in the 7th quarter prior to exit. Based on the logistic regression, veterans, people with disabilities, single parents, and people of minority ethnic groups were more likely to enroll in the WIA Adult program, while UI claimants were less likely.

Figure 1 shows predicted probabilities of participating in the two programs. As expected, the chart shows that propensity scores were lower for Labor Exchange clients than for WIA Adult clients. The mean propensity score was 0.45 among WIA Adult participants and 0.24 among Labor Exchange participants. A small number of Labor Exchange participants had a high probability of participating in WIA but did not do so. The remaining analysis excludes individuals with the highest and lowest five percent of propensity scores to maximize overlap between the groups.

As described previously, I used propensity score weights to adjust for compositional differences. Table 4 shows the demographic comparison of groups after this adjustment. WIA and Labor Exchange are statistically similar on all variables. The specification passes all three balancing tests previously described, with scores well below 20 for the standardized differences test. Thus, the resulting adjusted sample contains very similar groups that are suitable for comparison.

For reference, the quarterly state and national unemployment rates (not seasonally adjusted) during this time are shown in Figure 2. County-level unemployment varied substantially from the statewide average, with some counties experiencing official unemployment rates as high as 16 percent during the study period, and even higher rates when marginally attached workers are considered.

Average quarterly earnings as a function of the number of quarters from the time of program exit are shown in Figure 3. The quarter count is not aligned with calendar time because the first quarter after participation occurred at different times for different individuals. Without any adjustments for economic conditions or participant characteristics, earnings are higher among the Labor Exchange group than among

Table 4: Demographic Composition of Sample, Propensity Score Weighted

	WIA Adult		Labor Ex.		SD Test
	Mean	Std. Err.	Mean	Std. Err.	
Quarters Employed Prior to Exit	10.1	(0.1)	9.9	(0.1)	2.6
Earnings in 10th Quarter Before Exit	6139.1	(80.6)	6181.1	(54.6)	-0.7
Earnings in 7th Quarter Before Exit	6700.2	(76.4)	6826.9	(53.2)	-2.3
Earnings in 5th Quarter Before Exit	5741.3	(89.5)	5868.0	(58.2)	-2.0
Hours Worked in 7th Quarter Before Exit	380.2	(2.9)	380.6	(1.9)	-0.2
Age in 2001	37.0	(0.2)	37.1	(0.1)	-1.0
County Unemp. Rate in 2nd Qtr. Before Exit	5.99	(0.0)	6.0	(0.0)	1.2
Employed in 6th Quarter Before Exit	89.0	(0.4)	89.2	(0.3)	-0.9
Less than HS	8.8	(0.4)	8.8	(0.3)	0.2
HS or GED	39.6	(0.7)	39.5	(0.5)	0.2
Some College	28.8	(0.6)	28.9	(0.4)	-0.4
Associate's Degree	9.8	(0.4)	9.4	(0.3)	1.2
Bachelor's Degree	10.1	(0.4)	10.2	(0.3)	-0.3
Graduate Degree	2.9	(0.2)	3.1	(0.2)	-1.4
Nonwhite	27.0	(0.6)	26.2	(0.4)	1.7
Female	56.2	(0.7)	55.5	(0.5)	1.6
Veteran	28.4	(0.6)	27.0	(0.4)	3.1
UI Claimant	24.9	(0.6)	26.1	(0.4)	-2.6
Single Parent	20.9	(0.6)	21.2	(0.4)	-0.8
Primary Language not English	7.9	(0.4)	8.3	(0.3)	-1.5
Has a Disability	3.5	(0.3)	3.4	(0.2)	0.5
Accommodation and Food Services	7.0	(0.4)	7.2	(0.2)	-0.9
Admin and Support and Waste Mgmt.	11.9	(0.5)	11.6	(0.3)	1.1
Ag., Forestry, Fishing, and Hunting	2.7	(0.2)	3.0	(0.2)	-2.0
Arts, Entertainment, and Recreation	1.8	(0.2)	1.7	(0.1)	0.6
Construction	4.2	(0.3)	4.4	(0.2)	-1.1
Educational Services	3.4	(0.3)	3.1	(0.2)	1.7
Finance and Insurance	3.6	(0.3)	3.5	(0.2)	0.7
Health Care and Social Assistance	14.3	(0.5)	13.6	(0.3)	1.9
Information	2.1	(0.2)	2.2	(0.1)	-0.6
Mgmt. of Companies and Enterprises	0.1	(0.0)	0.1	(0.0)	-0.6
Manufacturing	15.7	(0.5)	15.7	(0.3)	0.2
Mining	0.1	(0.0)	0.1	(0.0)	0.2
Other Services (except Public Admin.)	5.2	(0.3)	5.1	(0.2)	0.1
Professional, Scientific, and Technical	3.9	(0.3)	4.3	(0.2)	-2.1
Public Administration	3.0	(0.2)	3.1	(0.2)	-0.6
Real Estate and Rental and Leasing	2.1	(0.2)	2.1	(0.1)	0.2
Retail Trade	11.8	(0.5)	11.9	(0.3)	0.0
Transportation and Warehousing	3.4	(0.3)	3.4	(0.2)	-0.2
Utilities	0.4	(0.1)	0.3	(0.1)	0.8
Wholesale Trade	3.3	(0.3)	3.5	(0.2)	-1.4
Observations	4903		11377		

Numbers are percentages except for quarters employed, earnings and age

Hotelling's T -squared=53.72, F =1.07 (p =0.34)

No values diff. from LE at $p < 0.05$

Figure 2: Quarterly State & National Unemployment Rate, 2001-2009Q1 (Bureau of Labor Statistics, 2009)

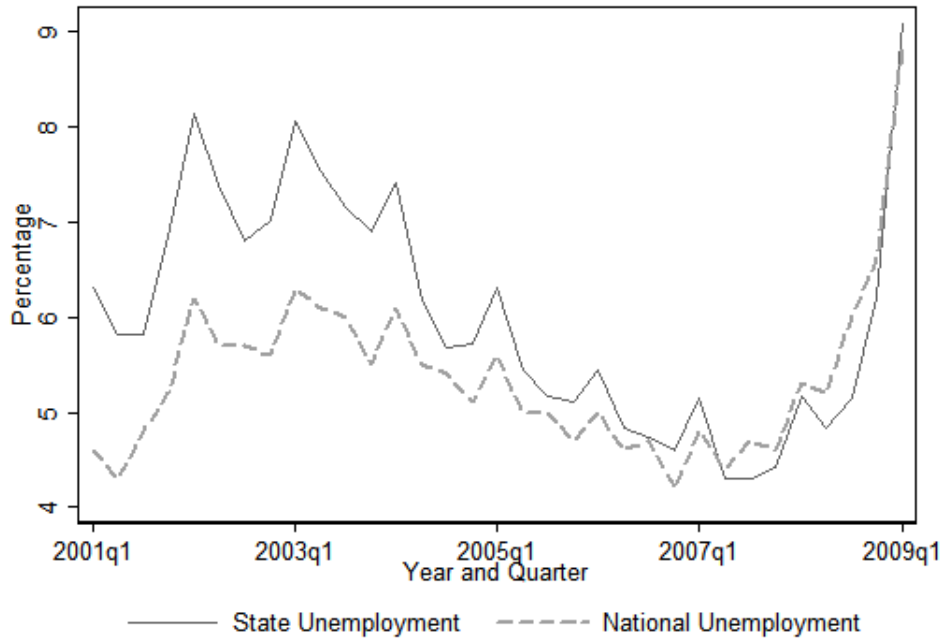


Figure 3: Average Earnings for Treatment and Comparison Groups

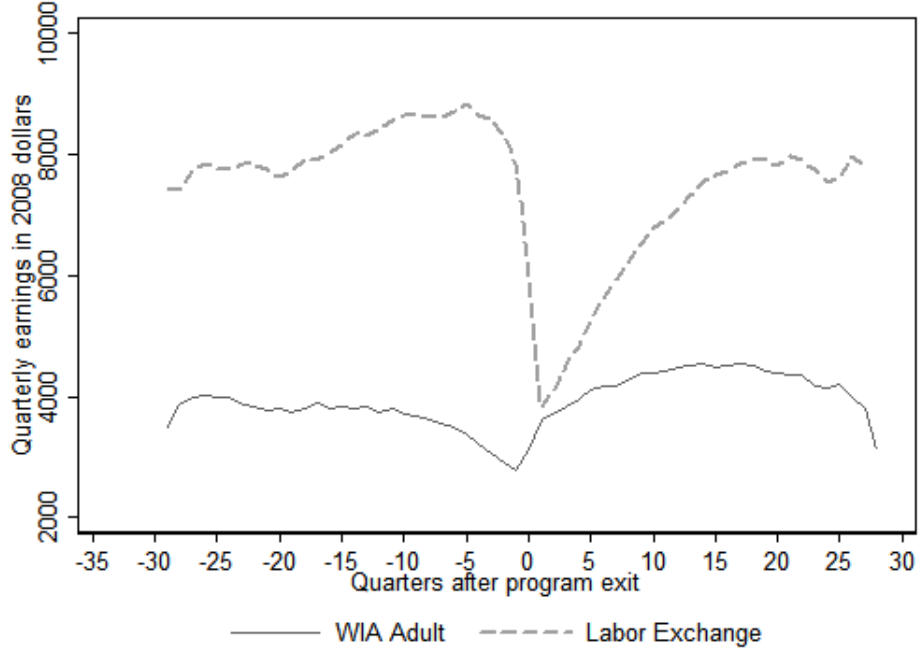


Figure 4: Average Earnings Residual Controlling for County Unemployment Rate

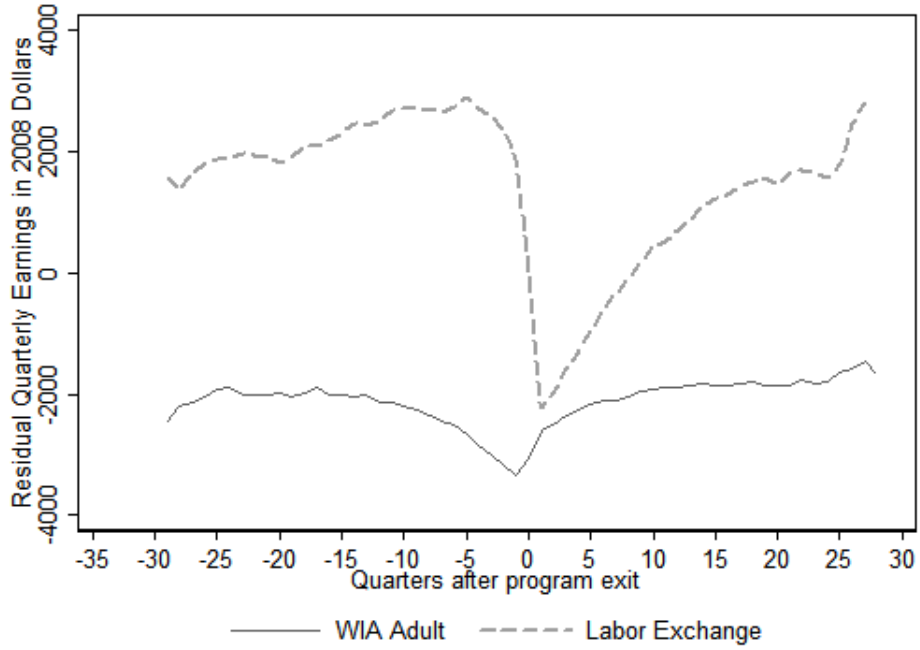


Figure 5: Residual Earnings in Treatment and Comparison, Propensity Score Weighted



Table 5: Propensity Score Prediction Logit Model

	Odds Ratio	Std. Error
County Unemp. Rate in 2nd Qtr. Before Exit	0.856***	(0.00)
Age in 2001	0.960***	(0.00)
Age in 2001, Squared	1.000***	(0.00)
Female	0.974	(0.03)
Nonwhite	1.254***	(0.04)
Hours Worked in 7th Quarter Before Exit	1.001***	(0.00)
Hours Worked in 7th Qtr. Before Exit, Squared	1.000	(0.00)
Less than HS	1.408**	(0.17)
HS or GED	1.112	(0.12)
Some College	0.971	(0.11)
Associate's Degree	0.874	(0.10)
Bachelor's Degree	0.557***	(0.07)
Earnings in 5th Quarter Before Exit	1.000***	(0.00)
Earnings in 5th Qtr. Before Exit, Squared	1.000***	(0.00)
Earnings in 5th Qtr. Before Exit, Cubed	1.000***	(0.00)
Earnings in 7th Quarter Before Exit	1.000***	(0.00)
Earnings in 7th Qtr. Before Exit, Squared	1.000***	(0.00)
Earnings in 7th Qtr. Before Exit, Cubed	1.000***	(0.00)
Earnings in 10th Quarter Before Exit	1.000***	(0.00)
Earnings in 10th Qtr. Before Exit, Squared	1.000***	(0.00)
Employed in 6th Quarter Before Exit	1.053***	(0.01)
Single Parent	1.859***	(0.02)
Earnings in 10th Qtr. Before Exit, Cubed	1.000***	(0.00)
UI Claimant	0.708***	(0.01)
Quarters Employed Prior to Exit	0.973***	(0.00)
Quarters Employed Before Exit, Squared	1.001***	(0.00)
Primary Language not English	1.503***	(0.02)
wdc==Benton-Franklin	3.546***	(0.07)
wdc==Eastern Washington Partnership	0.406***	(0.01)
wdc==North Central	9.674***	(0.24)
wdc==Northwest	0.826***	(0.02)
wdc==Olympic	2.137***	(0.04)
wdc==Pacific Mountain	1.767***	(0.03)
wdc==Seattle-King County	1.355***	(0.02)
wdc==Snohomish	0.964	(0.02)
wdc==South Central	0.552***	(0.01)
wdc==Southwest Washington	3.023***	(0.06)
wdc==Spokane	1.978***	(0.04)
Veteran	1.427***	(0.01)
Has a Disability	1.398***	(0.03)
Age in 2001*Female	1	(0.00)

Continued on Next Page...

Table 5 (Continued)

	Odds Ratio	Std. Error
Age in 2001*Nonwhite	0.997***	(0.00)
Age in 2001*Less Than HS	0.988***	(0.00)
Age in 2001*HS/GED	0.989***	(0.00)
Age in 2001*Some College	0.995*	(0.00)
Age in 2001*Associate's	0.994*	(0.00)
Age in 2001*Bach	1.007**	(0.00)
Age in 2001*Earnings in 5th Qtr. Before Exit	1.000***	(0.00)
Age in 2001*Earnings in 7th Qtr. Before Exit	1.000***	(0.00)
Age in 2001*Earnings in 7th Qtr. Before Exit, Squared	1.000***	(0.00)
Age in 2001*Earnings in 10th Qtr. Before Exit	1.000*	(0.00)
Veteran*Has a Disability	0.967	(0.04)
industry7==Accommodation and Food Services	1.583***	(0.09)
industry7==Admin. and Support and Waste Management	1.190**	(0.06)
industry7==Agriculture, Forestry, Fishing and Hunting	0.733***	(0.04)
industry7==Arts, Entertainment, and Recreation	1.226***	(0.07)
industry7==Construction	1.111	(0.06)
industry7==Educational Services	1.05	(0.06)
industry7==Finance and Insurance	0.929	(0.05)
industry7==Health Care and Social Assistance	1.970***	(0.11)
industry7==Information	0.855**	(0.05)
industry7==Management of Companies and Enterprises	1.054	(0.11)
industry7==Manufacturing	0.587***	(0.03)
industry7==Mining	0.492***	(0.04)
industry7==Other Services (except Public Administration)	1.386***	(0.08)
industry7==Professional, Scientific, and Technical Services	0.974	(0.05)
industry7==Public Administration	1.163**	(0.07)
industry7==Real Estate and Rental and Leasing	1.263***	(0.07)
industry7==Retail Trade	1.123*	(0.06)
industry7==Transportation and Warehousing	0.810***	(0.05)
industry7==Wholesale Trade	0.962	0.053
Observations	595221	
$\chi^2(71)$	169205.1	

Exponentiated coefficients

Reference categories: Graduate degree, Tacoma-Pierce WDC, utilities industry

Asterisks indicate significant predictor; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the WIA Adult group. For the Labor Exchange group, earnings are substantially lower near the quarter of program exit than during other quarters.

To take into account the potential association of macroeconomic factors with quarterly earnings, Figure 4 shows residual earnings after an OLS regression of the county-level quarterly unemployment rate on individual earnings. This adjustment removes the downturn in earnings that had been noticeable at the end of the observation period for individuals who had exited the program approximately 26 quarters previously.

An “Ashenfelter dip” is still present, particularly among the Labor Exchange group, even after controlling for the unemployment rate. Earnings declines are often the reason that individuals seek workforce development services in the first place.

Figure 5 shows residual earnings after weighting by $p(X_i)/(1 - p(X_i))$. Virtually all of the pre-program difference in earnings has been addressed by the propensity score procedure. Earnings for WIA participants begin to increase prior to exit because of their receipt of additional services after obtaining employment, unlike for most Labor Exchange participants.

The remaining tables show regression results from a variety of specifications. As a baseline, Table 6 is an unweighted OLS specification that does not account for selection. These unweighted results suggest that WIA participants experienced lower earnings growth following participation than Labor Exchange participants. In addition, WIA participants experienced a one-time decrease in earnings around the time of program exit. Examining Figure 5 reveals that this decrease should be understood as the shortfall in post-program earnings relative to pre-program averages. Program participants experienced substantial gains relative to the lowest level of earnings in the pre-exit dip, but on the whole these gains were insufficient to reach the same earnings levels as prior to any contact with the program.

Table 7 shows the results from the pooled OLS specification, weighted to account for selection. In the weighted results, the primary coefficient of interest is -\$17.48 for WIA Adult and \$15.22 for Labor Exchange. These coefficients are not statistically significantly different from zero or each other, revealing that earnings growth after program exit was approximately equal for the two groups. The other coefficients indicate that earnings were increasing slightly before individuals received services, by about \$49.02 per quarter. The sum shows that, after exit, the average quarterly increase in earnings was \$31.54 for WIA participants (\$49.02 - \$17.48) and \$64.24 for Labor Exchange participants (\$49.02 + \$15.22).

The other coefficients in this specification show that the county unemployment rate was negatively associated with earnings prior to WIA participation and that individuals with greater levels of educational

Table 6: Pooled OLS Results, Unweighted Baseline (Unweighted Equation (3))

	(1)	
	Quarterly earnings in 2008 dollars	
Quarters after program exit	79.27***	(5.180)
WIA exit indicator	-5022.8***	(223.2)
Labor Exchange exit indicator	-3429.8***	(192.2)
WIA Adult*Quarters after program exit	-49.77***	(12.90)
Labor Exchange*Quarters after program exit	56.18***	(10.72)
County unemployment rate	-277.9***	(22.09)
WIA Adult*County unemployment rate	72.65*	(34.93)
Labor Exchange*County unemployment rate	-223.6***	(31.08)
Age in years	87.12***	(3.629)
Female	-1973.1***	(81.70)
Nonwhite	-98.10	(89.37)
HS or GED	1132.5***	(125.9)
Some College	1629.1***	(136.7)
Associate's Degree	1569.6***	(161.0)
Bachelor's Degree	3265.3***	(184.5)
Graduate Degree	5163.0***	(388.4)
Single Parent	-314.1**	(98.18)
UI Claimant	191.0*	(81.87)
Primary Language not English	-1455.5***	(129.6)
Veteran	62.31	(92.13)
Has a Disability	-1355.0***	(214.1)
Constant	7197.4***	(255.3)
Observations	360183	

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Pooled OLS Results, Propensity Score Weighted (Weighted Equation (3))

	(1)	
	Quarterly earnings in 2008 dollars	
Quarters after program exit	49.02***	(5.85)
WIA exit indicator	-1877.8***	(231.9)
Labor Exchange exit indicator	-1678.7***	(227.6)
WIA Adult*Quarters after program exit	-17.48	(12.94)
Labor Exchange*Quarters after program exit	15.22	(12.04)
County unemployment rate	-153.8***	(28.48)
WIA Adult*County unemployment rate	-48.03	(37.56)
Labor Exchange*County unemployment rate	-141.9***	(37.80)
Age in years	65.09***	(3.85)
Female	-1259.4***	(88.99)
Nonwhite	-79.60	(99.09)
HS or GED	656.3***	(122.0)
Some College	1145.7***	(135.1)
Associate's Degree	1194.3***	(162.3)
Bachelor's Degree	2549.9***	(201.8)
Graduate Degree	4179.7***	(546.9)
Single Parent	-163.9	(96.40)
UI Claimant	276.7**	(88.97)
Primary Language not English	-866.0***	(124.8)
Veteran	38.98	(101.5)
Has a Disability	-1071.3***	(210.0)
Constant	4910.7***	(287.5)
Observations	360183	

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Averaged Individual-Level OLS Results, Propensity Score Weighted (Equations (1) and (2))

	WIA Adult	Std. Err.	Labor Ex.	Std. Err.
Quarter	75.45***	(9.79)	27.04	(7.20)
Post	-2141.36	(327.45)	-2243.28	(199.13)
Post*Quarter	-17.24	(36.01)	4.22	(19.86)
Unemp	-236.98*	(35.35)	-341.67	(22.48)
Post*Unemp	20.78	(43.72)	118.47	(26.31)
Constant	8402.1	(295.27)	8771.97	(186.10)
Observations	4903		11377	

Diff. from LE * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The standard errors are the average of individual-level standard errors, weighted with the propensity score weight. The standard error for the average coefficient $\frac{1}{n}\sum\beta_i$ is $\frac{1}{n}\sqrt{\sum var[\beta_i]}$.

attainment had higher earnings than those with less than a high school education. In particular, individuals with a bachelor's degree had quarterly earnings that were approximately \$2,549 more on average than those of individuals without a high school diploma. UI claimants earned an average of approximately \$277 more than non-claimants. On average, women earned \$1,259 less than men per quarter, people with disabilities earned \$1,071 less than people without disabilities, and individuals whose primary language was not English earned \$866 less than English speakers. Differences by ethnic background were not statistically significant.

Table 8 provides the averaged individual-level OLS results. The slope terms of interest have the value of -\$17.24 for WIA Adult participants and \$4.22 for Labor Exchange participants, and are not statistically significantly different from each other. The conclusion is consistent with the pooled results that earnings growth was not statistically significantly different among individuals who received less intensive workforce services and those who received WIA-funded services. The overall average earnings growth after exit is \$58.21 for WIA (\$75.45 - \$17.24) and \$31.26 for Labor Exchange (\$27.04 + \$4.22).

Table 9 provides averaged individual-level OLS results using the logarithm of quarterly earnings as the response variable. The slope coefficients are not different between the WIA Adult and Labor Exchange groups in a two-tailed t test. This result matches the previous finding that earnings progression was not statistically significantly different among individuals who received less intensive workforce services and those who received WIA-funded services. I also present the pooled model using the logarithm of quarterly earnings in Table 10. The individual-level specification is more appropriate in this case, however, because of its flexibility to account for heterogeneity among individuals who receive workforce development services.

Table 9: Averaged Individual-Level OLS Results, Propensity Score Weighted, Log Earnings

	WIA Adult	Std. Err.	Labor Ex.	Std. Err.
Quarter	0.14	(0.01)	0.14	(0.00)
Post	-2.31***	(0.19)	-3.25	(0.13)
Post*Quarter	-0.16	(0.03)	-0.16	(0.02)
Unemp	-0.2***	(0.02)	-0.38	(0.01)
Post*Unemp	0.02***	(0.02)	0.17	(0.02)
Constant	10***	(0.16)	10.96	(0.12)
Observations	4903		11377	

Diff. from LE * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The standard errors are the average of individual-level standard errors, weighted with the propensity score weight. The standard error for the average coefficient $\frac{1}{n}\sum\beta_i$ is $\frac{1}{n}\sqrt{\sum var[\beta_i]}$.

Table 10: Pooled OLS Results, Propensity Score Weighted, Log Earnings

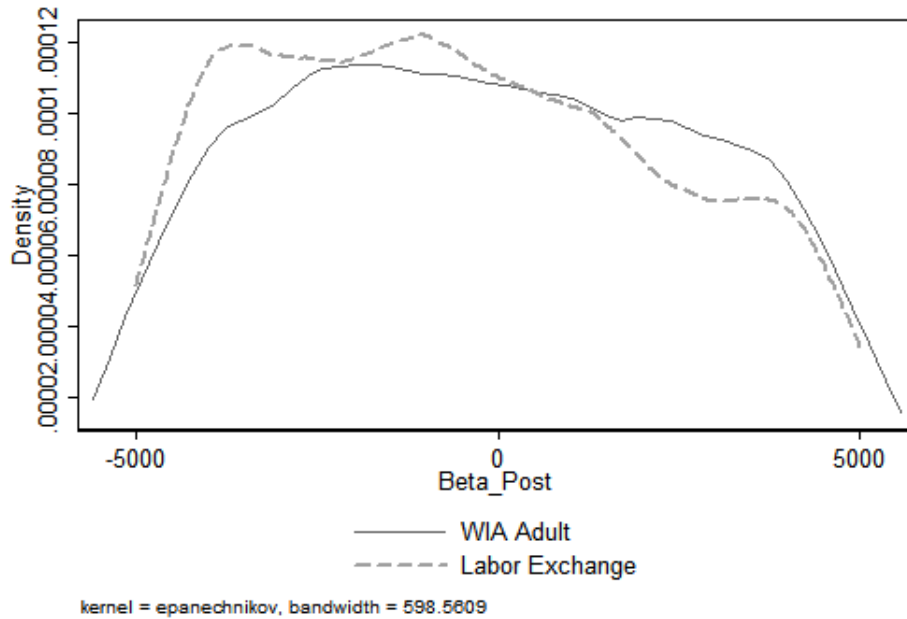
	(1)	
	Log of quarterly earnings in 2008 dollars	
Quarters After Program Exit	0.11***	(0.0041)
WIA Exit Indicator	-1.81***	(0.16)
Labor Exchange Exit Indicator	-1.92***	(0.16)
WIA Adult*Quarters After Program Exit	-0.14***	(0.0095)
Labor Exchange*Quarters After Program Exit	-0.11***	(0.0095)
County Unemployment Rate	-0.074***	(0.015)
WIA Adult*County Unemployment Rate	-0.046	(0.025)
Labor Exchange*County Unemployment Rate	-0.090***	(0.025)
Age	0.018***	(0.0025)
Female	0.013	(0.052)
Nonwhite	-0.053	(0.058)
HS or GED	0.18	(0.098)
Some College	0.27**	(0.10)
Associate's Degree	0.33**	(0.12)
Bachelor's Degree	0.32**	(0.12)
Graduate Degree	0.095	(0.18)
Single Parent	-0.0067	(0.067)
UI Claimant	0.67***	(0.051)
Primary Language not English	-0.088	(0.099)
Veteran	-0.32***	(0.062)
Has a Disability	-0.40**	(0.14)
Constant	7.89***	(0.18)
Observations	360183	

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figures 6-8 provide kernel density estimates of the weighted individual coefficients. For the coefficients on post interacted with quarter and post interacted with the county unemployment rate, there is a slightly wider spread among WIA participants than Labor Exchange participants. Overall, the distribution of individual coefficients is quite similar across the groups.

Figure 6: Kernel Density for Individual Post Coefficient



7 Conclusion

This research contributes to the literature and practice of workforce development by analyzing whether a large sample of individuals who obtained specialized career services experienced different patterns of earnings progression than individuals who had not. This question has received relatively little attention in labor economics (Gladden & Taber, 2000), and is of substantial importance to scholars, policy makers, and practitioners who seek to promote economic self-sufficiency among the poor.

These findings indicate that, once observable differences in the two groups were minimized, WIA participants in Washington State experienced approximately the same or lower earnings growth as their Labor Exchange counterparts who received less intensive services. This is consistent with the results of Mueser &

Figure 7: Kernel Density for Individual Post*Quarter Coefficient

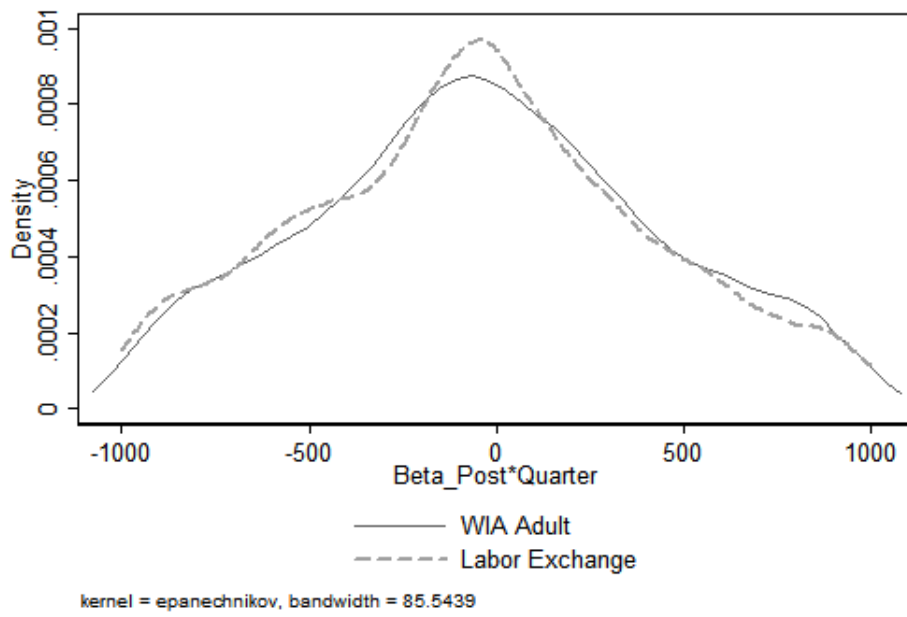
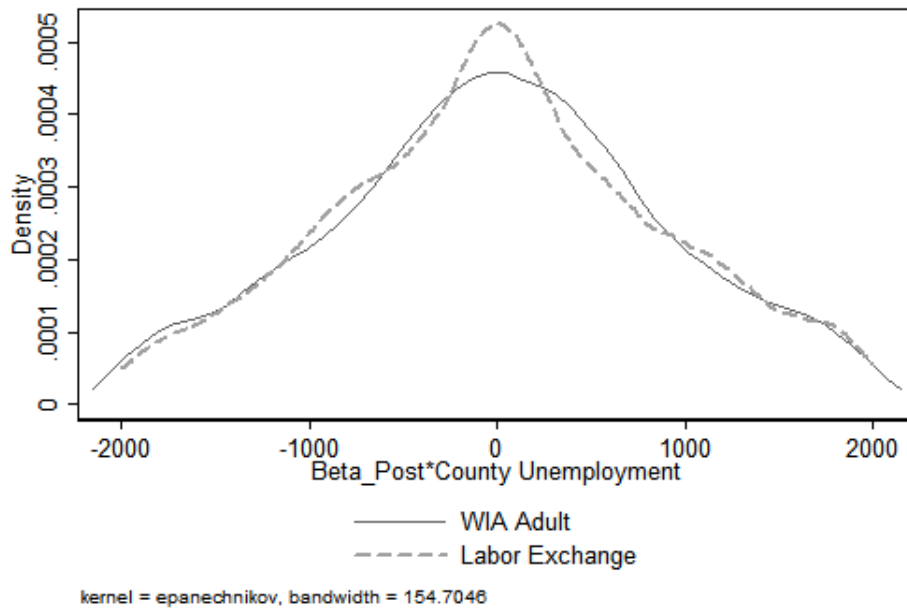


Figure 8: Kernel Density for Individual Post*County Unemployment Coefficient



Stevens (2003) that any initial differences in earnings growth across the WIA and Labor Exchange groups were quickly equalized. An important consideration is that WIA participants are more disadvantaged, on average, than Labor Exchange clients. Nevertheless, the results are somewhat surprising considering the resource investments in training and placement, as well as explicit efforts to assist workers obtain good jobs and higher incomes. It is possible that unobservable factors differentiated the comparison group from the treatment group and were not captured in the analysis.

The limitations of this study include a lack of wage data on workers not covered by UI, lack of random assignment to WIA and Labor Exchange services, and variation in program delivery that might not be adequately captured by geographic control variables. For future research, alternate designs should include a random assignment study as well as a differentiation of WIA and Labor Exchange services and more equal distribution of participants to allow for more comparability between treatment and comparison groups to assess the Workforce Investment Act more validly. Although workforce agencies do not directly control the quantity and quality of jobs that are available in their jurisdictions, and they have expended considerable effort identifying high-paying vacancies, this analysis suggests that patterns of earnings progression following existing WIA services are not distinguishable from those following the receipt of Labor Exchange services.

References

- Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *Review of Economics and Statistics*, 60(1), 47–57.
- Becker, G. S. (1993). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education* (Third ed.). Chicago: University of Chicago Press.
- Becker, S. O. & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, 2(4), 358–377.
- Brown, A. (1997). *Work first: How to implement an employment-focused approach to welfare reform*. New York: MDRC.
- Bureau of Labor Statistics (2008). Employment and wages, annual averages 2006. Retrieved June 14, 2009 from <http://www.bls.gov/cew/cewbultn06.htm>.
- Bureau of Labor Statistics (2009). Local area unemployment statistics. <http://www.bls.gov/lau/>.
- Cameron, A. & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge: Cambridge University Press.
- Chrisinger, C. K., Cowan, B. W., Scholz, J. K., & White, C. Z. (2008). Public assistance and workfare. In S. Lee, A. Mason, & K. Sul (Eds.), *Social Policy at a Crossroads: Trends in Advanced Countries and Implications for Korea*. Seoul: Korea Development Institute.
- Dahl, M., DeLeire, T., & Schwabish, J. (2009). Stepping stone or dead end? The effect of the EITC on earnings growth. *National Tax Journal*, 62(2), 329–346.
- Dehejia, R. H. & Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448), 1053–1062.
- Eberts, R. W. & Holzer, H. J. (2004). Overview of Labor Exchange policies and services. In D. Baldocchi, R. W. Eberts, & C. J. O’Leary (Eds.), *Labor Exchange Policy in the United States*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

- French, E., Mazumder, B., & Taber, C. (2006). The changing pattern of wage growth for low-skilled workers. In R. M. Blank, S. Danziger, & R. Schoeni (Eds.), *Working and Poor: How Economic and Policy Changes Are Affecting Low-Wage Workers*. New York: Russell Sage Foundation.
- Frolich, M. (2004). Finite-sample properties of propensity-score matching and weighting estimators. *The Review of Economics and Statistics*, 86(1), 77–90.
- Gelman, A. & Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge: Cambridge University Press.
- Gladden, T. & Taber, C. (2000). Wage progression among less skilled workers. In D. E. Card & R. M. Blank (Eds.), *Finding Jobs: Work and Welfare Reform*. New York: Russell Sage Foundation.
- Guo, S. Y. & Fraser, M. W. (2010). *Propensity Score Analysis: Statistical Methods and Applications*. Sage Publications, Inc.
- Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4), 605–654.
- Heinrich, C., Mueser, P., & Troske, K. R. (2008). Workforce Investment Act nonexperimental net impact evaluation. Occasional Paper ETAOP 2009-10, U.S. Department of Labor, Washington, D.C.
- Hollenbeck, K. & Huang, W. (2006). Net impact and benefit cost estimates of the workforce development system in Washington state. Upjohn Institute Technical Report TR06-020, W.E. Upjohn Institute for Employment Research, Kalamazoo, Mich.
- Holzer, H. J. (2009). Workforce development as an antipoverty strategy: What do we know? What should we do? In M. Cancian & S. Danziger (Eds.), *Changing Poverty, Changing Policies*. New York: Russell Sage Foundation.
- Imbens, G. (2000). The role of the propensity score in estimating dose-response functions. *Biometrika*, 87, 706–710.
- Lechner, M. & Wunsch, C. (2009). Are training programs more effective when unemployment is high? *Journal of Labor Economics*, 27(4), 653–692.

- Mead, L. M. (1993). *The New Politics of Poverty*. New York: Basic Books.
- Miller, C., Martin, V., & Hamilton, G. (2008). Findings for the Cleveland Achieve model: Implementation and early impacts of an employer-based approach to encourage employment retention among low-wage workers. MDRC.
- Mueser, P. & Stevens, D. W. (2003). Low-income and welfare client priorities: Patterns of earnings and welfare receipt for Workforce Investment Act participants. University of Missouri Department of Economics Working Paper 0313, prepared for the U.S. Department of Labor, Employment and Training Administration. http://economics.missouri.edu/working-papers/2003/WP0313_Mueser-Stevens.pdf.
- Navarro, D., van Dok, M., & Hendra, R. (2007). The Employment Retention and Advancement Project: results from the Post-Assistance Self-Sufficiency (PASS) program in Riverside, California. MDRC.
- O’Leary, C. J., Straits, R. A., & Wandner, S. A. (2004). U.S. job training: Types, participants, and history. In C. J. O’Leary, R. A. Straits, & S. A. Wandner (Eds.), *Job Training Policy in the United States*. Kalamazoo, Mich.: W.E. Upjohn Institute for Employment Research.
- Pavetti, L. & Acs, G. (1997). Moving up, moving out, or going nowhere? A study of the employment patterns of young women and the implications for welfare mothers. Washington, D.C.: The Urban Institute.
- Pirog, M. A., Buffardi, A. L., Chrisinger, C. K., Singh, P., & Briney, J. (2009). Are the alternatives to randomized assignment nearly as good? Statistical corrections to nonrandomized evaluations. *Journal of Policy Analysis and Management*, 28(1), 169–172.
- Rosenbaum, P. R. (1987). Model-based direct adjustment. *Journal of the American Statistical Association*, 82(398), 387–394.
- Rosenbaum, P. R. & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55.
- Rosenbaum, P. R. & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1), 33–38.

- Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *The Annals of Statistics*, 6(1), 34–58.
- Sianesi, B. (2004). An evaluation of the Swedish system of active labor market programs in the 1990s. *The Review of Economics and Statistics*, 86(1), 133–155.
- Smith, J. & Zhang, Y. (2009). The variety of balancing tests. Working Paper for the Association for Public Policy Analysis and Management 2009 Fall Conference.
- Sommers, P. (2001). Cluster strategies for Washington. Report for the Washington State Office of Trade and Economic Development.
- U.S. Census Bureau (2009). Washington fact sheet, 2005-2007 American Community Survey.
- U.S. Department of Health and Human Services (2007). Annual update of the HHS poverty guidelines. *Federal Register*, 72(15), 3147–3148.
- U.S. Government Accountability Office (2005). Workforce Investment Act: Labor and states have taken actions to improve data quality, but additional steps are needed. Report number GAO-06-82.
- Wallace, G. L. & Haveman, R. (2007). The implications of differences between employer and worker employment/earnings reports for policy evaluation. *Journal of Policy Analysis and Management*, 26(4), 737–754.
- Workforce Training and Education Coordinating Board (2008). Washington State annual report on the Workforce Investment Act Title I-B. Technical report, U.S. Department of Labor, Washington, D.C.