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JOB TRAINING IMPACTS ON WAGES: AN APPLICATION OF DIFFERENCE IN DIFFERENCE ANALYSIS

Abstract: *This study examines the relationship between job training and wages among the 1997 cohort using data from the National Longitudinal Survey of Youth (NLSY) in the USA. For this purpose, a propensity score matching (PSM) is estimated. Then difference in difference model is applied to examine the potential impact on training on wages. The study uses STATA for analysis the model and reports STATA codes for application of the similar model for future researches. According to analysis results, training has raised real income by about $2,675 to $4,484. Using the difference between real income in 2005 and 2008, I found that the average treatment of difference in difference was $2,084 between workers who participated in training programs and workers who did not.*

Key words: *Difference in Difference, Logit, Propensity Score Matching, STATA, Training, Wages.*

Language: *English*

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INTRODUCTION

Enhancing the skills of workers through training is necessary to increase productivity and competitiveness in the labor market. Training improves morale of workers and helps them to get job security and job satisfaction. This results in efficiency, high quality and quantity performance of workers (Tomer, 2007). In addition to improving productivity, training can increase workers' wages.

Models of competitive labor markets imply that wages paid to workers reflect their productivity. Many studies in the literature are used education as a proxy of workers' productivity and higher wages are paid to highly educated people (Feldstein, 2009). Moreover, some researchers argue that job training enhances workers productivity, and then trained workers should receive higher wages than workers with no training (Barron et. al, 1999).

Much of the empirical research on the human capital model (Becker 1962; Mincer 1962) has analyzed the impact of education, on wages. For instance, Jaeger (2003) examined the relationship between education and wages using cross-sectional data from the Current Population Survey (CPS). The study results indicated that individuals in the survey earning 10 percentages higher for every additional year of schooling completed. Wolpin (2005) shows that a male with college degree earns 80 percent more than a male high school graduate. Furthermore, a male high school graduate earns 57 percent more than a high school dropout (Wolpin, 2005). Zhang et al. (2005) examined economic returns to schooling in Urban China. Their study results indicated an increase in the wage premium for higher education.

On the other hand, research on the relationship between job training and wages is limited. Early studies examined the effect of training on wages used the NLSY79 database. For example, Lynch (1992) used data from 1980 to 1983 to estimate the effect of training on 1983 wages for youths with high school degree. The author used a separate equation for each of the study year and found that training improves workers' ability and productivity, and is positively correlated wages. Lengermann (1999) assessed the effects of training on wages over time and found that training has substantial effects on wages especially in the long term. For instance, the effects increase from

4.4 percent in the first year to 8.2 percent in after 9 years.

O'connell (1999) examined the general and specific training to the empirical task of estimating the returns to in-company training using firm level data set. The study results show that general training has a statistically significant impact but there is not any effect for specific training. One of the recent study estimated training impact on productivity and wages for Belgian firms (Konings and Vanormelingen, 2015). The authors show that the productivity premium for a trained worker is estimated at 23%, whereas the wage premium of training is estimated at 12% for Belgian from 1997 to 2006.

This study adds to the limited literature by examining the relationship between job training and wages using propensity score matching- (PSM) and difference in difference- (DID) using data from the NLSY97. This paper is examined as based on Dehejia and Wahba (1999) study that turn in was based on LaLonde (1986).

Based on the literature reviewed the following hypotheses were constructed:

H_0: There were no wages difference between workers who receive training and workers who did not receive training.

H_A: There were wages difference between trained workers and non-trained workers.

The rest of the paper is organized as follow: Section-2 describes the data set and methods while Section-3 presents the analytical results. Section-4 provides depicts the conclusion. In the Appendix section I report the STATA codes. It can be beneficial for application of DID model for future researches

MATERIAL AND METHODS

DATA

In this study, data set is obtained from the NLSY 1997 which is used to determine the effects of job training on workers' wages. The NLSY is sponsored by the U.S. Bureau of Labor Statistics. It is a nationally representative survey that follows the same sample of individuals from specific birth cohorts over time. The purpose of the NLSY97 survey is to obtain information about labor market activity, schooling, fertility, program participation, health. The NLSY97 concerns men and women born in the years 1980-1984.

"NLSY collects information in an event history format, in which dates are collected for the beginning and ending of important life events. The starting dates and ending dates of all jobs are recorded" (Veum, 1995). Also the timing of training programs which is the key factor for this study. Therefore, it allows creating measures of training received on the current job along with measures of training received on the prior job. Taking advantage of this fact, workers are separable who received training or not from the National Supported Work Training Program (NSW). The NSW is a U.S. federally and privately funded program. The purpose of the program is that to provide work experience for individuals who had faced economic and social problems prior to enrollment in the program (Hollister, Kemper, and May-nard, 1984). Candidates for the experiment were selected on the basis of eligibility criteria, and then were either randomly assigned to, or excluded from the training program (Dehejia and Wahba, 1999).

There are 2,700 observations in the data set, 2,500 controls (with t = 0) and 200 treated observations (with t = 1). The variables in the Table-1 describe the raw data set with:

t is treatment dummy variable indicating training (t=1) and no training (t=0). Age is completed age of individual. Education variable is calculated as completed year (educ) and if an individual has not any degree, nodegree dummy gets 1, 0 otherwise. If an individual is black, the black dummy gets 1, 0 otherwise. If an individual's ethnicity is Hispanic then hisp dummy gets 1, 0 otherwise. For marriage status, marr dummy gets 1 if an individual is married, 0 otherwise. To evaluate training impact I used yearly income of individuals for 2004 before training and 2008 is after training as the outcome variable.

METHODS

First a logit regression is estimated to find out how some variables influence the participation probability:

$$Training_i = f(age,\ marital\ status,\ ethnicity, gender,\ education, income) \qquad (1)$$

Then, propensity score (PS) is used to match individuals who participated in vocational programs and individuals who do not participate to vocational programs base on their characteristics.

Propensity Score Matching (PSM) is defined as the conditional probability of assignment to a particular treatment given a vector of observed covariates (D'Agostino, 1998).

$$P(x) = Pr(D = 1|X) = E(D|X) \qquad (2)$$

Where D is a dummy variable representing participation to vocational programs and X is a vector of covariates. The outcome variable is real earning in 2008. The ultimate goal of PSM is to estimate the average treatment effect on the treated (ATT):

$$ATT = E(Y_1|P(X),\ D = 1) - \\ -E(Y_0|P(X), D = 0) \qquad (3)$$

The matching methods used are the Kernel density method, the Nearest available Neighbor (NN), the Radius Matching and the Caliper Matching methods.

Although, I do not have real panel data on each of the covariates, but I have time series information (before and after the program) for real income. Therefore, I made a strong assumption that unobserved factors have a constant influence on real income and completed our analysis with a Difference in difference (DID) approach to evaluate the impact of job training on workers real income.

DID is defined as the difference in average income in the group of workers who receive training before and after training minus the difference in average income in the group of worker that did not receive training. Similar studies in the literature is used DID method for policy or training analysis. For instance, Lechner, (2011) used DID model estimation strategy and discusses major issues using a treatment effects perspective. Also, Guneysu-Atasoy, (2017) examined the policy impact in the Turkish labor market using DID model.

DID model is calculated as following equation:

$$\delta_{DiD} = (Y_1^T - Y_0^T) - (Y_1^C - Y_0^C) \qquad (4)$$

where Y= real income, T=treatment and C=control. The subscripts 1 and 0 are after and before in respectively.

ANALYSIS RESULTS

I report the descriptive statistics of the variables on the Table-1. Table-2 shows the results of the logit estimation. Most of the coefficients are significant except for the variable real income square. The estimated coefficients cannot be interpreted directly as they are not showing the marginal effects.

Table 1

Descriptive Statistics of the variables

Variable	Obs	Mean	Std.Dev.	Min	Max
t	2700	.0692	.253	0	1
age	2700	34.225	10.499	17	55
educ	2700	11.994	3.054	0	17
black	2700	.291	.455	0	1
hisp	2700	.0343	.182	0	1
marr	2700	.0819	.384	0	1
nodegree	2700	.333	.471	0	1
re04	2700	1.823	1.372	0	13.714
re08	2700	2.051	1.564	0	12.117
age2	2700	1281.61	766.84	289	3025
educ2	2700	1.531.865	70.633	0	289
re04_2	2700	5.205	8.466	0	1880.
blacku04	2700	.0549	.227	0	1

Source: author own calculation

Results of the treatment effect on the treated estimation are summarized in Table-3. The ATT estimation with the Nearest-Neighbor matching method (Table-3b) is $2,675 (0.267*10,000 because of scaling) with an estimated standard error of $2,960, which means that job training has raised real income by $2,960 for trained workers. The ATT estimation with the Kernel matching method (Table-3a) is $3,641 (0.3641*10,000 because of scaling) while the ATT estimation with the Radius matching method (Table-3c) is -$3,470 with a standard error of $5,370. The ATT with the Radius method is distinctive of the two other methods (-$3,470) but as it can be seen only 40 of the 200 treated observations had a neighbor within a range of 0.0001. However, after installing *psmatch2* in *STATA*, caliper matching with the logit propensity scores was implemented. The results of the true caliper method are $4,484 for the ATT and $4,381 for the standard error. This result is more comparable to the Kernel and NN results.

Table 2

Logistic regression

Number of obs = 2700 LR chi2(12) = 764.35
Prob > chi2 = 0.0000
Log likelihood = -319.4356 Pseudo R2 = 0.7003

t	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
age	1.332	.1203	2,76	0.006	.0958	.5675
age2	1.006	.0018	-3,43	0.001	-0,1003	-0,0027
educ	0.849	.3477	2,44	0.015	.1677	1,531
educ2	-3.051	.0172	-2,93	0.003	-0,844	-0,0168
marr	-6.885	.2993	-6,30	0.000	-2,4744	1,299
black	1.135	.3517	3,23	0.001	.4464	1,825
hisp	2.569	.5668	3,47	0.001	.8579	3,080
re04	-3.149	.3525	-3,00	0.003	-1,749	-0,3681
re04_2	4.538	.0642	3,72	0.085	.1129	0,3649
blacku04	13.144	.4268	5,02	0.000	1,307	2,982
_cons	-9.474	2,454	-3,06	0.002	-12,263	-2,685

Table 3a

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	**n. contr.**	**ATT**	**Std. Err.**	**t**
205	1157	0.3641	0.296	1.796

Source: author own calculation

Table 3b

ATT estimation with Nearest Neighbor Matching method
(Random draw version) Bootstrapped standard errors

n. treat.	**n. contr.**	**ATT**	**Std. Err.**	**t**
210	57	0.2675	0.216	1.437

*The numbers of treated and controls refer to actual nearest neighbour matches.
Source: author own calculation

Table 3c

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
40	185	-0.347	0.537	-1.033

*Source: author own calculation

Table 3d

ATT estimation with the Caliber Matching method
Bootstrapped standard errors

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Re08	Unmatched	.7349143	2.15539	-2.520477	.5154614	-13.17
	ATT	.8721715	.6435179	0.448453	.4381663	0.52

Source: author own calculation

Table 4

ATT estimation with DiD Approach

Variable	Sample	Treated	Controls	Difference
d_earn	Unmatched	3817.08818	2370.2894	3446.79878
	ATT	3817.08818	3573.0964	**2084.67911**

Source: author own calculation

To estimate the ATT with the DID approach, I generate the difference in income before and after job training (d_earn=realinc08-realinc04) and use that variable as outcome variable. With this approach, I find an ATT of $2,084 and shown in the Table-4. In other words, it can be said that real income of workers is raised by $2,084 because of training.

The results of the matching methods (NN, Kernel, Radius and caliper) are similar to that of Dehejia and Wahba (1999). However, there is a little increase in the ATT suggesting that workers who do not participate to training programs in the year 2000s are worst of than it was 50 years ago.

CONCLUSION

The objective of this paper was to estimate the effects of job training on workers' wages. Taking advantage of the nice features of the NLSY97, two groups of workers were constructed. The treatment group comprises workers who received job training and the control group is made of workers who did not receive training from the National Supported Work Training Program. A logit model was estimated to determine the propensity scores. Then matching was applied using four methods: Nearest Neighbor, Kernel, Radius, and Caliper Matching. After matching treated and control group, I found that participation to job trainings increase real income by about $2,675 to $4,484. Though I did not have time series data for each covariate, so I use the difference between real income in 2005 and 2008 as outcome variable and estimated a DID model assuming the effects of all the other variables are constant. The average treatment effect on the treated using DID was $2,084. This confirms the study results that job training increases workers' wages. Therefore the analysis results support to recent theories which evaluate *work related training by imperfect competition in the labor market* (Konings and Vanormelingen, 2015).

All in all the null hypothesis can be rejected that job training does not increase wage and encourage workers to participate to training programs not only to increase their skills and productivity, but also their wages.

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Appendix

STATA Codes for the Difference in Difference Model

```
gen age2=age*age
gen educ2=educ*educ
replace re04=re04/10000
replace re05=re05/10000
replace re08=re08/10000
gen re04_2=re04*re04
gen re05_2=re05*re05
gen d_earn=re08-re05
gen blacku04=black*(re04==0)
```

```
global X age age2 educ educ2 marr black hisp re04 re04_2 blacku04
tab global $X

pscore t $X, logit pscore(_pscore) blockid(_block) comsup
set seed 1234579

attk re08 t $X, pscore(_pscore) bootstrap comsup reps(25)

attnd re08 t $X, logit bootstrap reps(25)
attr re08 t $X, logit bootstrap comsup radius(0.0001) reps(25)

psmatch2 t $X, common logit caliper(0.0001) outcome(re08)

pstest age educ black married hisp nodegree re04 re05

psgraph, bin(10)
psmatch2 treated, outcome(d_earn) pscore(ps)
```