



An Econometric Analysis of the Effects of the Job Training Partnership Act on Self-Sufficiency

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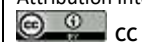
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Abstract

The primary purpose of the study is to investigate the likelihood of a Job Training Partnership Act (JTPA) participant getting a job placement after receiving training, and to identifying the factors that affect the attainment of self-sufficiency (Bloom and Charles, 2001; Friedlander, 1988; Gueron and Edward, 1991). Additionally, the research study focuses on learning more about the determinants of the wage rate at the time when a participant gets a placement.

This study has found that successful completion of training combined with prior work experience are the most important factors that affect the chance of getting a job placement. This finding is consistent with Eberts (2002) and Schexnayder *et al.* (1991). Furthermore, the results show that the most significant variables affecting self-sufficiency are (1) completion of long-term training and (2) reading ability. An additional finding of the study is that if the participant is a recipient of food stamps, then his/her probability of achieving self-sufficiency decreases. Our study's main contribution is the identification of significant variables to be included in the development of workforce policies aiming at promoting economic self-sufficiency and mitigating poverty in Florida.

Keywords: Demographics; Labor economics; Labor policy; Workforce development; Welfare.

1. Introduction

Following the nationwide initiatives to mitigate welfare assistance dependency back in the late 1990s, the Palm Beach County Workforce Development Board requested an econometric model to assist them in identifying factors affecting job placement and self-sufficiency for job seekers, dislocated workers, and welfare recipients.

The two independent variables are achieving employment and economic self-sufficiency for this study. Achieving employment is defined as getting and maintaining a job for at least two consecutive quarters and economic self-sufficiency is defined as achieving employment at an hourly wage above the poverty level (Neumark, 2016).

Getting the dislocated, unemployed worker back to work is a key factor that contributes to economic prosperity and poverty reduction. It impacts not only the individual or firm at the microeconomic level, but also has a positive effect at the macroeconomic level. In his paper, Fieldhouse *et al.* (2011) places a high emphasis on job creation and increasing employment levels and indicates that these are desperately needed because they promote stronger economic growth. In another report, the Mathematica Policy Research jobs study (Rotz *et al.*, 2015)¹ provided evidence that investing in the growth of enterprises, employment, and additional support services for workers, can have a positive impact on people's lives while lessening the burden on government resources. This includes benefits for taxpayers from reductions in government transfer payments to assist the unemployed, and increases in revenues for businesses. Additionally, Shaikh *et al.* (2015), when studying the main determinants of Gross Domestic Product (GDP), conclude that household final consumption expenditure is the biggest determinant of GDP. Household final consumption increases in the long run when the employment rate and wages growth rate increase.

It is interesting to note that the probability of becoming re-employed correlates highly with educational level, work experience, and market demand. According to Imbens and Lynch (2006) in their study titled "Re-employment probabilities over the business cycle," the probability of receiving a job offer and landing a job increases when factors such as education, work experience, and demand conditions are prevalent. Similarly, Petrongolo (2001) study concludes that reemployment pivots on local labor demand, human capital variables such as education and (un)employment history, and personal characteristics. Another study prepared by McGregor (1978) found that

¹This report was commissioned by the Roberts Enterprise Development Fund (REDF). <https://redf.org/about-us>.

skilled workers seeking jobs tend to find work more quickly than unskilled due to better relative job opportunities, though McGregor warns that his study did not measure motivational factors seeking employment.

Local workforce agencies in Miami, Broward, and Palm Beach Counties, which are diverse, populous counties in Southern Florida, following national trends in terms of cutting-edge approaches to mitigate welfare rolls, sought to determine which participants in welfare programs were most likely to return to work. An earlier profiling project, implemented in Kalamazoo, Michigan (Bartik, 2001; Black *et al.*, 2003), was designed to rapidly identify which clients require minimum, average or extensive interventions to make them work-ready and self-sufficient. The Palm Beach Workforce Development Board/ Work and Gain Economic Self-Sufficiency (WAGES) Program² Coalition wanted to create a statistical model, which would assist in determining the best "cocktail" of services for clients (Maxwell *et al.*, 2013; Rotz *et al.*, 2015).

Three major service tracks have been identified in the project. These vary in intensity of services and agency resources needed to support clients identified for each potential track. The model is based on a *mathematical formula* that uses the relationships between participant initial intake data (client characteristics & initial assessment data) and employment outcomes (i.e., employment, and earnings) to predict needed services. It is very important to notice the link between performance measures (input measures) and the data needed to run the research model.

(U.S. Department of Health and Human Services and the U.S. Department of Education, 1997, 2001) (U.S. Department of Labor, 1997, 2001).

The research project target population included all Palm Beach County JTPA³ participants during specified data collection and experimental phases in 1998. It excluded participants who were pre-designated for specific service tracks (e.g., refugee program, etc.).

The primary purpose of this project is to investigate the following questions. (1) What is the probability that a participant succeeds in getting a job placement (that is, achieves self-sufficiency) after he or she receives training and the factors that affect the likelihood of attaining self-sufficiency? (2) What is the probability that a participant completes the training program successfully and the factors that affect the successful completion of the program? (3) What are the determinants of the wage rate at the time that a participant gets a placement? The study reports estimates that address each of these questions.

2. The Model

Our study employs a Logit Model following Ebert's studies. The data set we employ comes from Palm Beach County. The variables used in this study are defined as follows:

- a. The variable SUFF is a measure of self-sufficiency. It takes a value of 1 if the customer gets employment placement after completing the training program and takes on a value of 0 otherwise.
- b. The variable SUC indicates the Successful completion of training. It takes on a value of 1 if the customer completes the training program. It equals 0 if the customer is still in training or drops out
- c. WAGE is the hourly wage rate at the time of placement.
- d. The variable HIST describes whether or not the participant has a work history. It equals 1 if he/she has been previously employed at any time and 0 otherwise.
- e. The variable AFDC⁴ = 1 if the participant is collecting benefits from the Florida Welfare System, and 0 otherwise, (Freedman *et al.*, 1996; Schexnayder *et al.*, 1991). The Welfare program provides financial assistance to cover for food, housing, home energy, childcare, and job training⁵.
- f. SSI = 1 if the customer received Supplemental security income, and 0 otherwise
- g. HRS = number of training hours. This variable takes on a value of 1 if the number of training hours exceeds 600, and a value of 0 if it fewer than 600 hours.
- h. AGE = Age in years
- i. SEX = 1 for males and 0 for females
- j. EDU = Number of years of education beyond 9th grade
- k. RACE = 1 for white persons, and 0 for nonwhite persons
- l. COMP = Collecting unemployment compensation. This variable equals 1 if the customer is a claimant, and equals 0 if the customer is no longer a claimant or does not collect compensation
- m. DRUG = 1 if the individual has a history of drug abuse and 0 otherwise
- n. OFF = Offender 1; for non-offenders = 0. In this study, the offender means any person who has been convicted of an offense and been released from any incarceration, paid all fines in conjunction with such conviction and been discharged from any probation or parole.⁶ This includes persons that are on probation (Hong *et al.*, 2014).
- o. READ = Reading test score

²[http://help.workworldapp.com/wwwwebhelp/florida_work_and_gain_economic_self_sufficiency_wages_program_overview.htm#:~:text=In%20Florida%2C%20Temporary%20Assistance%20for,%2DSufficiency%20\(WAGES\)%20Program.&text=Florida%20also%20provides%20%22Up%2DFront,prevent%20long%2Dterm%20welfare%20dependence.](http://help.workworldapp.com/wwwwebhelp/florida_work_and_gain_economic_self_sufficiency_wages_program_overview.htm#:~:text=In%20Florida%2C%20Temporary%20Assistance%20for,%2DSufficiency%20(WAGES)%20Program.&text=Florida%20also%20provides%20%22Up%2DFront,prevent%20long%2Dterm%20welfare%20dependence.)

³ The Job Training Partnership Act of 1982 (Pub.L. 97-300, 29 U.S.C. § 1501, et seq.) was a United States federal law passed October 13, 1982, by the United States Department of Labor during the Ronald Reagan administration. The law was the successor to the previous federal job training legislation, the Comprehensive Employment and Training Act (CETA). It was repealed by the Workforce Investment Act of 1998 during the administration of President Bill Clinton.

⁴ Aid to Families with Dependent Children (AFDC)

⁵ <https://www.usa.gov/benefits#item-36602>

⁶ <https://www.lawinsider.com/dictionary/ex-offender>

- p. MATH = Math test score
- q. LANG = Language test score
- r. FOOD = 1 if the customer currently receives food stamps and 0 otherwise
- s. UNEMP = Number of weeks collecting unemployment compensation
- t. INC = Household income (annual). This variable equals 1 if the household income is above the poverty level (\$24,000), and 0 if the household income is below that level ([US Department of Health and Human Services, 2002](#)).

3. Model Specification

We estimate the following logistic model

$$P(D_i = 1) = F(\alpha + \sum \beta_i X_i) = 1 / [1 + e^{-(\alpha + \sum \beta_i X_i + u_i)}] \quad (1)$$

where D_i is a binary choice variable, which in our regressions are SUFF and SUC defined previously, and X_i is a set of explanatory variables. P is the probability of attaining self-sufficiency or successfully completing the training program. The term, $P/(1 - P)$, is called the **odds ratio**. If, for example, D_i represents self-sufficiency, and $P(D_i = 1) = 2/3$, the odds ratio or the odds that the participant achieves self-sufficiency is 2 to 1 ($= 2/1$). According to Eq. (1), changes in X exert a constant (linear) impact on the log of the odds ratio, rather than on the probability of the event itself. It is more useful to measure the effects of various variables on self-sufficiency or on the successful completion of training programs in terms of probability. The impact of a change in X_i on the probability, $P(D_i = 1)$ is calculated by taking the partial derivative of P with respect to X_i :

$$\partial P / \partial X_i (= \Delta P / \Delta X_i) = \beta_i P (1 - P) \quad (2)$$

As this equation shows, the effect of X_i on the probability that $D = 1$ depends not only on the coefficient of X_i , but on the probability itself. Since this probability is itself a function of X_i , the rate of change above is not constant. Thus, Eq. (2) enables one to figure out the probability that an individual i achieves self-sufficiency (or obtains a job) or completes the training program, given the information about the individual (age, education, gender, race, income, etc.). The model is estimated using maximum likelihood estimation.⁷

4. Empirical Results - Self Sufficiency Estimation of Parameters

In order to determine the factors that affect the chance of getting a placement, we have estimated the following "Self-Sufficiency" Model:

$$\begin{aligned} \ln [P(\text{SUFF}=1) / (1 - P(\text{SUFF}=1))] = & \alpha + \beta_1 \text{SUC} + \beta_2 \text{HIST} + \beta_3 \text{AFDC} \\ & + \beta_4 \text{SSI} + \beta_5 \text{HRS} + \beta_6 \text{AGE} + \beta_7 \text{SEX} + \beta_8 \text{EDU} + \beta_9 \text{RACE} \\ & + \beta_{10} \text{COMP} + \beta_{11} \text{DRUG} + \beta_{12} \text{OFF} + \beta_{13} \text{READ} + \beta_{14} \text{MATH} \\ & + \beta_{15} \text{LANG} + \beta_{16} \text{FOOD} + \beta_{17} \text{UNEMP} + \beta_{18} \text{INC} + \varepsilon \end{aligned}$$

The SUFF, SUC, and WAGE variables are dependent variables: SUFF and SUC are dummy dependent variables in the Logit model ([Achia et al., 2010](#); [Berger et al., 2000](#)), and WAGE is a dependent variable in a multiple regression model. The SUC variable is also used as an independent variable in the model which is concerned with the attainment of self-sufficiency. All other variables (4 - 20) are explanatory variables that are believed to affect the dependent variables. We have employed the maximum likelihood method to estimate the Logit model and obtained the following results.

We have randomly selected 500 observations for inclusion in the data set⁸. We stratified the sample to generate a representative sample of the entire data set. Since many of the participants registered for the training program more than once, we have combined multiple characteristics of each participant into one row showing the participant's profile⁹.

⁷ The estimation procedure depends on whether the observed P is between 0 and 1 or whether it is binary and takes the value 0 or the value 1. (1) In the case in which P is strictly between 0 and 1 (for example, P is the fraction of participants obtaining a job), the method is simply to transform P and obtain $Y = \ln [P/(1 - P)]$. This allows the estimation of a model that is linear in the independent variables. However, there remains a potential problem with applying ordinary least squares (OLS), because the disturbances are heteroscedastic. (2) If P is binary, then the logarithm of $P/(1 - P)$ is undefined when P is either 0 or 1. In this case, we cannot use OLS. Instead, maximum likelihood (ML) estimation is used. Since the binary variables used in this study (self-sufficiency or successful completion of programs) take the value of either 1 or 0, the maximum likelihood method is appropriate for estimating Eq. (1) model.

⁸ On average, there were 4,200 participants benefiting from the services provided by the JTPA program in the year of 1999. We collected randomly a representative sample of 500. The sample data was stratified utilizing the following specific weights: Females, Non-White, Average Age (Years), % Less than HS/GED, Average Months Worked Past 2 Years; % Never Worked, etc.

⁹ When the JTPA database captures several intervention or training activity, it generates an entry for each new intervention or training activity. All the data were combined to create a dynamic profile of the participant, including the different interventions and/or training activities.

Table-1. Determinants of Attaining Self-Sufficiency

Variable	Coefficient	Standard Error	t Ratio
SUC	3.346***	0.756	4.429
HIST	- 0.154	0.617	- 0.251
AFDC	1.356	1.000	1.356
SSI	0.172	1.162	0.148
HRS	0.325	0.437	0.745
AGE	- 0.002	0.015	- 0.143
GENDER	0.117	0.343	0.340
EDU	0.009	0.086	0.107
ETHNICITY	0.223	0.472	0.473
COMP	0.141	0.406	0.348
DRUG	- 0.799	0.994	- 0.804
OFF	0.238	0.521	0.457
READ	- 0.042	0.109	- 0.386
MATH	0.069	0.078	0.884
LANG	- 0.012	0.043	- 0.280
FOOD	- 1.610**	0.809	- 1.990
UNEMP	- 0.0008	0.019	- 0.042
INC	- 0.239	0.409	- 0.585
CONSTANT	- 3.262**	1.439	- 2.267

It is interesting to note that SUC (successful completion of training) is highly significant at the 1 percent level of significance. Thus, the successful completion of training is the most important factor that affects the chance of getting a placement. Another significant factor that determines job placement is FOOD (collection of food stamps). The coefficient of the FOOD variable has a negative sign and is significant at the 5 percent level. This indicates that if the participant is a recipient of food stamps, then his/her probability of achieving self-sufficiency decreases. The coefficients of other variables have in general have their predicted signs, but these variables are insignificant.

The estimates can be used to estimate the probability of attaining self-sufficiency of a number of typical cases:

1. A white-male participant with a family income of \$24,000 or more having long training (600 hours or more), with work history, and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offense: $P = .584$ (58.4%) of attaining self-sufficiency after training. A person with exactly the same profile, if they had short instead of long training,¹⁰ would have a $P = .503$ (50.3%) probability of attaining self-sufficiency.
2. A white, female participant with a family income of \$24,000 or more having long training (600 hours or more) and work history, and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offense: $P = 0.555$ or 55.5%. Thus, the probability that a participant having attributes characterized by the above information gets a placement after training is 55.5 percent. If a person with the same profile has the short instead of the long training, her chance of getting placement after training is 47.4 percent.
3. A non-white male participant with a family income of \$24,000 or more having long training (600 hours or more) and work history, and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offense: $P = 0.529$ or 52.9% of getting a placement (Joseph, 2018). If the same individual has less than 600 hours of training, the probability decreases to 44.8%.
4. Nonwhite, female participant with a family income of \$24,000 or more having long training (600 hours or more) and work history and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, and offense has a probability of finding a placement of 50.1%. With fewer than 600 hours, the probability is 41.9%.
5. The Impacts of Training Programs-We can also estimate the impact of a change in any of the explanatory variables on the probability of getting a placement ($\partial P / \partial X_i$).

5. Determinants of the Successful Completion of Training

Since we have found that the successful completion of training is crucial for achieving self-sufficiency, we have examined the factors that affect successful completion of training. To this end, we have estimated the following model:

$$\ln [P(\text{SUC}=1) / (1 - P(\text{SUC}=1))] = \alpha + \beta_1 \text{ HIST} + \beta_2 \text{ AFDC} + \beta_3 \text{ SSI} + \beta_4 \text{ HRS} + \beta_5 \text{ AGE} + \beta_6 \text{ SEX} + \beta_7 \text{ EDU} + \beta_8 \text{ RACE} + \beta_9 \text{ COMP} + \beta_{10} \text{ DRUG} + \beta_{11} \text{ OFF} + \beta_{12} \text{ READ} + \beta_{13} \text{ MATH} + \beta_{14} \text{ LANG} + \beta_{15} \text{ FOOD} + \beta_{16} \text{ UNEMP} + \beta_{17} \text{ INC} + \varepsilon$$

¹⁰ Short-term training is any educational activity that takes less than 600 hours to complete. Long terms training is defined as any educational activity that takes 600 hours or more to complete.

Table-2. Successful Completion of Training

Variable	Coefficient	Standard Error	t Ratio
HIST	0.103	0.576	0.178
AFDC	0.355	0.901	0.394
SSI	- 1.515	0.876	- 1.731*
HRS	1.404	0.584	2.405**
AGE	0.004	0.018	0.217
SEX	0.619	0.427	1.451
EDU	- 0.079	0.010	- 0.788
RACE	- 0.222	0.557	- 0.398
COMP	0.621	0.473	1.314
DRUG	- 1.061	0.776	- 1.368
OFF	- 0.249	0.584	- 0.427
READ	0.234	0.119	1.968**
MATH	- 0.133	0.098	- 1.358
LANG	- 0.008	0.054	- 0.158
FOOD	- 0.325	0.636	- 0.512
UNEMP	0.021	0.021	0.983
INC	1.022	0.663	1.541
CONSTANT	- 0.556	1.347	- 0.413

5.1. The estimates reveal that HRS (number of training hours) and READ (reading test score) are significant determinants of the successful completion of training. More specifically, if the participant receives training for 600 hours or more prior to enrolling in the program and demonstrates having good reading skills, she is more likely to successfully complete the training program. Training programs under 600 hours are short-term training and could be job searching skills, resume writing, interviewing skills, dress for success, MS Office, etc. Some participants come to apply for services with already having taken these trainings¹¹. Participants who can demonstrate mastery of the competencies aligned to the respective training could request a training waiver to avoid repeating the efforts to get the skills. Any training that entails more than 600 hours could be part of an educational program like vocational education. Another interesting result is that reading ability (READ) is most important for the successful completion of training. It is worth noting that math and other language skills are less significant determinants of the successful completion of training.

5.2. The combined results of the two models we have estimated show that the most important factors affecting self-sufficiency are: successful completion of training combined with long-term training (600 hours or more) and reading ability. Gender, ethnicity, age, and work history are not key variables in achieving self-sufficiency.

5.3. Probability of Completion of Training

As in the "Self-Sufficiency" Model, we can estimate the probability of completing the training program for representative persons with various attributes.

1. A white, male participant with a family income of \$24,000 or more having long training (600 hours or more) and work history, and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offenses: For this individual, the probability of completion is $P = 0.976$ or 97.6%. If the same person received less than 600 hours of training, he would complete the program with $P = 0.902$ or 90.2%
2. A white, female participant with a family income of \$24,000 or more having long training (600 hours or more) and work history and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offense: her probability of completing the program $P = 0.956$ or 95.6%. If she were to have fewer than 600 hours of training, the probability decreases to 0.844 or 84.4%
3. A nonwhite, male participant with a family income of \$24,000 or more having long training (600 hours or more) and work history and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse, or offense: $P = 0.981$ or 98.1%, without long training, 92.6%
4. A nonwhite female participant with a family income of \$24,000 or more having long training (600 hours or more) and work history and not having food stamps, AFDC, SSI, unemployment compensation, drug abuse or offense: $P = 0.965$ or 96.5%. It would be 87.1% under short training.

5.4. Testing for Overall Significance of the Models

The value of the Log of the Likelihood Function (LLF) is used to construct alternative measures to R^2 and F-statistics. We test the hypothesis that

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_k = 0. \quad (3)$$

Testing the above null hypothesis entails comparing equation performance for the restricted model to the unrestricted models described above. The measure of performance utilized for each of these equations is the Log of the Likelihood Function (LLF), and The procedure used to perform this test is given by a

¹¹ Each qualified participant gets assigned a case manager who, based on an evaluation, refers participants to in-house training put together by the government career centers.

Likelihood Ratio Test. We estimate the Unrestricted Model and Restricted Models, with the maximum likelihood method and obtain the log of its likelihood function, ULLF, and RLLF respectively. The test statistic for the null hypothesis is

$$\lambda = -2 (\text{RLLF} - \text{ULLF}) \quad (4)$$

The ratio (λ) follows a chi-square distribution with k degrees of freedom, where k is the number of coefficients whose values are restricted to 0 in the null hypothesis (= number of restrictions). If the value of this test statistic exceeds the critical chi-square value with k degrees of freedom, we reject H_0 that the set of slope coefficients does not influence the dependent variable. Like the situation with a "large" F-statistic, we then conclude that the model is statistically significant.

The same Log-Likelihood Function can be used to construct a replacement for the coefficient of multiple determination (R^2). Since predicted probabilities derived from the logit model often differ from 0 or 1, the conventionally calculated R^2 will only approach 1.0 when the predictions derived from the equation consist almost entirely of 0's or 1's. Since this is extremely unlikely, alternative measures of R^2 have been derived. McFadden has derived a "pseudo- R^2 " defined as $\text{pseudo-}R^2 = 1 - \text{ULLF}/\text{RLLF}$. Like the traditional R^2 , McFadden's pseudo- R^2 lies between 0 and 1¹².

The log-likelihoods for the "Self-Sufficiency" Model are given by $\text{RLLF} = -154.37$ and $\text{ULLF} = -125.31$, with the resulting Likelihood Ratio (λ) = 58.116 with d.f. = 18. Since the likelihood ratio exceeds the critical chi-square value of 25.98942, we reject the null hypothesis that all the coefficients in the "Self-Sufficiency" Model are equal to zero. Thus, the "Self-Sufficiency" Model as a whole has statistical significance, with McFadden $R^2 = 0.118$, Cragg-Uhler $R^2 = 0.305$, Maddala $R^2 = 0.229$, and Chow $R^2 = 0.217$. Our results shown on page 20 illustrate a much greater $R^2 = 0.306$.

For the "Success" Model, the log-likelihood functions are $\text{RLLF} = -100.05$ and $\text{ULLF} = -113.73$, with a resulting Likelihood Ratio (λ) = 27.375 with d.f. = 17. The likelihood ratio is greater than the critical chi-square value of 24.76904, and we reject the null hypothesis that all the coefficients in the "Success" Model are equal to zero. Thus, we conclude that the "Success" Model as a whole has statistical significance (McFadden $R^2 = 0.120$, Cragg-Uhler $R^2 = 0.180$, Maddala $R^2 = 0.115$, Chow $R^2 = 0.130$).

Both models also produce relatively low R^2 's. This underscores the fact that the probability that one completes the training and gets a job depends mostly on idiosyncratic factors that are specific to the individual in question.

5.5. The Determination of the Wage Rate

Finally, in order to explore the factors that determine the wage rate at the time of placement, we have conducted the following regression analysis:

$$\begin{aligned} \text{WAGE} = & \alpha + \beta_1 \text{ HIST} + \beta_2 \text{ HRS} + \beta_3 \text{ AGE} + \beta_4 \text{ SEX} + \beta_5 \text{ EDU} + \beta_6 \text{ RACE} \\ & + \beta_7 \text{ READ} + \beta_8 \text{ MATH} + \beta_9 \text{ LANG} + \beta_{10} \text{ INC} + \varepsilon \end{aligned}$$

¹² A non-pseudo R-squared is a statistic generated in ordinary least squares (OLS) regression that is often used as a goodness-of-fit measure. In OLS, Image Psuedo3 where N is the number of observations in the model, y is the dependent variable, \bar{y} is the mean of the y values, and \hat{y} is the value predicted by the model. The numerator of the ratio is the sum of the squared differences between the actual y values and the predicted y values. The denominator of the ratio is the sum of squared differences between the actual y values and their mean.

There are several approaches to thinking about R-squared in OLS. These different approaches lead to various calculations of pseudo R-squareds with regressions of categorical outcome variables. R-squared as explained variability – The denominator of the ratio can be thought of as the total variability in the dependent variable, or how much y varies from its mean. The numerator of the ratio can be thought of as the variability in the dependent variable that is not predicted by the model. Thus, this ratio is the proportion of the total variability unexplained by the model. Subtracting this ratio from one results in the proportion of the total variability explained by the model. The more variability explained, the better the model. R-squared as improvement from null model to fitted model – The denominator of the ratio can be thought of as the sum of squared errors from the null model—a model predicting the dependent variable without any independent variables. In the null model, each y value is predicted to be the mean of the y values. Consider being asked to predict a y value without having any additional information about what you are predicting. The mean of the y values would be your best guess if your aim is to minimize the squared difference between your prediction and the actual y value. The numerator of the ratio would then be the sum of squared errors of the fitted model. The ratio is indicative of the degree to which the model parameters improve upon the prediction of the null model. The smaller this ratio, the greater the improvement and the higher the R-squared.

R-squared as the square of the correlation – The term "R-squared" is derived from this definition. R-squared is the square of the correlation between the model's predicted values and the actual values. This correlation can range from -1 to 1, and so the square of the correlation then ranges from 0 to 1. The greater the magnitude of the correlation between the predicted values and the actual values, the greater the R-squared, regardless of whether the correlation is positive or negative. When analyzing data with a logistic regression, an equivalent statistic to R-squared does not exist. The model estimates from a logistic regression are maximum likelihood estimates arrived at through an iterative process. They are not calculated to minimize variance, so the OLS approach to goodness-of-fit does not apply. However, to evaluate the goodness-of-fit of logistic models, several pseudo R-squareds have been developed. These are "pseudo" R-squareds because they look like R-squared in the sense that they are on a similar scale, ranging from 0 to 1 (though some pseudo R-squareds never achieve 0 or 1) with higher values indicating better model fit, but they cannot be interpreted as one would interpret an OLS R-squared and different pseudo R-squareds can arrive at very different values. Note that most software packages report the natural logarithm of the likelihood due to floating point precision problems that more commonly arise with raw likelihoods.

Table-3. Determinants of Wage in the First Job After Completing the Program

Variable	Coefficient	Standard Error	t Ratio
HIST	3.270	2.920	1.120
HRS	0.198	2.087	0.095
AGE	- 0.090	0.065	- 1.384
SEX	3.507	1.607	2.183
EDU	0.640	0.380	1.683
RACE	0.698	2.426	0.288
READ	- 0.661	0.474	- 0.140
MATH	0.057	0.343	0.166
LANG	0.331	0.180	1.838
INC	6.884	1.946	3.538
CONSTANT	3.352	5.569	0.602

R² = 0.306, DW = 2.020

The multiple regression analysis offers some insight into the determination of the wage rate at the time of placement. The immediate impression from this result is that EDU (number of years of education beyond 9th grade), SEX (gender), LANG (language test score), and INC (annual household income) are important determinants of the wage rate. In particular, the coefficients of the SEX and INC variables are highly significant at the 1 percent level of significance. This finding further suggests that there is some degree of the wage differential between male and female employees at the initial placement.

The p-value of the education coefficient is 0.096. This indicates that the coefficient of education is significant at the 10 percent level of significance. This observation is consistent with the common perception that labor productivity is closely related to the level of education. Put differently, the higher the level of education, the greater is the productivity of a worker, and the higher is the wage rate. In general, people with higher incomes get more education, and it is no wonder that income and education play an important role in the determination of the wage rate. Language skills also have a favorable effect on the determination of the wage rate at the time of placement.

6. Summary of Results

What variables are significant determinants of the completion of the training program or of successful job placement? Overall, we can conclude that successful completion of training (greater than 600 hours) and the ability to read well are significant determinants of successful job placement. Additionally, the study shows that educational attainment (number of years of education beyond 9th grade), SEX (gender), LANG (language test score) proficiency, and INC (annual household income) are important determinants of the wage rate. Together, successful completion of training and wage rate could help participants achieve a higher level of self-sufficiency.

What are the effects of gender and ethnicity on self-sufficiency and completing the training? A careful examination of the results presented in Table 4 suggests that gender and ethnicity have an impact on self-sufficiency. First of all, when comparing white to non-white males/females, the probability of self-sufficiency for whites is higher than those for non-whites. Then, when considering the amount of training comparing whites to non-whites, the results indicate that training longer hours (> 600 hours) has the most positive impact on self-sufficiency. Additionally, when comparing males to females in terms of achieving self-sufficiency, regardless of ethnicity, the study shows that males exhibit a higher level of self-sufficiency than females. This is regardless of training, but overall, longer training has a positive impact on achieving self-sufficiency.

Summary Table-4. Self-sufficiency

Ethnicity	Gender	Training (hrs)	Self-sufficiency
White	Male	600 hours or more	58.4 percent
		Less than 600 hours	50.3 percent
	Female	600 hours or more	55.5 percent
		Less than 600 hours	47.4 percent
Nonwhite	Male	600 hours or more	52.9 percent
		Less than 600 hours	44.8 percent
	Female	600 hours or more	50.1 percent
		Less than 600 hours	41.9 percent

Table 5 shows the factors affecting the completion of training. Our analysis shows that for non-white males/females, completion of training rates are higher than those for whites. Then, when considering the amount of training to compared whites versus non-whites, the results indicate that training longer hours (>600hours) still has a positive impact on the completion of training. Additionally, when comparing males to females in terms of training completions, the study shows that males exhibit a higher level of training completions than females.

Summary Table-5. Completion of Training

Ethnicity	Gender	Training (hrs)	Completion of Training
White	Male	600 hours or more	97.6 percent
		Less than 600 hours	90.2 percent
	Female	600 hours or more	95.6 percent
		Less than 600 hours	84.4 percent
Nonwhite	Male	600 hours or more	98.1 percent
		Less than 600 hours	92.6 percent
	Female	600 hours or more	96.5 percent
		Less than 600 hours	87.1 percent

7. Discussion

This study is correlational and offers some suggestive evidence that more workforce training improves outcomes. This is necessary to take into account when developing policies to assist the unemployed – dislocated workers. However, historical analyses of existing data are not adequate for the task of determining causality. Nevertheless, the paper uncovers some potential relationships between education, reading skills, wage rate, and self-sufficiency. Policymakers and labor economists should be aware of the dynamic relationship between all these variables if there is a genuine feeling for passing and implementing legislation that has a positive impact on remediating poverty. Further research is required to expand on the understanding of the determinants of attaining self-sufficiency and the alignment to respective policies that provide support for training opportunities (Wefler, 2018). A more attractive proposition for future studies would be to put in place a research initiative that includes an experimental group and a control group utilizing the econometric model to measure the success of the treatments and policies.

The results show that the most significant variables affecting self-sufficiency are (1) completion of long-term training and (2) reading ability. An additional finding of the study is that if the participant is a recipient of food stamps, then his/her probability of achieving self-sufficiency decreases. Our study's main contribution is the identification of significant variables to be included in the development of workforce policies aiming at promoting economic self-sufficiency and mitigating poverty. It is important to keep in mind that every new federal administration has the prerogative of imposing new eligibility requirements for participants and new guidelines for the JTPA workforce programs, including federal budget allocations. These variations in policy and funding allocations need to be taken into account to accurately measure the success of the policies implemented. The battle against poverty continues by promoting sustainable employment and economic self-sufficiency; nevertheless, more tools are becoming available to aid economists and policymakers in craft more sensitive and viable approaches. It is our hope this study and subsequent papers contribute to this aim.

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