ECON 4140 Final Report
"The effect of JTPA job training program on workers' earnings"

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For *a policy perspective*, our research hopes to highlight the effect of the Job Training Partnership Act (JTPA) service program on the participant's post-program wages. This policy evaluation of the training program's relevance in participants' post-program earnings is relevant especially when considering today's context: the U.S. government had invested $46.4 billion in Employment and Training Administration's federal job training programs[1], yet the country had still faced an ongoing youth unemployment crisis.[2]

1. **What is the treatment in this dataset?**

The treatment in this case is the **unit[3]'s eligibility for the Job Training Partnership Act (JTPA) service program.** In particular,

- D = 0: control group - not assigned eligibility to participate in JTPA
- D = 1: treatment group - assigned eligibility to participate in JTPA

2. **Be explicit and precise about the causal effect that you are able to learn from this dataset. Discuss whether this causal effect may be of interest in real policy-making situations.**

The JTPA service program aims to assist economically disadvantaged adults and youths, by providing them the competitive skills needed for in-person jobs. Theoretically, by closing skill gaps in a more competitive and resilient workforce, the JTPA service program can improve its participants' economic welfare, and therefore increase its participants' sum of earnings 30 months following the program.

The research study estimates **the causal effect of the unit's eligibility onto their earnings**, not participation. To be explicit, the outcome variable (Y) is the participants'

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[1]USAFacts. (2025, September 17). What does the Employment and Training Administration (ETA) do? USAFacts. https://usafacts.org/explainers/what-does-the-us-government-do/subagency/employment-and-training-administration/

[2] Economic Times. (2025, November 25). Unemployment among US college graduates hits record high, young adults face sharp job market challenges in. The Economic Times; Economic Times. https://economictimes.indiatimes.com/news/international/us/unemployment-among-us-college-graduates-hits-record-high-young-adults-face-sharp-job-market-challenges-in-2025/articleshow/125559595.cms?from=mdr

[3] The 'unit' this study refers to are the individual applicants to the JTPA service program.

sum of earnings 30 months following the program. We chose to analyze eligibility and not participation, because participation in the JTPA service program is endogenous and dependent on some covariates—and therefore invalid for consideration. A covariate that could endogenously influence participation is income—in which a higher earning individual is more likely to participate in job training programs, than a lower earning individual. On the other hand, eligibility is randomly assigned by the government, but not decided by the individuals or covariates. Knowing that the treatment is randomly assigned and hence independent of the unit's potential outcome, the research study can thus safely assume Randomized Controlled Treatment (RCT) (further elaborated below).

We want to answer 2 questions through this report: 1. What is the Average Treatment Effect (ATE) of the general service program on all participants' earnings? 2. What is the ATE of the service program on certain subgroups?

Investigating this causal effect is important in real policy-making situations, as it allows governments to understand whether similar job-training programs are actually effective in improving people's welfare. In addition to investigating the extent through which salaries are improved by the program, governments will understand how much of the budget could be allocated towards future job training services. Governments can also identify vulnerable sub-populations to target such programs towards.

3. What is the identification strategy you need to rely on and why?

The identification strategy this research study relies on is using Doubly-Robust Estimator to estimate Average Treatment Effect (ATE). Under unconfoundedness and overlapping conditions, Doubly-Robust Estimator is a more reliable estimator through its combination of propensity score and outcome regression. Through this combination, we just need either the estimator of the outcome regression or the propensity score to be correctly specified, but not necessarily both, to correctly estimate E [Y(1)] and E [Y(0)], and hence recover the ATE correctly.

Assumptions Needed:

The Doubly-Robust Estimator relies on two key assumptions: unconfoundedness and overlap. Firstly, understanding that participants are randomly assigned treatment (either to the program group or the control group), this research study can thus assume that it is a RCT. As in, the treatment assignment D is statistically independent of potential outcome (Y(1), Y(0)):

$$D \perp Y(1), Y(0)$$

Within the RCT, this study thus safely assumes unconfoundedness: that treatment is randomly assigned among *observationally* identical units, and that conditioned on observed covariates, treatment is independent of potential outcome:

$$(Y(0),Y(1)) \perp D \mid X$$

In order to estimate the propensity score, we assume overlap. The dataset satisfies the overlap assumption, as for each group of certain covariates (X = x) all units have a strictly nonzero probability of being assigned to either control or treated group. This means:

$$\pi(x) = P\{D = 1|X = x\},$$

$$0 < \pi(x) < 1, \text{ for all } x \in X$$

While we cannot check unconfoundedness, we can, and hence decided to check overlap. We utilized logistic regression to estimate propensity score for both treatment and control group.

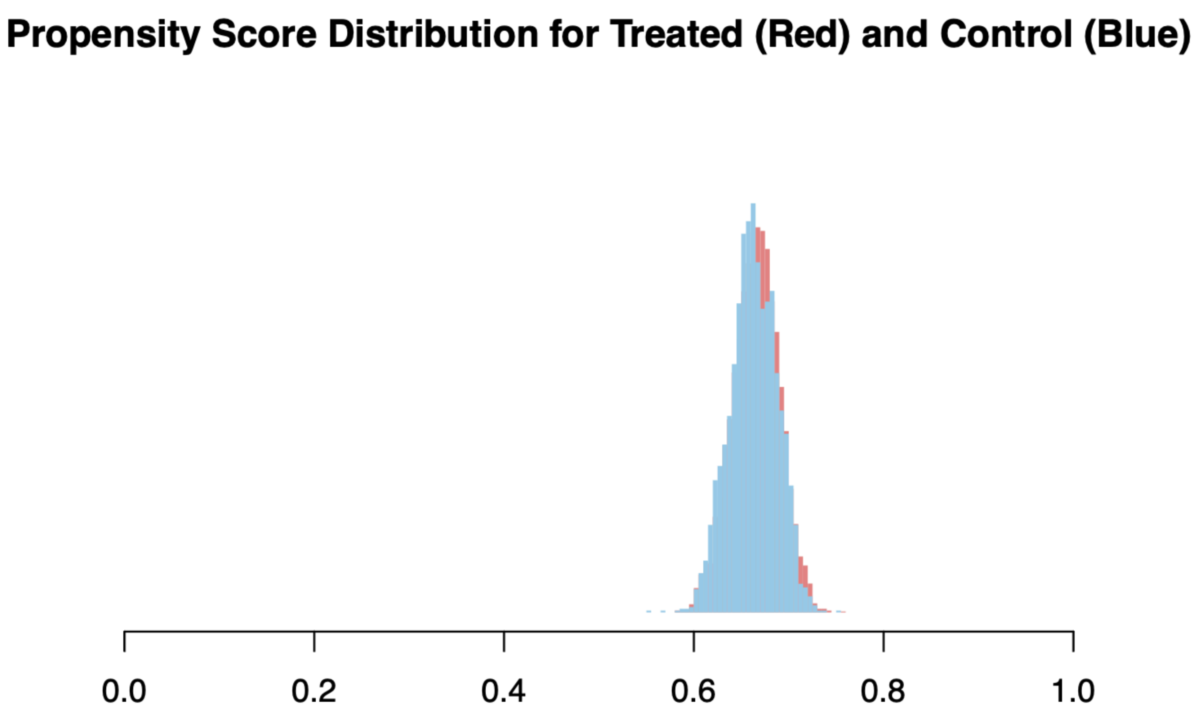

Figure 1: Propensity Score Distribution for Treated and Controlled Group

Based on Figure 1, we can see that the propensity score for both treated and controlled groups is strictly between 0 and 1, confirming that overlap condition is fulfilled. In addition, we use the inverse propensity score to conduct a covariance balancing check, as shown in Figure 2 below.

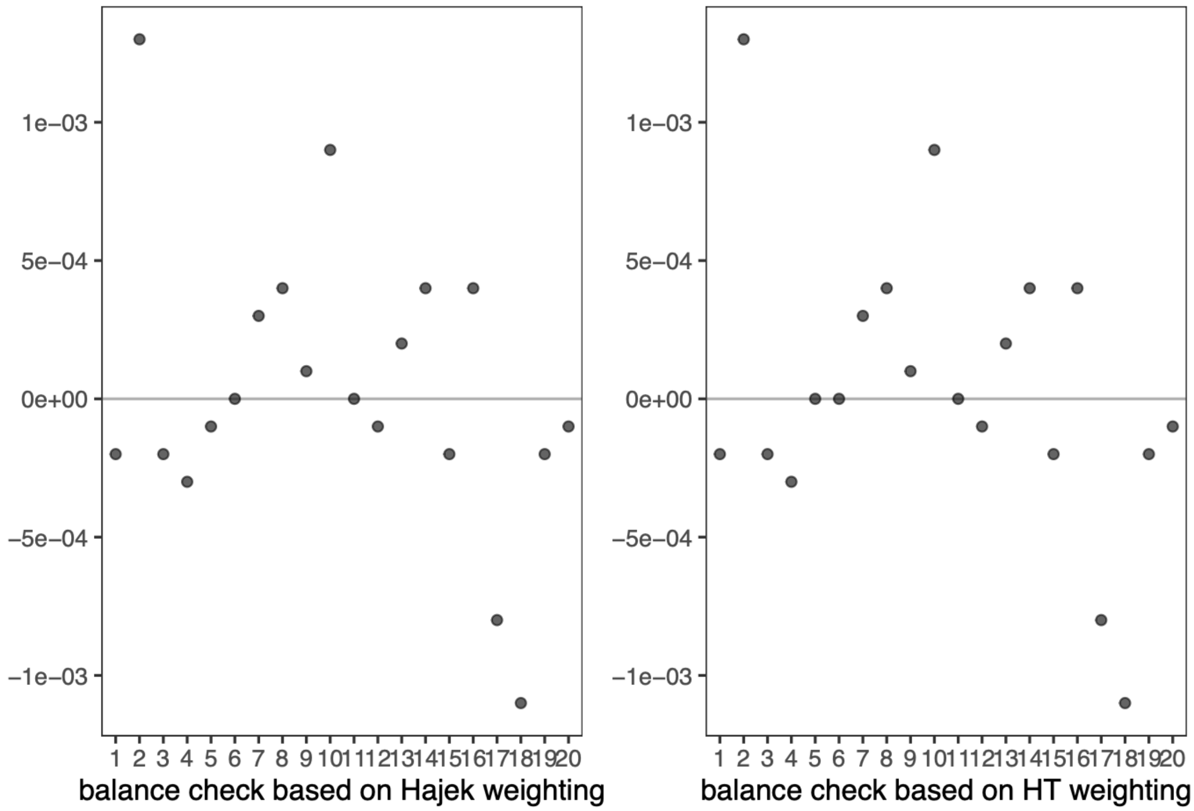

Figure 2: Covariance balancing check using Hajek and HT Propensity Score Weighting

Based on Figure 2, we can see that the difference is very small (between -0.001 and 0.001), close to 0. With that, we can further confirm that the distribution of covariates is the same in both treated and control groups, which is the evidence that supports RCT since the covariates distribution is independent of the treatment assignment status.

In terms of constructing Doubly Robust Estimator to estimate ATE, we use the following equations:

Equations:

We estimate our causal object θ to be

$$\theta = E [Y(1)] - E [Y(0)].$$

Using Doubly Robust Estimator, we can thus construct E [Y(1)] and E [Y(0)] as such:

$$E [Y(1)] = E [\gamma_1(x) + (D / \pi(X)) (Y - \gamma_1(x))]$$

$$E [Y(0)] = E [\gamma_0(x) + (1 - D / 1- \pi(X)) (Y - \gamma_0(x))]$$

where our predictive objects $\gamma_1(x)$ and $\gamma_0(x)$ can be written as:

$$\gamma_1(x) = E[\ Y \mid X = x, D = 1\ ],$$

$$\gamma_0(x) = E[\ Y \mid X = x, D = 0],$$

$$\pi(x) = E[\ D \mid X=x\ ] = P\{D = 1|X = x\}.$$

In this project, we use double debiased machine learning methods, together with sample splitting and cross-fitting, to estimate the Doubly Robust Estimator. These methods enable us to construct high quality point and interval estimates for causal effect, with lower standard error that improve accuracy, especially in the high-dimensional model here where we include all covariates.

We decided against using only Simple Linear Regression (SL, i.e. Simple Difference in Mean estimator), Classical Regression Analysis (CRA), and Interactive Regression Analysis (IRA). This is because we plan on including all covariates in our analysis (as we are unsure which covariates would be useful), thus allowing for high dimensionality in our dataset. High dimensionality results in unstable ATE estimates with high standard errors. In addition, using SL, CRA and IRA alone assumes linearity in relationships between the observed outcome and the covariates, of which its validity we are unsure of in the true dataset. However, we would just use the ATE estimate from SL, which is Simple Differences in Mean estimator, as the baseline model.

4. **How robust is your causal estimates to**

(4A) the inclusion of different control variables?

Even though the experiment is a RCT, we decided to include **all control variables (covariates)** into our analysis, which can be shown in Figure 3. This is because some covariates might be correlated with the outcome variable (earnings 30 months following the program), but we are unsure exactly which. In addition, by including and controlling the variables in the model, we can explain part of variation in outcome variable that is due to covariates, and hence the ATE estimators obtained will better explain the sole effect of receiving treatment and improve accuracy by lowering standard error.

In particular, we grouped the covariates into five groups, with rationale why we think the covariates might be correlated with and affect the observed variables, where we detailed in Table 1 below.

Demographics	**Variables:** male, age, age dummies, black, hispanic, married

	Demographics capture persistent differences in labor market opportunities, preferences, and constraints. They often modify how people respond to training because of differences in baseline job attachment, discrimination, caregiving responsibilities (affecting flexibility to participate), and physical/learning capacity across age and gender. Including them helps both precision and understanding—e.g., does JTPA help younger vs older participants differently? Are effects gendered?
Education	**Variables:** bfeduca, hsorged, class_tr, ojt_jsa Training interacts with prior human capital: more-educated people might gain less in returns from basic training but more from advanced placement; alternatively, low-education participants might gain more absolute earnings. class_tr/ojt_jsa helps capture baseline skill needs and program targeting—important to control for because the recommended strategy might predict both outcomes and responses.
Pre-treatment work status	**Variables:** bfyrearn, bfwage, bfhrswrk, wkless13 These variables measure the heterogeneity effects in earnings improvement. Controlling these variables ensures that individuals are evaluated fairly from their respective baselines to correctly estimate the ATE.
Poverty indicators	**Variables:** afdc These reflect household economic constraints and benefit-dependency that can change incentives to join the labor market. They may predict differential take-up of job offers and capacity to invest in job search or relocation. For women, AFDC is an essential moderator.
Miscellaneous: data collection measures	**Variables:** f2sms Controls for measurement differences or systematic reporting differences across follow-ups, which improves the comparability of earnings and reduces measurement error

	bias.

Table 1: Covariates groups and rationales why they are important in estimating ATE

```
# Define Y, D, X
# In this case, we decided to include all covariates.

# Construct y,d,x
y <- jtpa$earnings
d <- jtpa$D

# We include all 20 covariates, excluding index, recid since they are irrelevant
x <- model.matrix(~ male + age + age2225 + age2629 + age3035 + age3644 + age4554 + black + hispanic +
married + bfeduca + hsorged + class_tr + ojt_jsa + bfhrswrk + wkless13 + bfyrearn + bfwage + f2sms + afdc,
data=jtpa)[,-1]
```

Figure 3: The construction of y, d and covariates matrix x, which includes all 20 covariates in the JTPA dataset

(4B) the use of different machine learning methods?

In estimating the ATE, we carried out the following steps:

1. We first conducted Simple Linear Regression to estimate the Difference-in-Mean estimator as our baseline for ATE estimation.
2. Then, we use 4 different Double Debiased Machine Learning methods (Lasso, Forest, Tree, Single-Layer Neural Network) with 3-fold cross-fitting to calculate the Doubly Robust Estimator.
3. Within the machine learning model, we conducted Interactive Regression Model to estimate the ATE for heterogeneous treatment effect model and Partial Linear Regression for homogeneous treatment effect model.
4. Eventually, we selected our best performing ML model in estimating ATE, based on the model with the smallest mean prediction square error (RMSE) for outcome (Y) and the propensity score.

Results using heterogeneous treatment effect model

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
ATE estimate	1326.78372	1324.04169	1330.40229	1454.67623	2491.15344
Standard error	388.08747	357.12636	376.226	367.01868	778.99138
95% CI (Lower Bound)	566.13228	624.07403	592.99933	735.31962	964.33034
95% CI (Upper Bound)	2087.43517	2024.00935	2067.80526	2174.03284	4017.97655
RMSE of outcome	1.6812309×10^4	1.5483378×10^4	1.5618222×10^4	1.6063454×10^4	1.6500529×10^4
RMSE of propensity score	-	0.47219	0.47909	0.47218	0.47434

Table 2: ATE estimation results for heterogeneous treatment effect model

Table 2 describes the performance of our baseline Difference-in-Mean model and the four Double Debiased Machine Learning Methods: Lasso, Forest, Trees and Single-Layer Neural Network. Assuming a heterogeneous treatment effect, we can observe that all ATE estimates are similar and stable within the 1300 - 1450 interval, thus allowing us to conclude a robust ATE prediction.

The only exception in our analysis is the Single-Layer Neural Network, which reports a higher ATE estimate of 2491.15344. Due to its significantly higher RMSE of outcome, we believe its ATE is not as reliable and accurate as the other 3 ML methods. This is because we had only used a single-layer (when multiple layers is usually recommended in research) and 3 folds in our cross-fitting, leading to its high standard error and instability. Its ATE is very much higher than the ATE from other ML methods.

The Lasso method reports the lowest Standard Error of 357.12636, and Root Mean Square Error of outcome and propensity score: 1.55×10^4 and 0.472 respectively.

Results using homogeneous treatment effect model

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
ATE estimate	1326.78372	1295.79653	1374.56652	1478.97383	1212.29151
Standard error	388.08747	356.4193	354.41078	368.36566	378.67296
95% CI (Lower Bound)	566.13228	597.21471	679.92139	756.97713	470.0925
95% CI (Upper Bound)	2087.43517	1994.37836	2069.21165	2200.97053	1954.49051
RMSE of outcome	1.6812309×10^4	1.5462503×10^4	1.5544141×10^4	1.601761×10^4	1.6572781×10^4
RMSE of propensity score	-	0.47224	0.47932	0.47229	0.47493

Table 3: ATE estimation results for homogeneous treatment effect model

The above table lists the same information on the baseline model and four Double Debiased Machine Learning Methods, but under a homogenous treatment effect assumption.

The only exception in our analysis is the Single-Layer Neural Network, which reports a lower ATE estimate of 1212.29151. Due to its significantly higher RMSE of outcome, we believe its ATE is not as reliable and accurate as the other 3 ML methods. This is because we had only used a single-layer (when multiple layers is usually recommended in research) and 3 folds in our cross-fitting, leading to its high standard error and instability. Its ATE is very much lower than the ATE from other ML methods.

Under the homogenous treatment assumption, the Lasso method also reports the lowest Standard Error of 356.42, and Root Mean Square Error of outcome and propensity score: 1.55×10^4 and 0.472 respectively.

(4C) whether the treatment effect is homogeneous or heterogeneous?

A homogenous treatment effect can be formally defined as when the causal effect of a treatment is identical for every unit within the population—in this case, it would mean that the JTPA services would increase the sum of every individual’s earnings, by the same amount. This is shown by:

$$E[Y(0) \mid X] = a_0 + b'_0X$$

$$E[Y(1) \mid X] = a_1 + b'_1X$$

where in general, $b_0 = b_1$.
This implies that:

$$\text{Conditional ATE: CATE}(X) = E[Y(1) \mid X] - E[Y(0) \mid X] = a_1 - a_0$$

$$\text{ATE} = E[E[Y(1) \mid X] - E[Y(0) \mid X]] = a_1 - a_0$$

Where our ATE is independent of covariates.

On the other hand, a heterogenous treatment effect occurs when the treatment does not affect the units in the same, uniform way—which translates to the JTPA services increasing the sum of each individual's earnings by a non-uniform amount, dependent on their covariates. This can be shown as such:

$$E[Y(0) \mid X] = a_0 + b'_1X$$

$$E[Y(1) \mid X] = a_1 + b'_2X$$

where in general, $b_0 \neq b_1$.
This implies that:

$$\text{Conditional ATE: CATE}(X) = E[Y(1) \mid X] - E[Y(0) \mid X] = a_1 + b'_2X - a_0 - b'_1X$$

$$\text{ATE} = E[E[Y(1) \mid X] - E[Y(0) \mid X]] = a_1 - a_0 + (b'_2 - b'_1)X$$

where our ATE is dependent on covariates.

ATE estimate comparison

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
Heterogeneous	1326.78372	1324.04169	1330.40229	1454.67623	2491.15344
Homogeneous	1326.78372	1295.79653	1374.56652	1478.97383	1212.29151

ATE Standard error comparison

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
Heterogeneous	388.08747	357.12636	376.226	367.01868	778.99138
Homogeneous	388.08747	356.4193	354.41078	368.36566	378.67296

Table 4: ATE and standard error comparison between heterogeneous and homogeneous treatment effect model

To decide whether the dataset fits a homogeneous or heterogeneous treatment effect model, we compare the ATE estimates and their standard errors between these models across 4 machine learning methods. Based on Table 4, we can see that except for the Single-Layer Neural Network method, all the other methods yield very similar ATE estimates and standard errors.

As inferring heterogeneity or homogeneity in our model does not alter the ATE estimates and standard errors much for different ML models, we can generally conclude that assuming either homogeneity or heterogeneity is not a very important identification here.

However, we will derive our final ATE estimate specifically from our heterogeneous treatment effect model. This is because the heterogeneity model is a more flexible assumption, allowing us to account for different combinations of covariates that could have led to different treatment effects. In particular, we will use the ATE estimate from the Lasso method, since it has the smallest mean square prediction error for observed outcome and treatment.

In conclusion, the ATE estimate of the eligibility to participate in a job training program on individuals' earnings 30-months after the program is **$1324.04169.**

5. According to estimates from earlier studies, the average cost of services per treatment assignment is $774. How would your answers to Q4 above change?

$1324.04169 - $774 = $550.04169

We can interpret the Average Treatment Effect as the net increase in income, after the treatment. By subtracting $774, we can conclude that there is a net increase in an individual's post-treatment yearly income of $550.04, meaning that it's still beneficial to implement for social welfare.

Our adjusted confidence interval for the net increase in earnings is also: [-$149.92597, $1250.00935]. Though its negative extreme implies that there is some uncertainty around a net increase in earnings, its higher positive end gives us confidence that the training program should still be implemented.

Therefore, we still recommend implementing the service program to the workforce of <u>that generation.</u>

6. Explore which subgroups of the population would benefit most/least from the treatment assignment. Then, discuss the policy implications of your findings. Think carefully about whether your definition of subgroups is fair/legal in the society.

The two covariates we have chosen to conduct subgroup analysis are:
- Bfhrswrk (the individual's hours worked per week before the assignment)
- Bfeduca (the individual's years of education before the assignment)

Below (Table 5) is our justifications as to how we determined which variables are fair/legal first, and why we believe it is legal/fair to base program eligibility conditions on the following criteria:

Bfhrswrk (the individual's hours worked per week before the assignment)	We believe from a legal standpoint, **it is fair** to set program eligibility requirements over hours worked, as hours worked shows the participants' availability and commitment towards getting the most they can from the program. It is legal to assume that policy-makers will want to target participants that have the most availability on their hands, as that means they are more likely to commit more time and effort towards learning in the program.
Bfeduca (the individual's years of education before the assignment)	The research study will compare ATE differentiation on individuals with differing levels of education, to understand at which stage of education the training programs target. We believe this **research focus is fair**, as individuals with lesser education levels often need resume help, GED preparation, basic job-readiness skills—implying that the job training program might be especially valuable for them. One real-life is Job Corps, a federally funded job training program whose eligibility requirements include being a high school dropout (as learnt from PUBPOL 5230).[4]
afdc (whether the female individual is recipient of the Aid to Families with Dependent	We believe that **this is a fair eligibility condition**, as AFDC recipients would face more challenges in finding jobs due to lack of time, money, limited work experience and childcare responsibilities. One real-life program that demonstrates how AFDC recipients face greater challenges is New Moms, a

[4] Job Corps' Eligibility Requirements. (n.d.-b). https://www.dol.gov/sites/dolgov/files/ETA/jobcorps/pdfs/Exhibit 1-1 Job Corps Eligibility Requirements.pdf

Children program)	nonprofit organization that coaches new moms both professional development and family support skills.[5]
bfyrearn (annual sum of earnings before the assignment).	The measure bfyrearn indicates the relative poverty of the individual. This research study believes that **it is a legitimate eligibility condition** for the JTPA service program, as more lowly-earning individuals can benefit more from job-training services—and therefore earn more money—than higher-earning individuals.

Table 5: Justifications on why bfhrswk, bfeduca, afdc and bfyrearn is legal and fair definition of subgroups

From those fair/legal variables, **we decided that it was best to run our subgroup analysis on ATE differentiation on a combination of just two variables: bfhrswrk and bfeduca.** This is to essentially understand how the effect of the JTPA program differs in individuals of varying educational and employment histories.

We believe that understanding ATE differentiation of subgroups divided by bfhrswrk and bfeduca takes precedence over other subgroup combinations of other legal variables.

Why bfeduca is more important?

Studies show that education levels serve as a systematic barrier towards higher-earning employment. Though high school education serves as the highest barrier to overcome, graduate education levels beyond college also correlate to "with higher earnings, lower unemployment rates, and a broader range of opportunities."[6]

With that reasoning, we sought to divide the continuous variable into three categories: individuals who had spent less than 12 years in education (had not completed their high school education), individuals who spent exactly 12 years in education (obtained just a high school degree), individuals who had spent more than 12 years in education (pursuing higher education).[7]

Why bfhrswk is more important?

We hope to use this variable to reflect differently skilled workers—as certain skilled jobs call for different hours worked per week (i.e. lawyers work longer hours compared to a waitressing part-timer). The research study will use bfhrswrk to reflect the differently skilled workers and their potentially differentiating ability to earn more post-program. As

[5] *New Moms' "What We Do" Page*. New Moms. (n.d.). https://newmoms.org/what-we-do/

[6] Baum, S. (2018, April 23). *How well does graduate school pay off?* Urban Institute. https://www.urban.org/urban-wire/how-well-does-graduate-school-pay

[7] *Understanding the American Education System*. (2021, November 7). Studyusa.com. https://www.studyusa.com/en/a/58/understanding-the-american-education-system

for those who are unemployed, longer unemployment risks further reduced chances of equally-paying employment, due to skill degradation. The more weeks a unit is unemployed for, the more their skills deteriorate or become obsolete, therefore adversely affecting their employment prospects.[8]

In order to incorporate both unemployment and differently skilled workers, we divided this continuous variable into four groups: individuals who had worked 0 hours in a week (unemployed individuals); individuals who had worked less than 35 hours in a week (part-timers[9]); individuals who had worked between 35 and 40 hours in a week (full-time workers); individuals who had worked more than 40 hours in a week (individuals with heavier working schedules[10]).

Why afdc and bfyrearn are less important?

Even though afdc and bfyrearn are fair and legal variables to measure, we chose not to conduct subgroup analysis on them. This is because both variables are already correlated with pre-program earnings. They are also less systematic barriers to higher-earning employment compared to the other two variables.

As a result, we have 12 subgroups to analyze (Subgroups are shown in Table 6).

To estimate the subgroup ATE, we use the simple estimation strategy incorporating Doubly Robust Estimator. Referring to the Figure 4 below, we estimate a, b0 and b1 using the whole datasets. Then, we compute the fitted values of gamma1, gamma0 and propensity score using 12 subgroup data respectively. Finally, we computed miu1, miu0 and hence ATE (miu1 – miu0) to estimate the subgroup average treatment effect.

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[8] Keane, M. P., & Wolpin, K. I. (1997). The Career Decisions of Young Men. Journal of Political Economy, 105(3), 473–522. https://doi.org/10.1086/262080

[9] Nardone, T. J. (1986). *MONTHLY LABOR REVIEW February 1986 " Part-Time Workers*. https://www.bls.gov/opub/mlr/1986/02/art2full.pdf

[10] U.S. Bureau of Labor Statistics (BLS). (2005, June). Time-Consuming Occupations and What they Pay. Https://Www.bls.gov/Careeroutlook/2005/Summer/Oochart.pdf.

Simple estimation strategy

- Given sample $\{X_i, Y_i, D_i\}_{i=1}^n$, we may consider the following simple estimation strategy:
  - obtain the fitted values of the propensity scores: $\tilde{\pi}(X, \hat{a})$
  - obtain the fitted values of the outcome means: $\tilde{\gamma}_1(X, \hat{b}_1)$ and $\tilde{\gamma}_0(X, \hat{b}_0)$
  - construct the doubly robust estimator for ATE as

$$\hat{\mu}_1^{DR} - \hat{\mu}_0^{DR},$$

where

$$\hat{\mu}_1^{DR} = \frac{1}{n}\sum_{i=1}^{n}\left[\tilde{\gamma}_1(X_i, \hat{b}_1) + \frac{D}{\tilde{\pi}(X_i, \hat{a})}\left(Y - \tilde{\gamma}_1(X_i, \hat{b}_1)\right)\right],$$

$$\hat{\mu}_0^{DR} = \frac{1}{n}\sum_{i=1}^{n}\left[\tilde{\gamma}_0(X_i, \hat{b}_0) + \frac{D}{\tilde{\pi}(X_i, \hat{a})}\left(Y - \tilde{\gamma}_0(X_i, \hat{b}_0)\right)\right].$$

Figure 4: Simple Estimation Strategy using Doubly Robust Estimator (Quoted from ECON 4140 Lecture Notes)

Our subgroup analysis with Doubly Robust revealed the following. The ATE had been adjusted to account for the cost of -$774 (netATE).

bfhrswk	bfeduca	no.treat	no.control	total	ATE	netATE
hours=0	years<12	368	215	583	1021.71	247.71
hours=0	years=12	315	144	459	1126.80	352.80
hours=0	year>12	105	47	152	-5047.09	-5821.09
0<hours<35	years<12	527	284	811	892.46	118.46
0<hours<35	years=12	739	368	1107	1555.09	781.09
0<hours<35	year>12	379	182	561	-747.19	-1521.19
35<=hours<=40	years<12	922	481	1403	2463.89	1689.89
35<=hours<=40	years=12	1075	526	1601	2545.97	1771.97
35<=hours<=40	year>12	446	216	662	-137.22	-911.22
40<hours	years<12	156	87	243	-810.12	-1584.12
40<hours	years=12	200	90	290	41.00	-733.00
40<hours	year>12	92	48	140	5767.49	4993.49

Table 6: Subgroup ATE results for 12 subgroups

The subgroup that benefited the most is **individuals who had worked between 35 and 40 hours, and had approximately 12 years of education**—they have demonstrated the highest net ATE of $1771.97.

The subgroup that benefited the least were **individuals who had worked no hours in a week (who we assume to be unemployed) and had approximately more than 12 years of education**—they had demonstrated the lowest ATE of -$5821.09.

In addition, we believe that heterogeneity has been fully explored in our models. The total units for each subgroup are sufficient enough; but further splitting down will risk a reduction in statistical power (i.e. further division of the group who had worked more than 40 hours in a week and spent more than 12 years in education will reduce the number of units each to below 100).

Based on the results above, we identified these five groups that do not benefit from the assignment of eligibility for the job training program:

- Unemployed people (hours=0) with more than 12 years in education (years>12)
- Part-timers (0<hours<35) with more than 12 years in education (years>12)
- Full-timers (35<= hours <=40) with more than 12 years in education (years>12)
- Individuals who worked more than 40 hours in a week (hours>40), with less than 12 years in education (years<12)
- Individuals who worked more than 40 hours in a week (years>40), with 12 years in education (years=12)

Our **policy recommendation** is that we should offer the JTPA program to all subgroups that demonstrate a positive net ATE, and exclude the above listed five subgroups that demonstrate a negative net ATE, because their earnings decrease on average after assigning the eligibility of the JTPA program. This informs the government to offer separate, tailored alternatives to subgroups who suffered negative post-program ATE.

As a sidenote, we decided against using the following variables, as they are illegal/unfair/impossible due to the following reasons in Table 7.

male	**It would be illegal** to restrain eligibility conditions on gender, so we decided not to analyze ATE differentiation on gender-based groups. As according to the U.S. Equal Employment Opportunity Commission: "It is illegal for a training or apprenticeship program to discriminate on the bases of race, color, religion, sex (including transgender status, sexual orientation, and pregnancy), national origin, age (40 or older), disability or genetic information. For example, an employer may not deny training opportunities to African-American

	employees because of their race."[11]
black, hispanic	Referring again to the US Equal Employment Opportunity Commission[12] as well as Griggs v. Duke Power Co[13], **it would be illegal** to prohibit job training programs on the basis of race, so we decided not to analyze ATE differentiation on race-based groups.
married	**It would be impractical** to analyze ATE differentiation based on marital status, as we do not believe that marital status is an accurate representative of the individual's capability to work.
ageXXXX (age dummies) and age	**It would be unfair** to constrain job training program eligibility to the participant's age.[14] Equal employment opportunities and job training program eligibility should not depend on age, as both older and younger workers can equally benefit from updating relevant skills to stay in the workforce.
class_tr, ojt_jsa	The kind of job training the unit will participate in does not yield meaningful information about the unit's demographic background nor their work conditions, therefore this research study does not believe there would be any purpose in comparing ATEs based on the kind of job training participated in.
f2sm	From a logistic standpoint, it is impossible to determine a unit's eligibility to enrol in a job training program, based on future timing of the unit's report of their earnings after receiving the treatment. In addition, f2sm does not convey meaningful information about the unit's demographic background or work conditions, so there is no purpose in analyzing ATE differentiation between f2sm groups.

[11] *Prohibited Employment Policies/Practices*. U.S. Equal Employment Opportunity Commission. (n.d.). https://www.eeoc.gov/prohibited-employment-policiespractices
[12] *Prohibited Employment Policies/Practices*. U.S. Equal Employment Opportunity Commission. (n.d.). https://www.eeoc.gov/prohibited-employment-policiespractices
[13] *Griggs v. Duke Power Co.* | *401 U.S. 424 (1971)* | *justia U.S. Supreme Court Center*. U.S. Supreme Court. (n.d.). https://supreme.justia.com/cases/federal/us/401/424/
[14] *Prohibited Employment Policies/Practices*. U.S. Equal Employment Opportunity Commission. (n.d.). https://www.eeoc.gov/prohibited-employment-policiespractices

bfeduca	**It is illegal** to restrain training eligibility conditions on the years of education the units hold,[15] so we decided not to analyze ATE differentiation based on the level of education. It is also an ambiguous variable—as in it is not clear when they started in high school, or university—anyways it would be unfair to restrain program eligibility on the level of education of units.
bfwage	We do not analyze ATE differentiation based on bfwage, because the variable is not an accurate measure of the units' overall earnings and therefore the units' poverty. For example, a low hourly wage could imply higher earnings because the unit works longer hours; a higher hours worked per week could imply lower earnings if they have a lower hourly wage.
hsorged (high school or non-high school graduates)	We chose not to analyze hsorged, because it is a binary variable that incorporates non-binary data, This variable is thus not credible and hard to interpret.
wkless13 (individuals who worked less or more than 13 weeks in a year)	We chose not to analyze wkless13, because it is a binary variable that incorporates non-binary data, This variable is thus not credible and hard to interpret.

Table 7: Justification on not including other covariates due to its illegalness, unfairness, and not necessary.

Conclusion and Next Steps

We conclusively **recommend this training program to the workforce of 1987 and 1989**—but not necessarily of today's generation due to the following limitations. Due to the individual heterogeneity in benefitting from the job training program, we should only offer the JTPA program to all subgroups that demonstrate a positive net ATE, and exclude the five subgroups that demonstrate a negative net ATE (refer Table 6), because their earnings decrease on average after assigning the eligibility of the JTPA program.

[15] *Griggs v. Duke Power Co. | 401 U.S. 424 (1971) | justia U.S. Supreme Court Center*. U.S. Supreme Court. (n.d.). https://supreme.justia.com/cases/federal/us/401/424/

Despite the conclusion above, our analysis needs to take into account three shortcomings. The first limitation is data validity (our data set is outdated, its survey was conducted in between 1987 and 1989, and may not be fully representative of today's workforce). We have also noticed the dataset's flaw of data credibility (the binary variables we accounted for in our baseline model have non-binary data). Lastly, our ATE interpretation can only translate to program eligibility implications, and has no relevant implications regarding the program's effectiveness itself.

Acknowledging those three shortcomings, we believe that there are three possible next steps this research direction could take, respective to handling the limitations we highlighted. We recommend conducting a more up-to-date pilot study, to gather more representative data on today's workforce; ensure high data quality (as in, ensure binary variables only have binary data); and use research mandates to track the effectiveness of program participation, and not just eligibility.

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Pertaining to the second requirement in the Final Report Submission Portal:

Henry had run the code for the propensity score, covariance balancing check, baseline ATE and ML methods for both homogenous and heterogenous models, as well as subgroup analysis. Ashley wrote out the final report: answers for all the questions, equations, citations, and interpreted results in relation to the relevant questions.