Presentation
“The effect of JTPA job training program on workers’ earnings”

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Agenda

1. Policy Question
2. Causal Effect Estimation: Setup and Assumptions Check
3. Investigating the Robustness of ATE (Covariates, Different ML, Homogeneous VS Heterogeneous)
4. Subgroup Average Treatment Effect
5. Conclusion, Limitations and Policy Implications of the study

Problem Statement

Job Training Partnership Act

1. Introduced by President Ronald Reagan
2. Goal: Shift job training away from public-sector employment programs; Move toward **employer-driven, skills-focused training**; Reduce federal spending and decentralize program administration.

Is JTPA Effective?

1. The National JTPA Study was a large **randomized controlled trial (RCT)** (20,000+ applicants, 1987–1989) evaluating job training programs for **economically disadvantaged adults and youths**.

2. Earnings and employment outcomes were collected through **surveys and state unemployment insurance records**.

Dataset

1. This analysis focuses on **adult men and adult women**, the two largest applicant groups.

2. Dataset contains **8,012 individuals** with **treatment assignment,** demographics, training participation, and labor market outcomes.

Q2: Policy Question and Why it's important for policy?

Policy Relevance

From a policy perspective, our research hopes to highlight the effect of the Job Training Partnership Act service program on the participant's post-program wages

Why is this important?

1. Government had invested $46.4 billion in Employment and Training Administration's federal job training programs[1] – is it effective?
2. Youth Unemployment Crisis: recent grads now make up 25.3% of total unemployment—can government intervention fix this?

***Policy Question ≠ Causal Question**

[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

Q1 & 2: Treatment and Causal Question

What is our Causal Question?

1. **How does JTPA eligibility affect a participant's earnings?**
2. **Which subpopulation groups are likely to benefit most/least from the job training program?**

Treatment and Unit

1. Units: 8012 economically-disadvantaged adult women and men
2. The treatment is the unit's **eligibility for the JTPA service program.**
   - **a.** **D = 0**: control group - not assigned eligibility to participate in JTPA
   - **b.** **D = 1**: treatment group - assigned eligibility to participate in JTPA

Why treatment = eligibility but not participation

1. **Theoretical:** Eligibility is randomly assigned; individuals are either in the program or control group. → Qualifies for RCT
2. **Practical:** the government can only give units eligibility, and cannot compel them to actually participate in the program

Outcome

The participants' sum of earnings 30 months following the program (***earnings***).

Q3: Identification Strategy of Causal Effect

This experiment is a **Randomized Controlled Trial (RCT)**

1. Units are randomly assigned eligibility of participation
2. The treatment assignment D is statistically independent of potential outcome (Y(1), Y(0)): $D \perp Y(1), Y(0)$
3. By definition, each unit has a non-zero probability of assigned D

Thus we can safely assume

Unconfoundedness

Treatment is randomly assigned among *observationally* identical units, and that conditioned on observed covariates, treatment is independent of potential outcome:

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

Overlap

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:

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

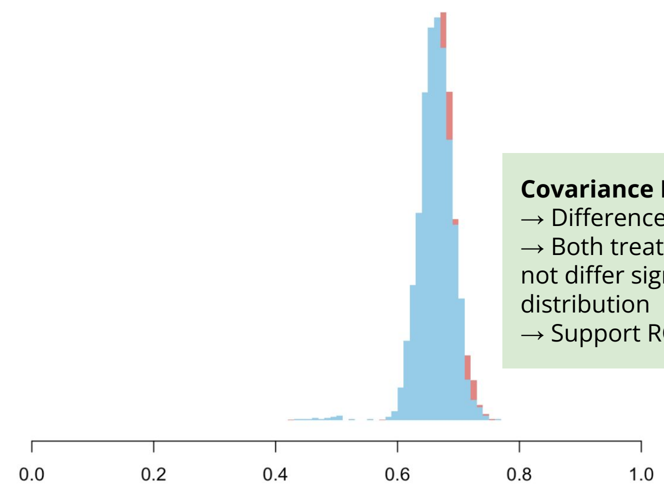
$$0 < \pi(x) < 1, \text{ for all } x \in X$$

Q3: Identification Strategy of Causal Effect

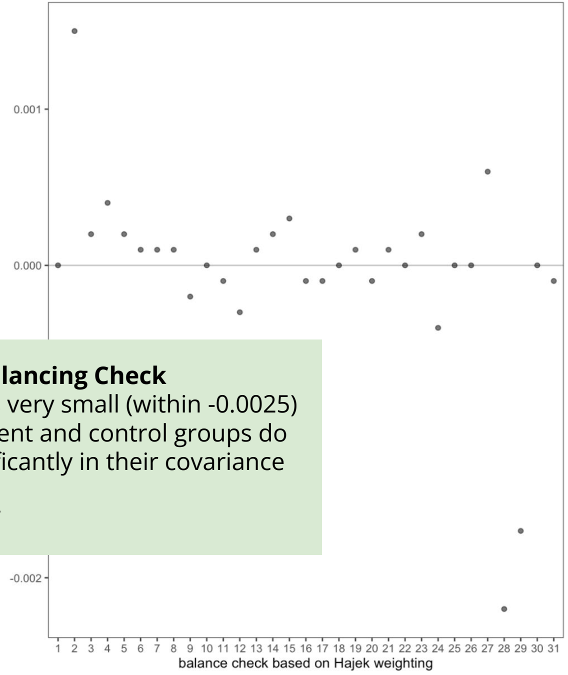
Overlap and Covariance Balancing Check As Evidence to Support RCT

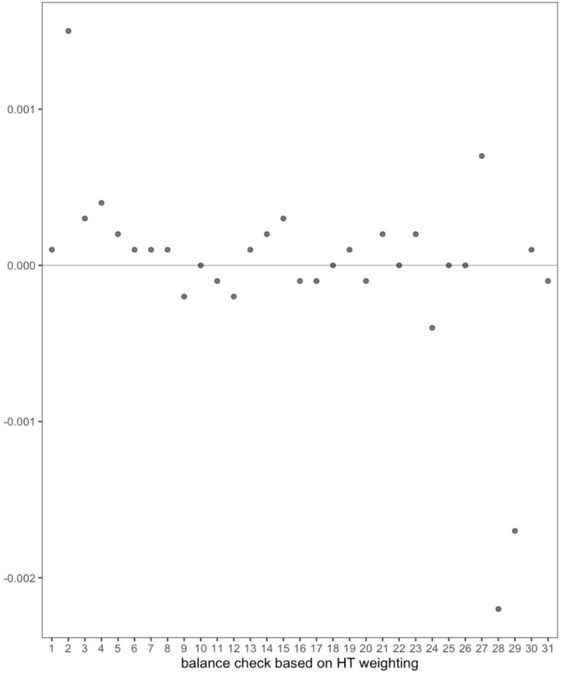
Propensity Score Distribution for Treated (Red) and Control (Blue)

Satisfy overlap conditions
(Propensity score between 0 and 1 - estimated with logistic regression)



Covariance Balancing Check
→ Difference is very small (within -0.0025)
→ Both treatment and control groups do not differ significantly in their covariance distribution
→ Support RCT





Q3: Identification Strategy of Causal Effect

ATE Estimator: Doubly Robust Estimator

We estimate our causal object θ to be

$$\boldsymbol{\theta = E\,[\,Y(1)\,] - E\,[\,Y(0)\,].}$$

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:

$$\gamma_1(x) = E[\,Y \mid X = x,\, D = 1\,];\; \gamma_0(x) = E[\,Y \mid X = x,\, D = 0];\; \pi(x) = E[\,D \mid X{=}x\,] = P\{D = 1 \mid X = x\}.$$

Why Doubly Robust Estimator:

1. Combination of inverse propensity score weighting and outcome regression methods
2. The ATE estimate is **unbiased** as long as **either** predictive objects γ(x) **or** π(x) is correctly specified.

Debiased ML Methods

Estimating low dimensional ATE with a high dimensional nuisance parameter (we include all covariates here → high dimensional), high quality

Cross-fitting

1. Ensure accuracy of the ATE predicted
2. Eliminate bias caused by overfitting
3. K = 3 folds in our models

Q3: Identification Strategy of Causal Effect

Why not Simple Linear Regression, Regression Adjustment (CRA/IRA)

High Dimensionality Problem

1. We decided to include most of the covariates in the analysis (15 covariates)
2. We are dealing with a high dimension problem
3. Unstable ATE estimates with high standard errors

That said, we still use Simple Linear Regression (i.e. Simple Difference in Mean estimator) as our baseline model of ATE estimate because it is **unbiased** under **RCT settings.**

Q4A: How robust is your causal estimates to the inclusion of different control variables?

Why including all 15 covariates?

1. Some covariates might be correlated with outcome (i.e. earnings), but unsure which
2. Controlling covariates isolate the effect of covariates on earnings variation, ATE estimate explain the sole effect of D.

Demographics

Variables: male, age, black, hispanic, married

Differences in background, baseline job attachment and discrimination affect flexibility to participate in labor market and hence earnings.

Exclude age dummies since it contains overlapping info with age

Education

Variables: bfeduca, hsorged, class_tr, ojt_jsa

Education background captures baseline skills need and levels, hence affecting their current earnings.

Pre-treatment Work Status

Variables: bfyrearn, bfwage, bfhrswrk, wkless13

Controlling these variables ensures that individuals are evaluated fairly from their respective baselines **(heterogeneity)** to correctly estimate the ATE.

Poverty Indicators

Variables: afdc

Reflect household economic constraints and benefit-dependency that can change incentives to join the labor market, hence earnings.

Miscellaneous

Variables: f2sms

Controls for measurement differences or systematic reporting differences across follow-ups.

Q4A: How robust is your causal estimates to the inclusion of different control variables?

```r
jtpa$hsorged <- factor(jtpa$hsorged)
jtpa$bfeduca <- factor(jtpa$bfeduca)
jtpa$married <- factor(jtpa$married)
jtpa$wkless13 <- factor(jtpa$wkless13)

y <- jtpa$earnings
d <- jtpa$D
x <- model.matrix(~male + age + black + hispanic + married + bfeduca +
    hsorged + class_tr + ojt_jsa + bfhrswrk + wkless13 + bfyrearn + bfwage +
    f2sms + afdc, data = jtpa)[, -1]
```

We turned the covariates that has multiple categories into **factors.**

Note: Each variable should be **binary,** but there are multiple levels in the dataset.

Our X (i.e. covariates) matrix =
15 covariates

Q4B: How robust is your causal estimates to the use of different machine learning methods?

Our Approach

1. SLR (Simple Difference in Mean) as Baseline ATE
2. Double ML + Doubly Robust + Interactive Regression Model (Heterogeneous)
3. Double ML + Doubly Robust + Partial Linear Regression (Homogeneous)
4. We compare models with RMSE of outcome Y and propensity score

Results using heterogeneous treatment effect model

1. ATE estimate is pretty similar and stable (around 1300-1400) across different models → Robust ATE
2. Lasso has the lowest RMSE of outcome & Propensity Score

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
ATE estimate	1326.78372	1332.14733	1286.88301	1470.8753	1440.03428
Standard error	388.08747	357.06473	376.85121	367.32206	376.60453
95% CI (Lower Bound)	566.13228	632.30045	548.25464	750.92405	701.88941
95% CI (Upper Bound)	2087.43517	2031.99421	2025.51137	2190.82655	2178.17915
RMSE of outcome	1.6812309×10^4	1.5499652×10^4	1.5633924×10^4	1.6064132×10^4	1.6560762×10^4
RMSE of propensity score	-	0.47218	0.47768	0.47218	0.47259

Q4B: How robust is your causal estimates to the use of different machine learning methods?

Our Approach

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4. We compare models with RMSE of outcome Y and propensity score

Results using homogeneous treatment effect model

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
ATE estimate	1326.78372	1301.97353	1391.68447	1478.97383	1281.78076
Standard error	388.08747	356.67108	358.49549	368.36566	387.7634
95% CI (Lower Bound)	566.13228	602.89822	689.0333	756.97713	521.76449
95% CI (Upper Bound)	2087.43517	2001.04883	2094.33563	2200.97053	2041.79703
RMSE of outcome	1.6812309×10^4	1.5460455×10^4	1.5569164×10^4	1.601761×10^4	1.6824497×10^4
RMSE of propensity score	-	0.47224	0.47681	0.47229	0.47432

1. ATE estimate is pretty similar and stable (around 1300-1400) across different models → Robust ATE
2. Lasso has the lowest RMSE of outcome & Propensity Score

Q4C: How robust is your causal estimates to whether the treatment effect is homogeneous or heterogeneous?

ATE estimate and standard error is pretty similar and stable (around 1300-1400) across different homogeneous and heterogeneous models → Robust ATE

ATE estimate comparison

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
Heterogeneous	1326.78372	1332.14733	1286.88301	1470.8753	1440.03428
Homogeneous	1326.78372	1301.97353	1391.68447	1478.97383	1281.78076

Use heterogeneous ATE since more flexible
Lasso (Smallest RMSE Outcome and Propensity Score)

ATE Standard error comparison

matrices	Simple Differences in Mean	Lasso	Forest	Trees	Single-Layer Neural Network
Heterogeneous	388.08747	357.06473	376.85121	367.32206	376.60453
Homogeneous	388.08747	356.67108	358.49549	368.36566	387.7634

ATE of assigning eligibility of participation in job training program (D) on workers' earnings =

$1332.14733

Q5: According to estimates from earlier studies, the average cost of services per treatment assignment is $774. How would your answers to Q4 above change?

$1332.14733 - $774 = $558.14733

Beyond a net increase in an individual's earnings post-treatment, we also conclude that each dollar invested will yield **$1.72 increase in earnings post-treatment on average.** *(1332.14733/774)*

95% CI: [-141.69955, 1227.04883]

However, our adjusted confidence interval shows that there may be some unreliability in estimating the net increase in the unit's earnings in 30 months—implying that there is some uncertainty around a net increase in earnings.

We would generally **recommend** the training program to the workforce, **of that time period**.

Q6: 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

Considered

hsorged (high school or non-high school graduates)[3]
wkless13 (individuals who worked less or more than 13 weeks past year)
afdc (whether the female individual is recipient of the Aid to Families with Dependent Children program)[4]
bfyrearn (annual sum of earnings before the assignment).

Not Considered

male	Illegal[5]
black and/or hispanic	Illegal[6]
married	Impractical
ageXXXX, and age	Unfair[7]
class_tr/ojt_jsa	Not meaningful
f2sm	Logistically impossible
bfeduca	Illegal[8]
bfwage, bfhrswrk	Not accurate representations of poverty

[3] *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*
[4] *New Moms' "What We Do" Page. New Moms. (n.d.). https://newmoms.org/what-we-do/*
[5 6 7] *Prohibited Employment Policies/Practices. U.S. Equal Employment Opportunity Commission. (n.d.). https://www.eeoc.gov/prohibited-employment-policiespractices*
[8] *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/*

Q6: 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.

Subgroup combination of hsorged and wkless 13	...excluding afdc and byrearn
Not only high-school diploma a systematic barrier towards higher earnings,[9] but so is employment history: the longer a unit is unemployed, the less likely they are to enter employment or work a job of an equal wage as before, due to **skill degradation.**[10]	Lowly-paid employed people still stand a better chance of continued employment due to likelier skill upgrade, compared to than unemployed people.[11] AFDC recipients qualify based on 'standard of need', a condition we believe is already associated with annual earnings.

[9] *Thiem, K. C., & Dasgupta, N. (2022). From Precollege to Career: Barriers Facing Historically Marginalized Students and Evidence-Based Solutions. Social Issues and Policy Review, 16(1), 212–251. https://doi.org/10.1111/sipr.12085*
[10] *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*
[11] *Ljungqvist, L., & Sargent, T. J. (1998). The European Unemployment Dilemma. Journal of Political Economy, 106(3), 514–550. https://doi.org/10.1086/250020*

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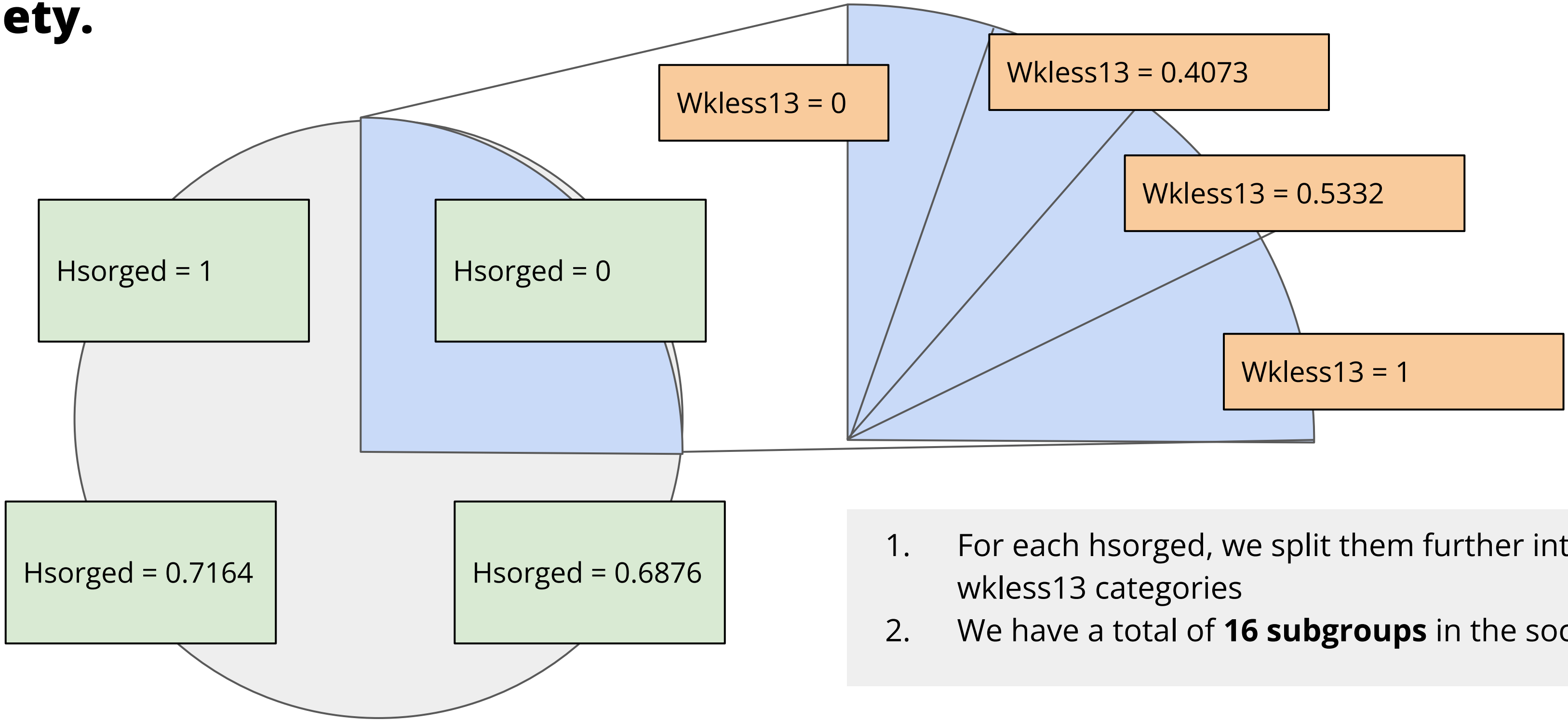

1. For each hsorged, we split them further into wkless13 categories
2. We have a total of **16 subgroups** in the society.

Q6: 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.

hsoged

0	non-high school graduates who had dropped out of school before and during their first year
0.6876	non-high school graduates who had dropped out of school in their third year
0.7164	0.7164 = non-high school graduates who had dropped out in their second year
1	High school graduates

wkless13

0	individuals who had worked a **full-time job** more than 13 weeks
0.4073	individuals that have worked a **part-time job** more than 13 weeks
0.5332	individuals that had worked a **part-time job** less than 13 weeks
1	individuals who had worked a **full-time job** for less than 13 weeks

Rationale: Account for different job-mode (part-time & full-time)
Note: This is subjective interpretation

Legal?

Neither are protected classes.

Heterogenous?

We believe that **heterogeneity had been fully explored** in our subgroups. Further division of our subgroups will risk losing statistical power (some of the subgroups have 0 observations).

Q6: 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

- 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

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

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

Ref: ECON 4110 Lecture Slide Handout 6 Pg 14

We estimate **b1, b0 and a** using the **whole dataset.**

Our Approach

1. We use Doubly Robust Estimator to estimate subgroup ATE.
2. We estimate the parameter within gamma and propensity score with the **whole dataset**
3. We calculate the fitted value of gamma and propensity score with **subgroup data.**
4. Then, we calculate the ATE using Doubly Robust Estimator formulae.

Q6: 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.

hsorged	wkless13	no.treat	no.control	sum	ATE
0	0	628	331	959	1103.75
0	0.4073359	19	16	35	5546.31
0	0.5332298	29	15	44	2717.78
0	1	708	407	1115	938.99
0.6876773	0	79	40	119	2852.77
0.6876773	0.4073359	5	0	5	-6718.90
0.6876773	1	57	27	84	-6434.58
0.716404	0	60	30	90	989.60
0.716404	0.5332298	7	3	10	1001.39
0.716404	1	80	41	121	3367.79
1	0	1924	981	2905	1347.92
1	0.4073359	51	20	71	-585.66
1	0.5332298	53	22	75	2328.13
1	1	1624	755	2379	1524.76

The group that benefited the most:
non-high school graduates with a part-time employment history of over 13 weeks.

The group that benefited the least:
those with a partial high school education (having dropped out their third year) and a full-time employment history of less 13 weeks.

Policy Implication

1. JTPA program eligibility conditions should not exclude individuals without a high school diploma and unemployment histories (because they got the benefit).
2. When implemented, give **special attention, guidance and incentive** to those who struggle to gain much from the program (negative ATE).

Conclusion

Conclusion

We generally recommend this training program to the workforce of 1987 and 1989—but not necessarily of today’s generation due to the following limitations.

Limitations

1. **Data validity** - outdated data, might not be get the same effect in this era
2. **Data credibility** - seemingly binary variables have different categories, thus different interpretations and conclusions
3. **ATE interpretation** - our conclusions are dependent on program eligibility, and not actual program participation

Next Steps

1. **Conduct a pilot study** on a subgroup to collect up-to-date data
2. **Ensure** high data quality
3. **Use research mandates** to track effectiveness of program participation—not just eligibility

Citations

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

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