Estimating the Causal Impact of a Growth Mindset Intervention on Student Achievement

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Abstract

Can a quick online lesson reshape how students think and ultimately how they perform?

This project examines the power of a simple intervention to develop a growth mindset with the use of synthetic data inspired by the National Study of Learning Mindsets (NSLM).

We use a mixed set of causal inference methods which include linear regression but also propensity score matching plus inverse probability weighting (IPW) in order to assess academic achievement results.

Data Description

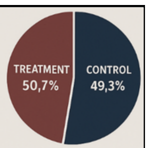
SAMPLE SIZE
10,000 STUDENTS

SCHOOLS
76 U.S. PUBLIC HIGH SCHOOLS

STUDENT VARIABLES
selfrpt, race, gender, fgen

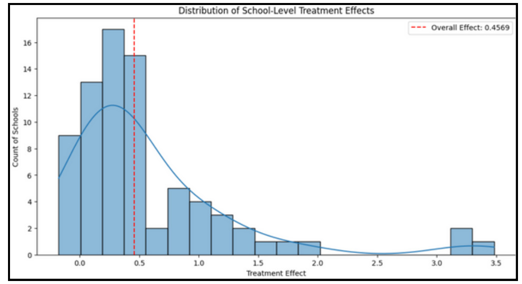
SCHOOL VARIABLES
urban, mindset, test, sch_race, pov

KEY VARIABLES
- y Achievement: Outcome measured after intervention (continuous)
- Z Treatment: Received growth mindset intervention



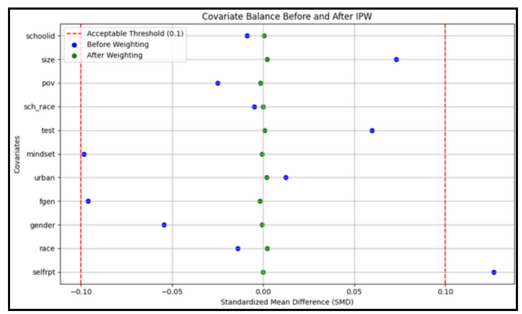
Causal Assumptions
- ✅ Ignorability
- ✅ Positivity (Overlap)
- ✅ SUTVA

Data Analysis



School-Level Impact: Not One-Size-Fits-All
- Most schools cluster around the average effect (0.46)
- Some show exceptional gains, revealing where the intervention works best

Takeaway: Broadly effective, but context amplifies impact.

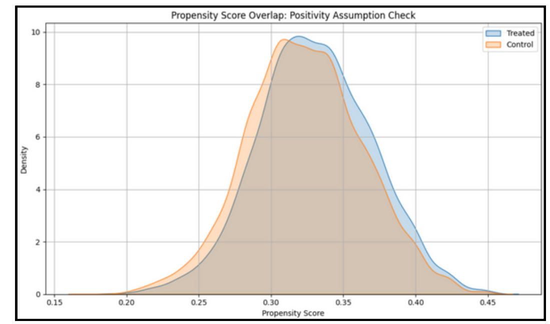


SMD Plot (🔵 Before | 🟢 After IPW): All covariates within ±0.1 -> **strong balance**
✅ Supports Conditional Ignorability 🎯 Ensures unbiased ATE estimation

Results

Methods	ATE Estimate
Linear Regression	+0.413
Propensity Score Matching	+0.415
Inverse Probability Weighting (IPW)	+0.414

The three approaches give comparable estimates of **ATE (~ +0.41)** which point to the same treatment effect. It also implies that **covariates are well balanced and confounding is minimal**; and therefore avoiding rival good results across methods.



Propensity Score Overlap (Positivity Check): 🟦 Treated vs 🟧 Control show **strong overlap**
✅ Common support confirmed ✅ Supports Positivity Assumption for causal inference

Methods

Estimated the Average Treatment Effect (ATE) using multiple casual inference methds:

OLS
Y --> Z + covariates
Adjusted for observed confounding directly through regression.

Propensity Score Matching
1:1 Nearest Neighbor
selected identical untreated peers for treated students using calculated treatment (propensity scores).

Inverse Probability Weighting (IPW)
used individuals' inverse probabilities of receiving their observed treatment status for creating a randomized experiment design.

Causal Validity Checks: Covariate Balance | Propensity Score Overlap (Positivity)

Conclusion

- Growth mindset intervention has a positive significant effect in achievement.
- Consistent ATE across OLS, Matching, and IPW **confirms robustness**.
- Balance checks + overlap **test causal assumptions**.
- Scalable, low-cost interventions **can boost student outcomes** when backed by rigorous methods.

⚠ **Limitations:**
Hidden Confounders: Unmeasured variables may bias results.
Model Dependence: Results rely on correct model specification.

References

- Austin, P. C., & Stuart, E. A. (2015). Moving towards best practice when using inverse probability of treatment weighting (IPTW). Statistics in Medicine, 34(28), 3661–3679.
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41–55.