RUTGERS

Statistical Models and Computing

Causal Impact of a Growth Mindset Intervention on Academic Achievement

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1. Introduction

A lot of students believe their intelligence is fixed — that they're either smart or they're not. This kind of mindset can limit their motivation and performance in school. To help shift that belief, a short online "nudge-like" intervention was created to encourage a growth mindset — the idea that intelligence can grow with effort.

This project explores whether that kind of mindset intervention can actually improve student achievement, using a synthetic dataset modeled on the National Study of Learning Mindsets (NSLM).

2. Data Exploration

- 10,391 students across 76 public high schools
- Outcome:
  - y : standardized academic achievement score
- Treatment:
  - z = 1 : received growth mindset intervention
  - z = 0 : control
- covariates:
  - Student level: selfrpt, race, gender, fgen
  - School level: urban, mindset, test, sch race, pov, size

3. Appropriate Visuals

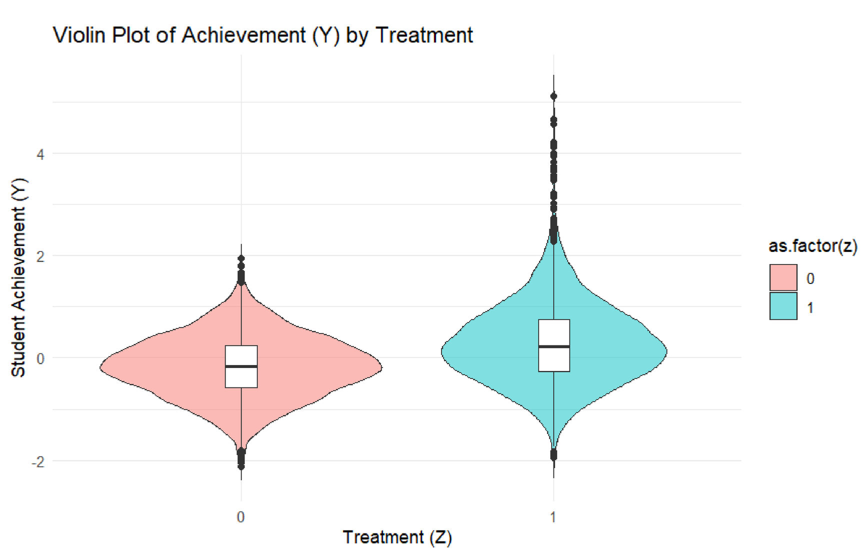

Figure 1: Violin plot to Compare Distributions

The violin plot shows that the treatment group (Z = 1) tends to have slightly higher achievement scores overall. The median is higher compared to the control group (Z = 0), and the distribution is more spread out, especially in the upper range. This suggests that while most students benefited moderately from the intervention, a few showed a substantial boost in achievement. In contrast, the control group has a tighter distribution around the lower median, with fewer extreme high performers. This visualization supports the idea that the intervention may have had a positive effect for a wider range of students.

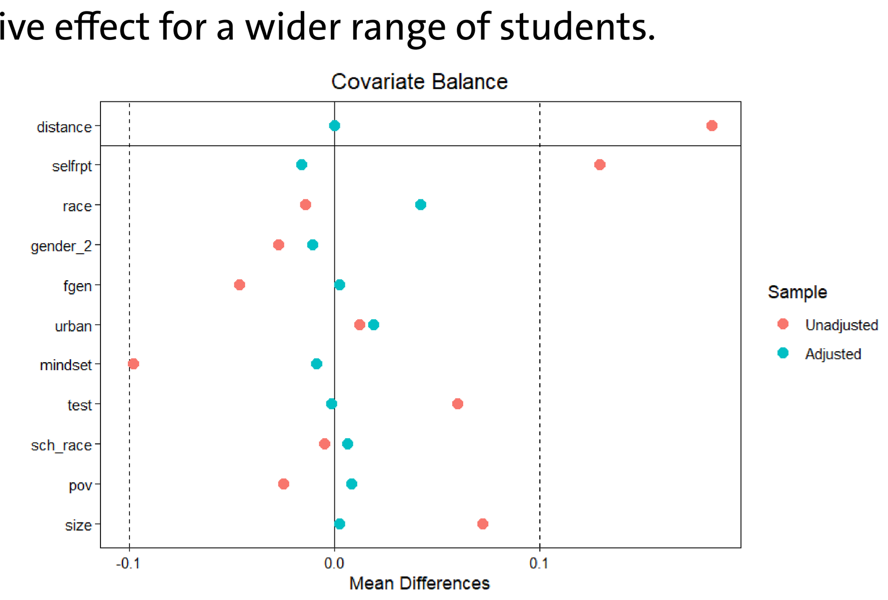

Figure 2: Covariate Balance Plot (after Matching)

Red dots show the covariate imbalance before matching, while blue dots show how things look after matching. The dashed lines at -0.1 and 0.1 mark the threshold for good balance. After adjustment, most covariates fall well within this range — suggesting that matching helped make the treatment and control groups more comparable on observed characteristics.

4. Assumptions

Assumptions for Valid Causal Interpretation

- Ignorability: no unmeasured confounders
- Overlap (Positivity): treatment and control groups are comparable across the covariate space
- SUTVA: No spillover effects between students
- Correct Model Specification
- Independence of Observations

5. Methods used and results

Method	Description	Estimates
OLS	Linear Regression with covariate adjustment	0.413
Bootstrap	Uncertainty quantification (percentile CI)	0.414
LASSO	Regularized regression (feature selection)	0.415
Matching	Propensity score matching	0.419
IPW	Inverse probability weighting	0.417
AIPW	Augmented IPW doubly robust	0.415
Bayesian	Posterior estimate of treatment effect	0.417

Table 1: Methods Used and their Treatment Effect Estimates

6. Subgroup Analysis

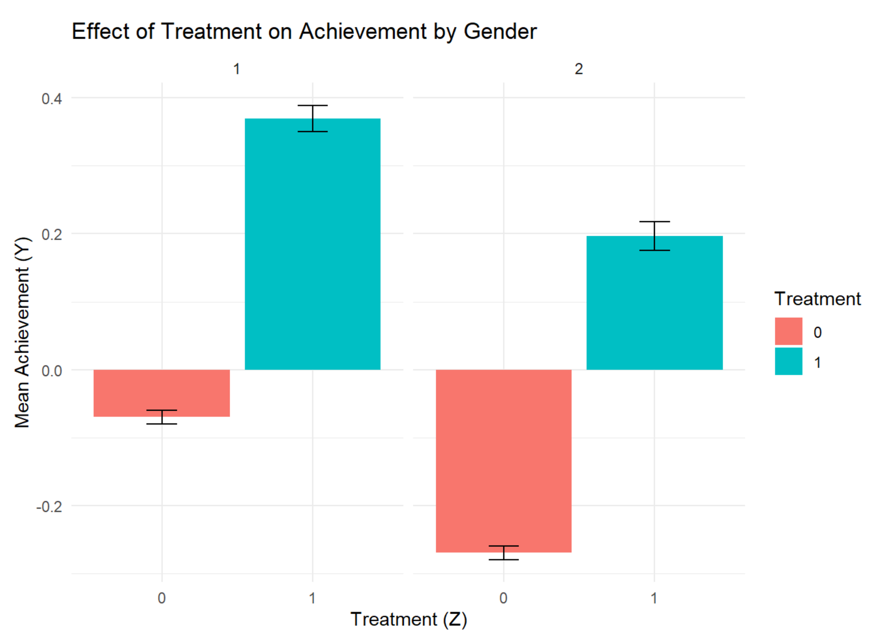

Figure 3: Effect of Treatment on Achievement by Gender

The intervention positively impacts both gender groups by improving achievement scores compared to the control group. The effect size appears stronger for females, but both groups benefit from the nudge-like intervention. In males, the treatment seems to "rescue" students from a negative achievement trend. Also tested these results using ANOVA and that also supported our results from the plot "treatment effect is similar for both genders—it helps both, without a major difference in impact".

Whereas for fgen, ANOVA test supports the claim that "The intervention works differently for first-generation students than for non-first-generation students" (The interaction term is statistically significant: $p < 0.05$). So the results suggest that First-generation students have lower achievement scores than their non-first-generation peers.

7. Interpretation

- The intervention improves achievement by approximately **0.41 standard deviations**, and the effect is consistent across all methods used.
- Bootstrap and Bayesian estimates both confirm that this effect is statistically robust.
- The treatment appears more effective for students with higher motivation (selfrpt) and non-first-generation students.
- Covariate balance after matching supports a valid causal interpretation of the results.

8. Limitations

- While based on actual experimental structures, patterns, and distributions, synthetic data lacks the natural noise, missingness, and real-world variability of actual educational datasets.
- The intervention's success might vary across: different cultural contexts, age groups, and socioeconomic settings
- The treatment (z) was not randomly assigned in this synthetic version

9. Conclusions

Our analysis finds strong evidence that a growth mindset intervention significantly improves student achievement. Across multiple causal methods—including regression, matching, and weighting—the estimated treatment effect is consistently positive, around **0.41 standard deviations**. This suggests the intervention is effective and robust to different modeling strategies. While based on synthetic observational data, these findings are consistent with real-world evidence and highlight the promise of mindset-focused programs in education.

10. References

- *An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies* — Link
- *Causal Inference for Statistics, Social, and Biomedical Sciences* — Link
- *A Growth Mind-Set Intervention Improves Interest but Not Academic Performance in the Field of Computer Science* — Link