Unlocking Student Potential: A Causal Analysis of Growth Mindset Interventions

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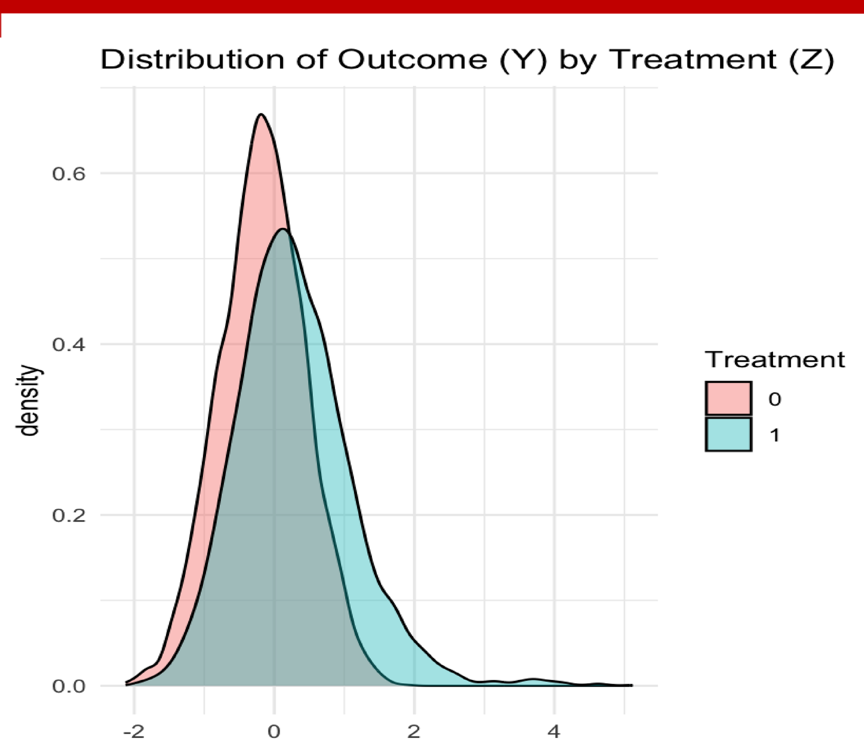
Introduction

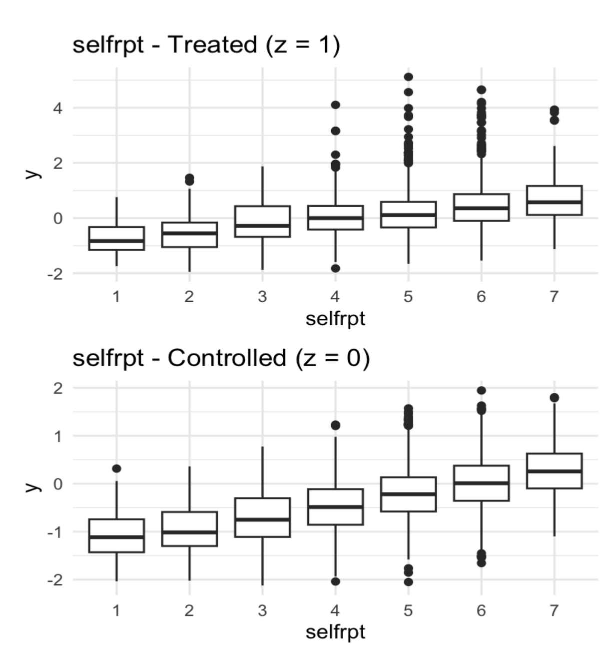
Academic achievement is shaped by more than just inherent ability—students' beliefs about learning also play a critical role. A growth mindset, which holds that intelligence can be developed through effort, contrasts with a fixed mindset, the belief that intelligence is static. Prior work by Yeager et al. (2019) demonstrated that brief, nudge-style interventions promoting growth mindset principles can positively influence student performance.

In this analysis, we examine a synthetic observational dataset modelled after the National Study of Learning Mindsets (NSLM) to estimate the causal impact of such an intervention on student outcomes. While the original NSLM utilised a randomised design, our dataset reflects an observational framework, requiring careful adjustment for confounding.

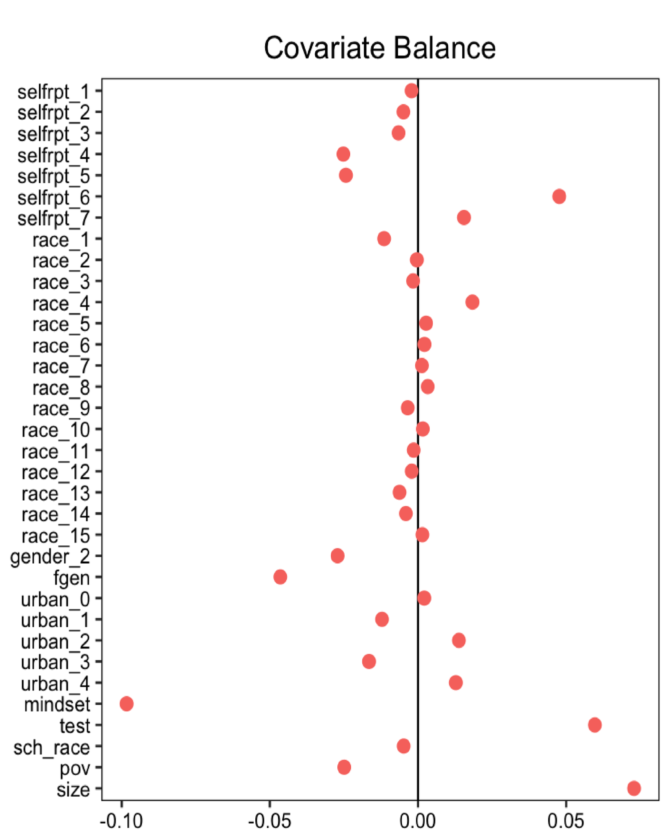
To estimate the Average Treatment Effect (ATE), we apply a range of causal inference methods, including regression adjustment, Inverse Probability Weighting (IPW), Augmented IPW (AIPW), and propensity score stratification. Our analysis emphasises covariate balance, clear modelling choices, and the assumptions needed for valid causal conclusions.

Data Exploration





Students who received the intervention (Treatment = 1) show a rightward shift in their outcome distribution relative to the control group (Treatment = 0).



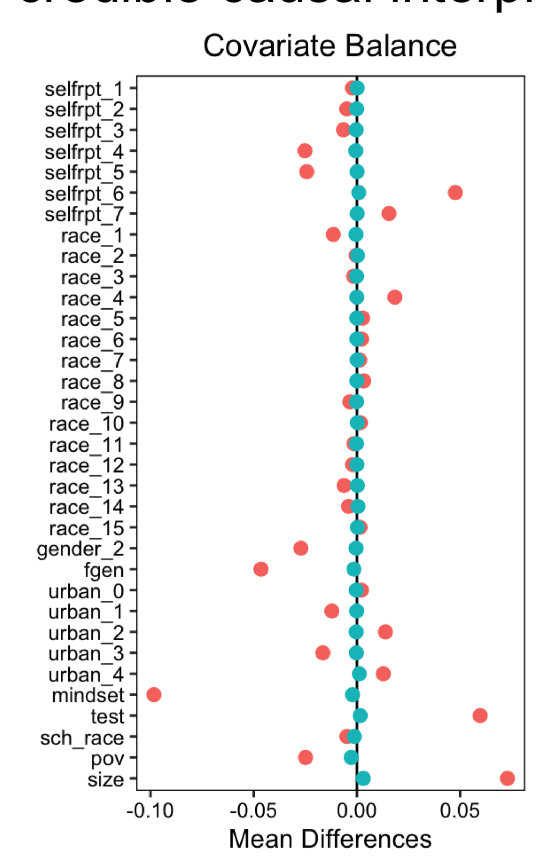
Higher selfrpt scores are linked to higher achievement in both groups. The intervention appears more effective for students with stronger initial expectations.

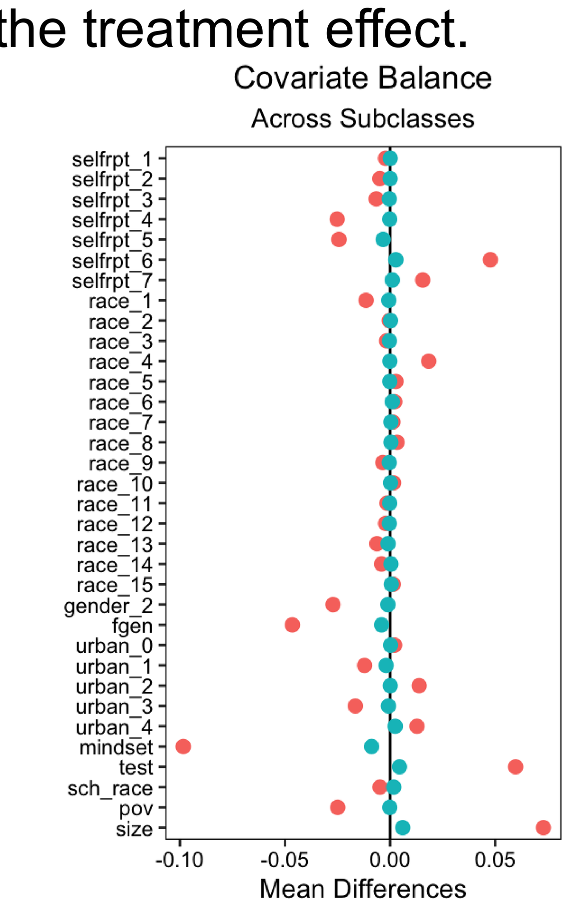
This love plot displays mean differences in covariates between the treatment and control groups before adjustment. Several covariates show non-negligible deviations from zero, particularly mindset, urban_4, and pov, indicating baseline imbalance.

Methods

However, since the data is observational, the difference between treatment and control group from the density plot may be partially confounded by covariate imbalance, necessitating further adjustment using causal inference methods before drawing conclusions.

This imbalance underscores the importance of applying causal adjustment techniques, such as propensity score weighting or stratification, to achieve covariate balance and support a more credible causal interpretation of the treatment effect.





The plots compares covariate balance before and after weighting using **inverse probability weights and post-stratification balance(left and right)** derived from estimated propensity scores. The red points (unweighted) show noticeable imbalance for several covariates, while the blue points (PSWeighted) are tightly centred around zero.

After weighting, the improved alignment of covariates indicates that propensity score weighting successfully reduced confounding, helping create a pseudo-randomised sample and strengthening the validity of causal estimates.

After stratifying into five propensity score subclasses, most covariates align closely around zero, indicating that stratification substantially improved covariate balance. This supports the validity of the stratified estimate of the average treatment effect (ATE) and reduces bias due to confounding in this observational study.

The Hajek estimator indicates a positive treatment effect of approximately **0.412** units on student achievement after adjusting for propensity scores.

Hajek estimator relies on correct modelling, no unmeasured confounding, positivity, and SUTVA.

Trimming extreme propensity scores, the IPW estimate shows a **0.412** unit gain in achievement due to the intervention.

Results

Estimator	ATE Estimate	95% Confidence Interval	SE	CI Method
Naive Mean Diff	0.457	(0.426, 0.488)	0.0159	Normal Approximation
OLS	0.457	(0.429, 0.485)	0.014	From Model Summary
IPW	0.412	(0.384, 0.439)	~0.014	Bootstrap (B = 1000)
AIPW	0.411	(0.383, 0.439)	0.014	Bootstrap (B = 1000)
Stratification	0.415	(0.385, 0.445)	0.0156	Normal Approximation

Estimator	Assumptions
Naive Mean Diff	• No confounding (as-if randomized) • No covariate adjustment • Likely biased in observational data
OLS	• Linear model for outcome • No omitted variables • All confounders included
IPW	• Correct PS model • Positivity • No unmeasured confounding
AIPW	• Either PS or outcome model correct • Positivity • No unmeasured confounding
Stratification	• Balance within strata • Sufficient overlap • No unmeasured confounding within strata

Discussion

The table summarises the estimated Average Treatment Effects (ATE) of the growth mindset intervention using various causal inference methods. All estimates suggest a positive effect on student achievement, ranging from **0.411 to 0.457**.

The Naive and OLS estimates are the largest, as they do not account for confounding as rigorously as other methods. IPW, AIPW, and Stratification offer more reliable estimates by adjusting for observed covariate imbalances.

The tight confidence intervals (CIs) and consistency across adjusted methods provide support for the robustness of the treatment effect under different modelling strategies.

Trimming helps improve the reliability and robustness of the estimate by focusing on units where treatment assignment is more comparable across groups.

These findings underscore the potential of nudge-like interventions to meaningfully enhance student performance when properly evaluated using modern causal inference techniques.

Limitations

Observational Data: Unlike the original NSLM trial, this synthetic dataset is observational. As a result, we cannot completely rule out the effect of unmeasured confounding, which may bias our estimates.

Model Dependence: Estimators such as OLS and IPW are sensitive to model misspecification. Inaccurate modelling of the outcome or treatment assignment could affect validity.

Overlap & Positivity Violations: Limited overlap in propensity scores between treatment groups may challenge the positivity assumption, impacting the stability of some estimates.

Synthetic Nature: Although based on real data, the dataset is simulated. This may reduce generalizability to actual student populations.

References:

Ding, Peng. *A First Course in Causal Inference*. Chapman & Hall/CRC, 1 June 2024.