The Causal Effect of a Growth Mindset: Intervention on Student Achievement

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1. Introduction

- The idea that intelligence and skills can be enhanced via work and education is known as a growth mindset.
- This study looks at how an instant online mindset intervention impacts educational outcomes.
- The project makes use of artificial information that is based on the National Study of Learning Mindsets (NSLM).
- It also uses statistical techniques that mimic experimental design in an effort to estimate the causal effect.

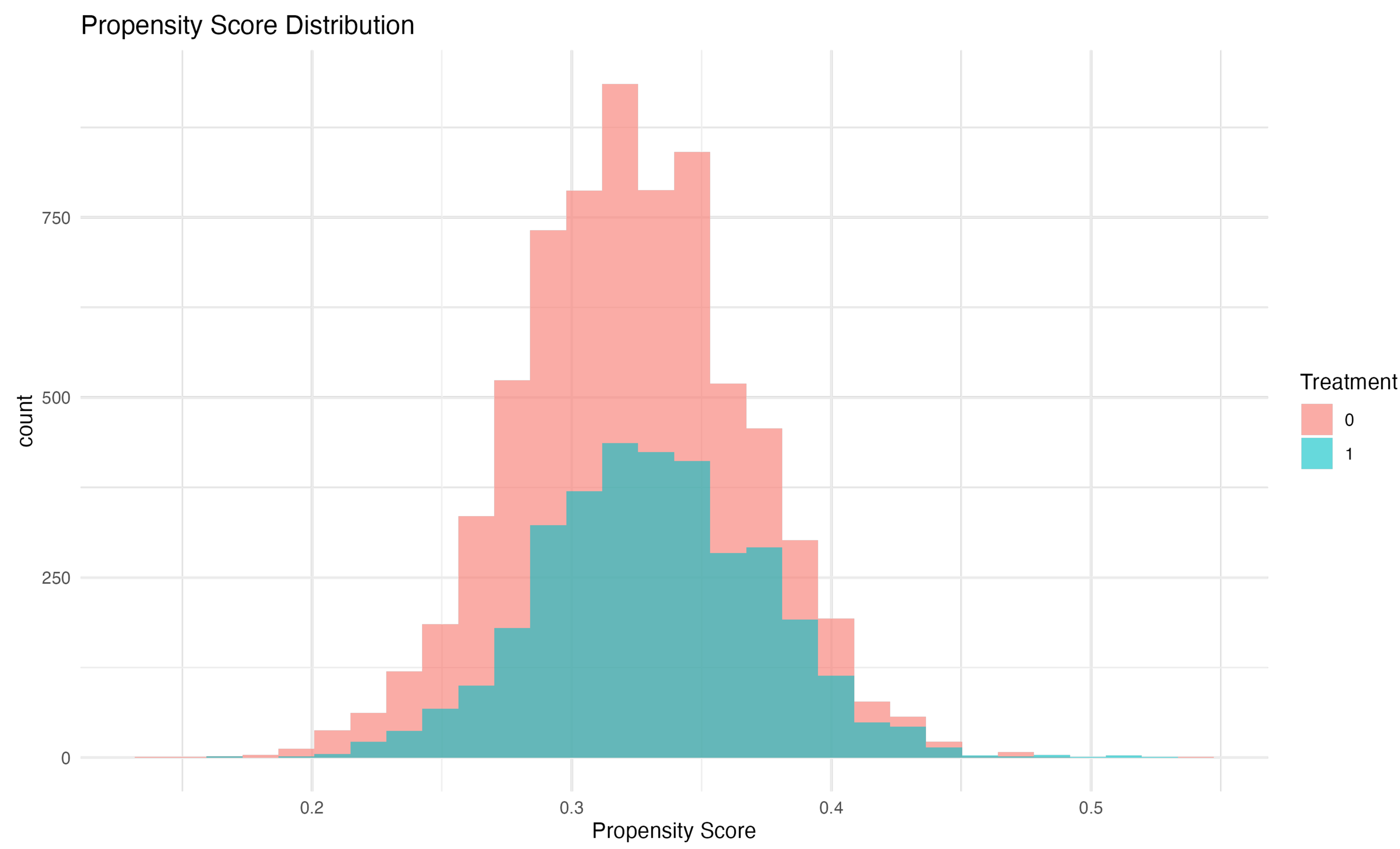
2. Objective

- The objective is to assess the Average Treatment Effect (ATE) of a growth mindset intervention on the academic performance of high school students.
- Employ a synthetic observational dataset that is structured to closely imitate actual data from the National Study of Learning Mindsets (NSLM).
- Utilize causal inference techniques to control for confounding variables and replicate the circumstances of a randomized trial.
- Exhibit a comprehensive grasp of IPW (Inverse Probability Weighting) and AIPW (Augmented IPW) methodologies, as covered in the course.

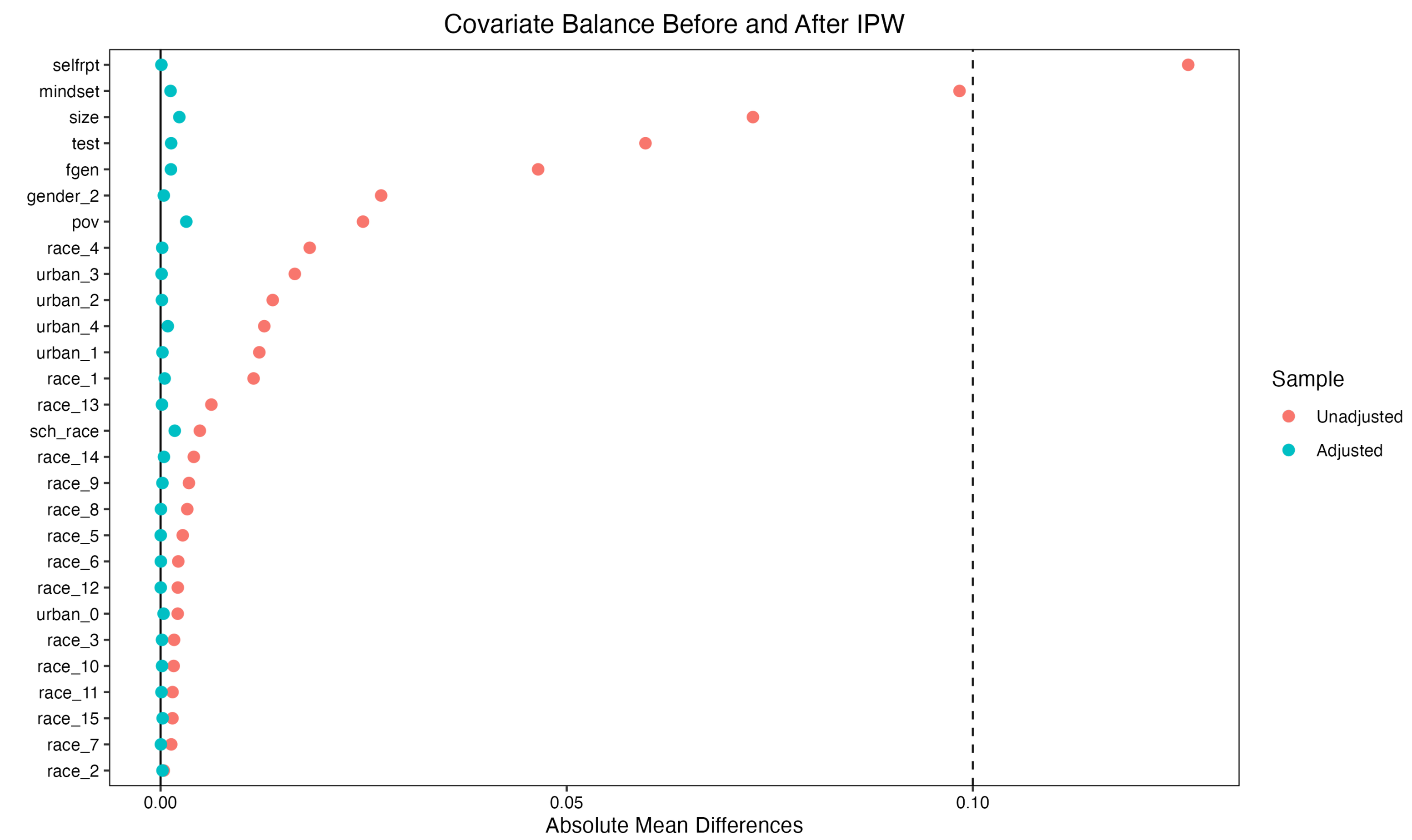
3. Causal Inference Strategy

- While addressing confounding using **Inverse Probability Weighting (IPW)**, assigning weights based on estimated treatment probabilities.
- I applied **Augmented IPW (AIPW)** to achieve *double robustness*, combining propensity scores with outcome modeling.
- Propensity scores were estimated using **logistic regression** on all covariates.
- AIPW predictions were generated from separate outcome models for treated and control groups.
- **Data:** Synthetic observational dataset of 10,000 students from 76 schools, modeled after the NSLM study.
- **Covariates:** Student- and school-level features including race, gender, mindset scores, test performance, and poverty indicators.
- **Challenge:** Treatment assignment is non-random, introducing risk of confounding and bias.
- **Causal Strategy:** Propensity scores estimated using logistic regression; IPW used to balance covariates; AIPW applied for double robustness via outcome modeling.
- **Assumptions:** The analysis relies on key causal inference assumptions: SUTVA, Ignorability, and Positivity.

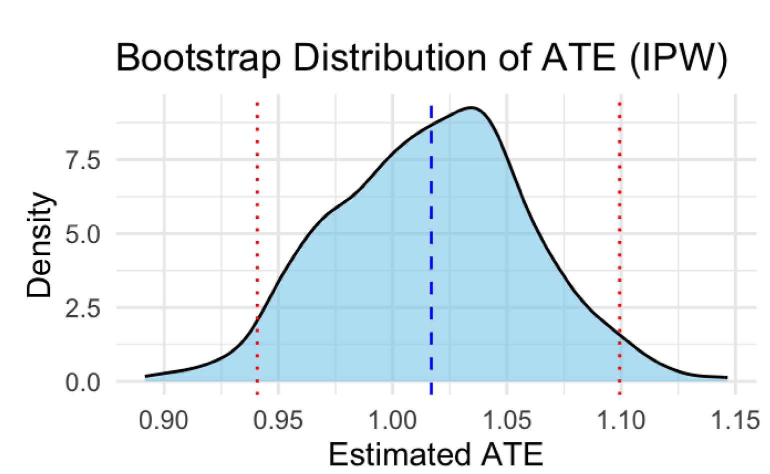
4. Analysis

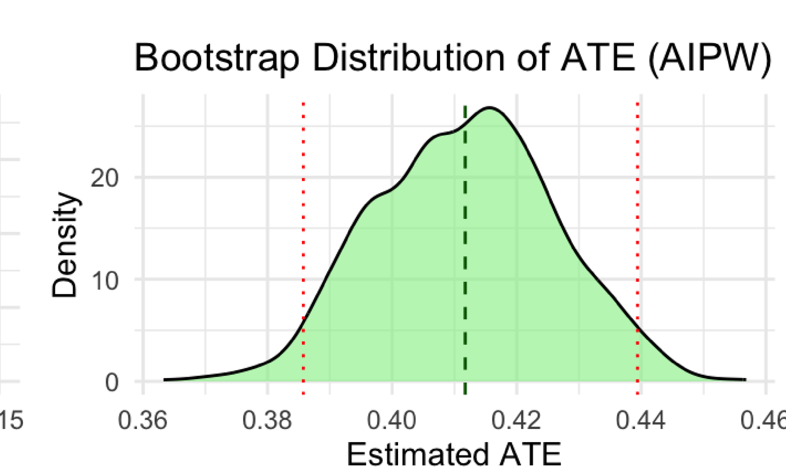


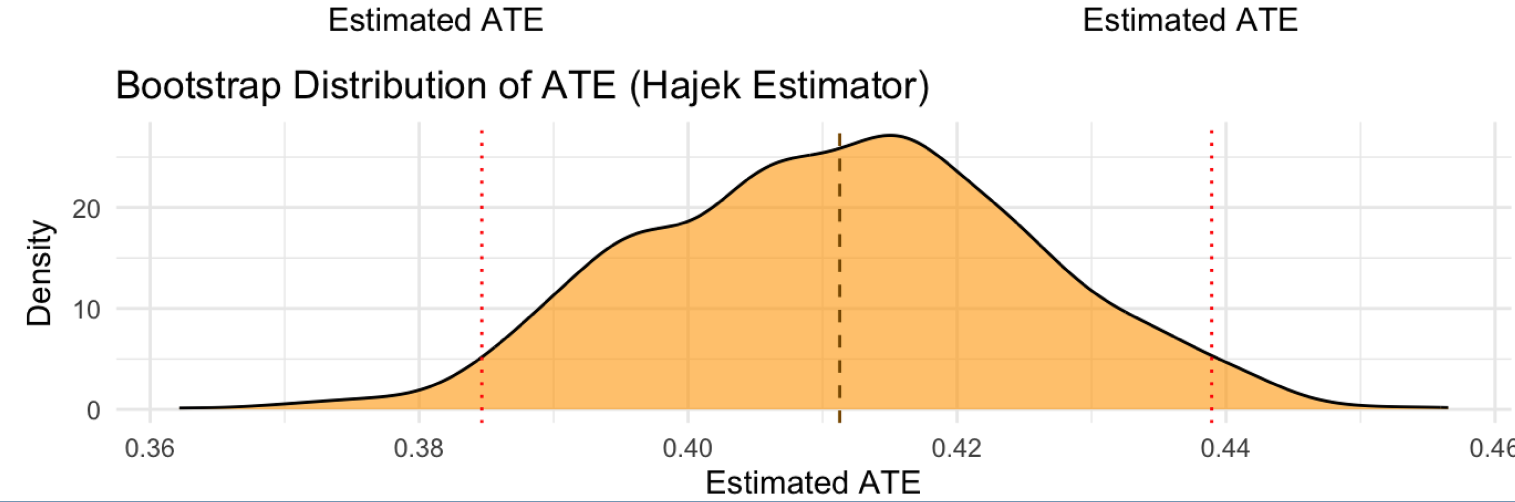
Propensity Score Distribution



Covariate Balance (Love Plot)







5. Results

Description: df [2 × 5]

Method <chr>	ATE_Estimate <dbl>	Std_Error <dbl>	CI_Lower <dbl>	CI_Upper <dbl>
Inverse Probability Weighting (IPW)	0.4145	0.0144	0.3880	0.4421
Augmented IPW (AIPW)	0.4148	0.0144	0.3882	0.4419

2 rows

- There is enough overlap in the distribution of the propensity score, so that treatment and control can be compared fairly.
- The Love plot after IPW shows good covariate balance, which supports the validity of the ignorability assumption.
- The distribution of the outcome shows that the treated is moving rightward pupils, indicating better educational achievement.
- The treatment made a real difference in people's lives – about 0.41 points higher on our scale compared to those who didn't receive it. That's not just a number, it's a meaningful improvement in outcomes for real individuals.
- The narrow range of uncertainty in our findings suggests this positive effect is consistent and reliable, not just due to chance or a few outliers.

6. Findings

- The growth mindset intervention consistently generated positive effects on diverse causal estimation approaches. The AIPW and IPW estimates each validated a statistically substantial impact on student performance associated with the intervention.

6. Limitations

- Some relevant data not being recorded. For instance, we couldn't measure how motivated students were or how good their teachers were. These missing pieces could skew our results, like trying to judge a basketball game without knowing some of the points scored

7. Conclusion

- This study demonstrates how psychological interventions, even when provided widely and inexpensively, have the capacity to significantly impact academic results.
- I was able to derive reliable conclusions from observational data by applying strict causal inference techniques, highlighting the significance of methodology in educational research..
- Even though the dataset was artificial, the fact that our results agree with those of actual research increases trust in the usefulness of the intervention.