Comparative Effectiveness of Machine Learning Methods for Causal Inference

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Selected Poster prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

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ML methods for causal inference may find significant estimates that were not found before due to confoundedness or nonlinearity

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RESEARCH QUESTIONS

- Are machine learning-based methods able to extract causal treatment effects in presence of confoundedness or nonlinearity in the model?
- How do these ML-based causal models compare in terms of bias in the estimation of the average treatment effect (ATE)?

MOTIVATION

- Traditional regression techniques can produce biased estimates of causal effects due to dimensionality, heterogenous treatment effects, and functional form misspecification.
- In big data sets, confoundedness is more likely.
- Three popular ML approaches to address these issues are:
  - Double machine learning (Chernozhukov et al. 2018) utilizes the non-inversion feature to learn the ATE & ATT under unconfoundedness. DML also corrects for bias through orthogonalization and cross-validation.
  - Causal forest (Wager and Athey 2018) utilizes ML's classification power to maximize difference across recursively generated data partitions in the relationship between outcome and treatment, thus uncovers heterogeneity in causal effect.
  - A matching method, e.g., using ML for propensity matching (Ikezawa et al. 2022) to minimize the distance between treatment and control groups.
- Many studies have adopted these methods for more flexible and informative causal analysis. However, no study so far has compared the effectiveness of these models.

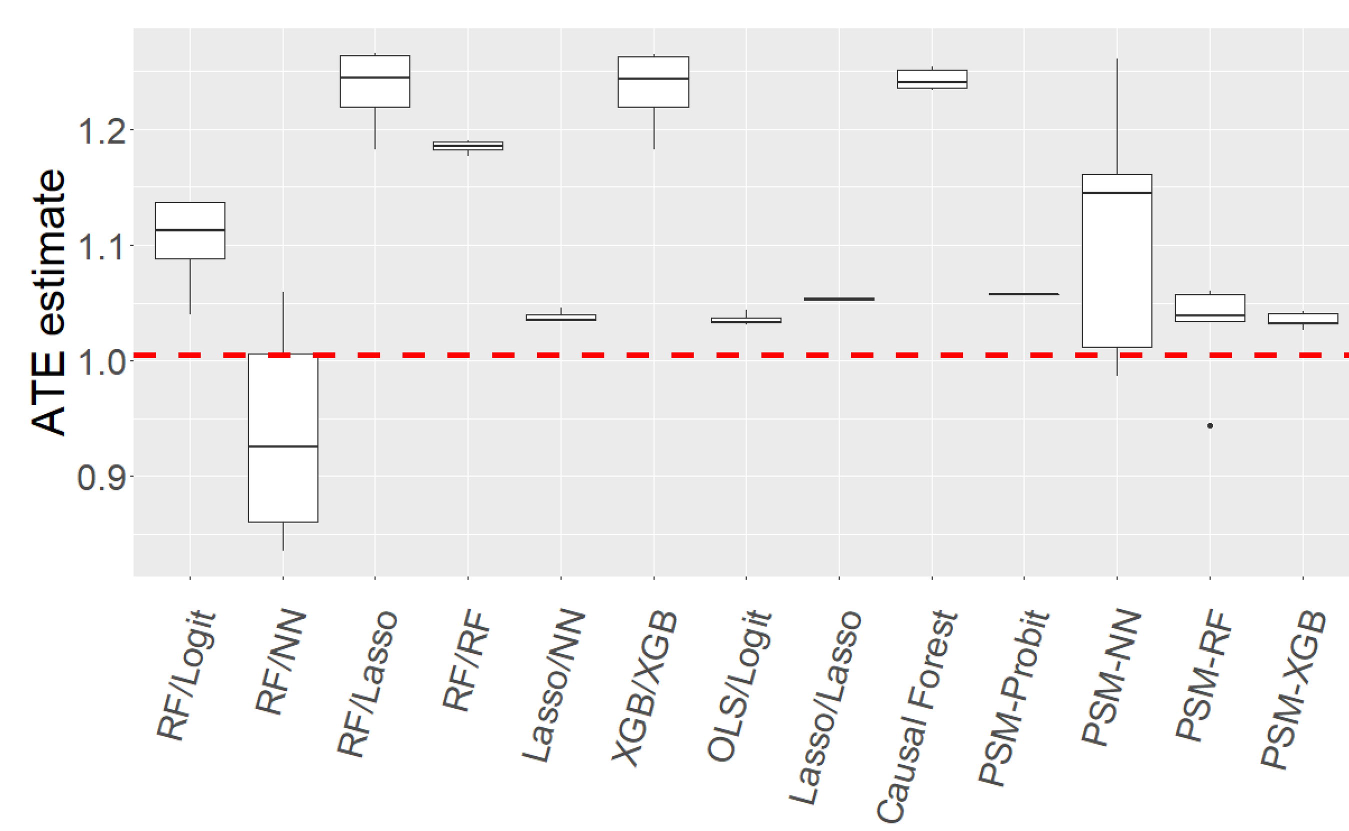
DATA & METHODS

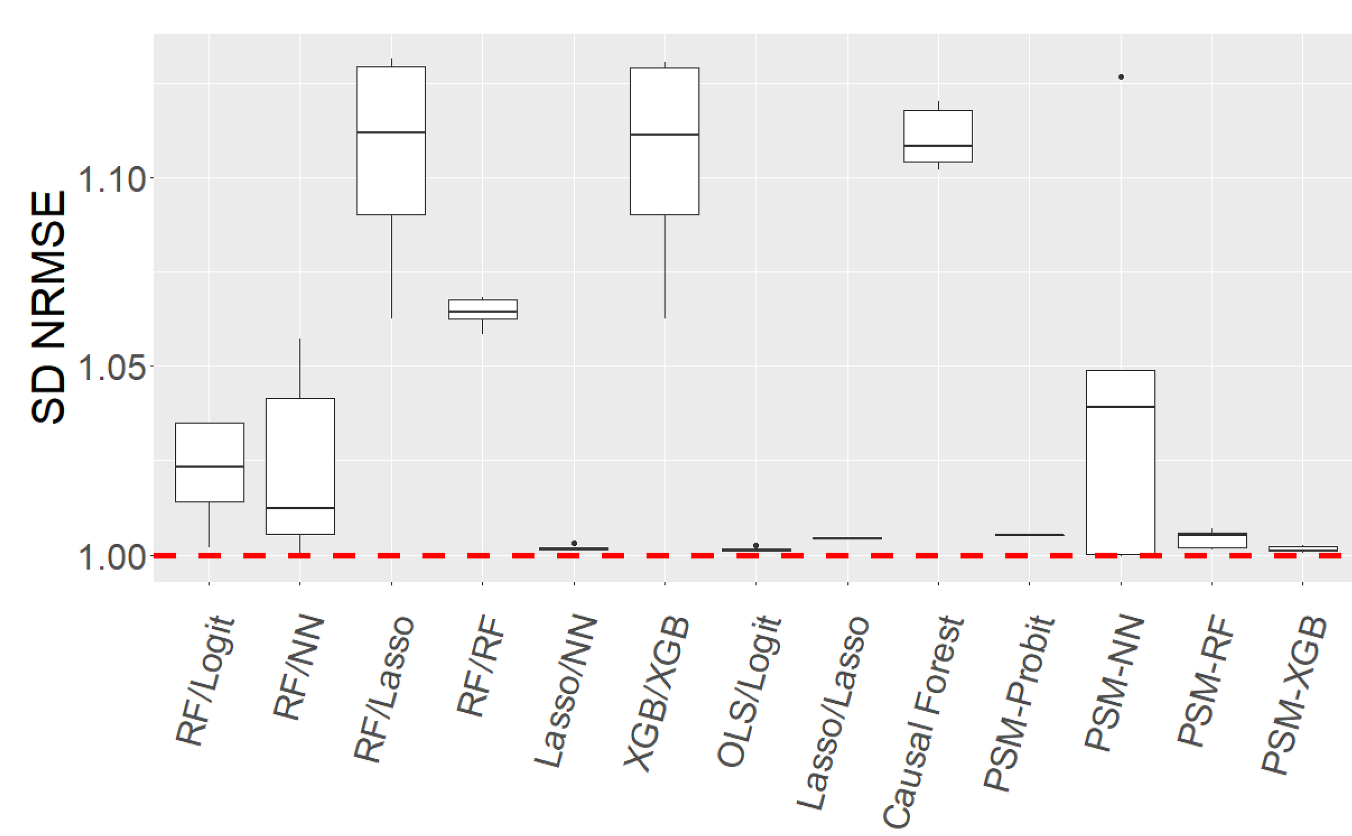
- Data from (Dhurandhar et al., 2014) to obtain the impact of breakfast recommendations on weight loss.
- Data from (Bryan et al., 2014) to obtain the impact of cash transfer to promote out-migration on seasonal food security.
- Synthetic data generation with continuous dependent variable and 10 continuous independent variables and exogenous binary treatment.
- We study and compare three approaches: (1) causal forest (CF), (2) double machine learning (DML), and (3) propensity score matching with ML (PSM-ML) for causal analysis.

KEY RESULTS

- ☐ Using PSM-ML is only advantageous in smaller data sets, especially under linear specifications, followed by DML and CF.
- ☐ DML has a relatively lower rate of error and exhibits better estimation accuracy as the data dimension grows.
- ☐ Results indicate that dimension reduction and a more flexible functional form with ML might help find the causal estimate previously undetected by simple regressions.
- ☐ For instance, we found a significant association between breakfast recommendations and weight loss for Dhurandhar et al. (2014) using Lasso/Lasso approach of DML.

SYNTHETIC DATA: ATE=1





Note. For Double ML, Method=Response Model/Treatment Model

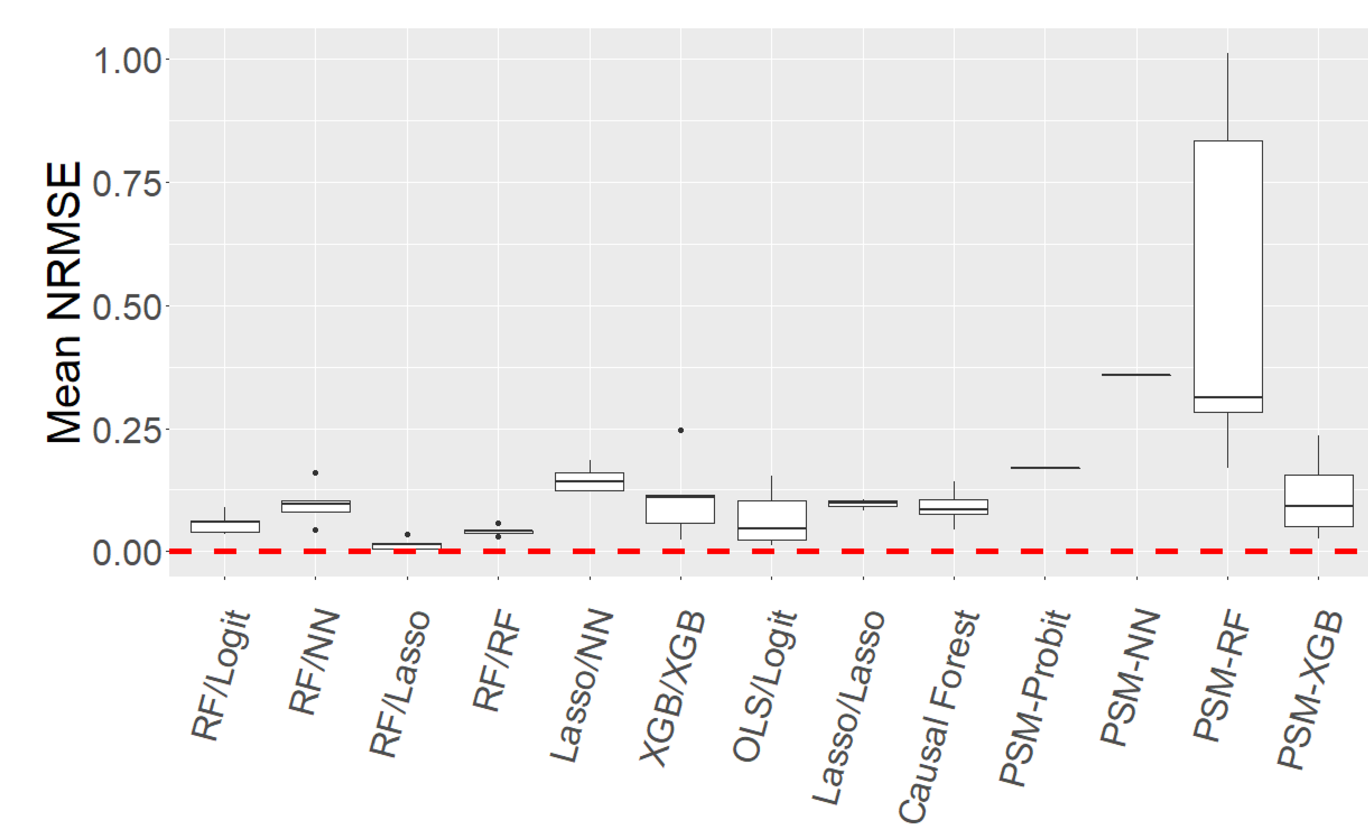
DHURANDHAR ET AL: ATE=NULL

	RF/ Logit	RF/ NN	RF/ Lasso	RF/ RF	Lasso/ NN	XGB/ XGB	OLS/ Logit	Lasso/ Lasso
ATE	-0.26	-0.16	-0.20	-0.11	-0.23	-0.20	-0.26	-0.12
(SD)	(0.44)	(0.45)	(0.44)	(0.45)	(0.46)	(0.40)	(0.44)	(0.04)

	Causal Forest	PSM-Probit	PSM-NN	PSM-RF	PSM-XGB
ATE	-0.09	-0.27	0.15	-0.08	-0.18
(SD)	(0.47)	(0.49)	(0.62)	(0.51)	(0.44)

Note. For Double ML, Method=Response Model/Treatment Model

BRYAN ET AL. (2014): ATE=44.43



Note. For Double ML, Method=Response Model/Treatment Model

REMARKS

- Many data sets, e.g., agricultural and food-related data sets are often high dimensional and involve variables related to soil, plant, animal, market, geographic information, demographics, climate, etc. that are closely related, and controlling for one's movement implicitly controls for others. We show that ML approach may offer a viable alternative to traditional ATE regression for their flexible, data-driven nature, predictive accuracy, and dimension reduction capabilities.

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