Predicting Preventable Hospital Readmissions with Causal Machine Learning



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BACKGROUND

Many systems-level and population health management interventions rely on predictive algorithms to identify and prioritize patients at highest risk.

However, these approaches fail to account for potential risk-based heterogeneous treatment effects (or rHTE) which can be substantial in some settings.

METHODS

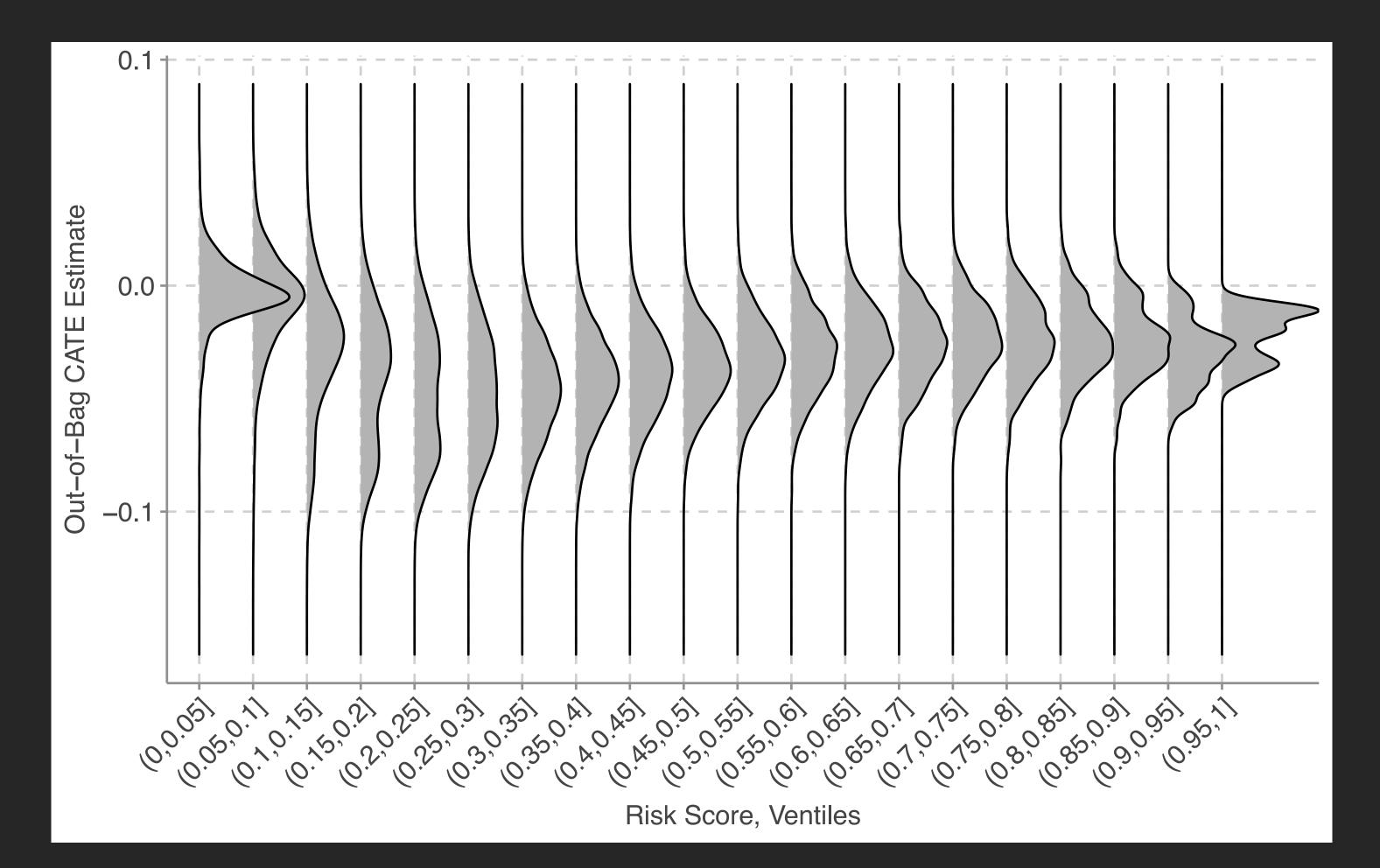
- Data from before and after deployment of readmission prevention intervention linked to EHR-based predictive algorithm (*n* = 1,539,285 hospital discharges, 2010-2018)
- Goal: Characterize extent of rHTEs and estimate marginal gains wit.
- Causal forest analysis: Estimate conditional average treatment effects (CATEs) using causal forest on set of patient-level features

RESULTS

- Substantial rHTE (see figure) with moderate and lower-risk patients experiencing largest treatment effects compared to those at higher risk.
- Notional estimates: possible to prevent ~4x as many readmissions annually with CATEbased vs. risk-based targeting
- Predicted CATEs were generally wellcalibrated

For more details, see our preprint: https://arxiv.org/abs/2005.14409

Risk-treatment effect mismatch may blunt the impacts of clinical deployments of predictive algorithmlinked interventions.



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ma; stupor; and brain damage	Endocrine & related conditions	Fluid and electrolyte disorders	GI bleed	Hematologic conditions
Highly malignant cancer	Hip fracture	III defined signs and symptoms	Less severe cancer	Liver and pancreatic disorders
Ronal failure (all)	Aiscellaneous neurological condition:		Other cardiac conditions	Other infectious conditions
Renal failure (all)	Residual codes	Sepsis		

Conclusions and Recommendations

- Practitioners should be aware of risk-treatment effect **mismatch** in deployments of predictive-algorithm linked interventions.
- In particular, prioritizing patients at highest risk may not yield best ROI in terms of clinical impact.
- Instead, should attempt to prioritize based on estimated treatment effects.
- But to do so, may need to rethink deployment processes & practices.
- Pilot RCTs are one starting point for obtaining these estimates
- Alternatively: bespoke trial designs which estimate rHTE directly (under development by our team)
- Ben Marafino, Alejandro Schuler, Vincent Liu, Gabriel Escobar, Mike Baiocchi

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