



Target Trials in Policy Evaluation: A Case Study in Medical Cannabis Laws

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Original Research

Effects of U.S. State Medical Cannabis Laws on Treatment of Chronic Noncancer Pain

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This work will appear in the July issue of Annals of Internal Medicine.

Please limit outside discussion of substantive findings until then!

Disclosures

I have a family member employed by a cannabis distributor in Michigan.

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Medical Cannabis: A Partial Solution?



- Cannabis industry and advocates have argued that medical cannabis could be a partial solution to the opioid overdose crisis [1]
 - Substitution of cannabis for opioids to treat chronic non-cancer pain
- Clinical guidelines do not recommend cannabis
- Chronic non-cancer pain is a qualifying condition for medical cannabis under all 38 existing state (+DC) programs [2]
- Some evidence of substitution of cannabis for prescription opioids among patients [3]

• Question: What are the effects of state medical cannabis laws on receipt of opioid and guideline-concordant non-opioid pain treatments for chronic non-cancer pain?

^{1. &}lt;u>https://thecannabisindustry.org/combating-the-opioid-epidemic/</u>

 $^{2. \}quad \underline{https://www.ncsl.org/health/state-cannabis-policy-enactment-database}$

^{3.} Bicket MC, et al. *JAMA Network Open.* 2023.

Policy Evaluation is Hard



- Necessarily limited sample size
- Often high variability in definitions of treatment
 - States are the laboratories of democracy" [1]
- Hard to isolate a policy's effects when other policies go into place around the same time

Partial solution: Be very thoughtful about design! (surprise)

Trial Emulation Framework: Estimand & Scientific Question



Hypothetical Target Trial

- Estimand is typically ATE:
 E[Y(1) Y(0)]
- "In general, what is the effect on outcomes of a state implementing a medical cannabis law versus not implementing a medical cannabis law?"

Our Policy Trial Emulation Analogue

- ► Estimand is ATT: *E*[*Y*(1) *Y*(0) | *A* = 1]
- "Among states that implemented a medical cannabis law, what was the effect of the law on outcomes relative to what would have been observed had those states not implemented a medical cannabis law?"
- Only interested in studying policies on the books, rather than hypothetical policies

(ATT = ATE under random assignment or no treatment effect heterogeneity)

Trial Emulation Framework: Units



Hypothetical Target Trial **AND** our Policy Trial Emulation Analogue

- 12 "treated" states implemented a medical cannabis law between 2012 and 2019 and did not also implement a recreational cannabis program in that time.
- 17 "control" states did not implement medical or recreational cannabis laws



Trial Emulation Framework: Exposure & Outcomes



Hypothetical Target Trial **AND** our Policy Trial Emulation Analogue

- Exposure: Implementation of a medical cannabis law that includes chronic non-cancer pain diagnoses as qualifying conditions for receipt of medical cannabis
- <u>Outcomes</u>: Various measures of opioid and guideline-concordant non-opioid prescribing measured in time period after policy implementation (or lack of implementation)

Trial Emulation Framework: Assignment Procedure

Hypothetical Target Trial

- Random assignment of states to implement or not implement a medical cannabis law after 4 years of baseline data collection.
- Unblinded: states will be aware of randomization status
- Essentially cluster-randomized (data from individuals within states)

Our Policy Trial Emulation Analogue

 Nonrandom policy adoption, possibly influenced by both known and unknown state-level characteristics





Staggered Adoption of Medical Cannabis Laws



Time

Staggered Adoption Causes Problems with Traditional Methods

Research question in medical cannabis study is about an ATT

E[Y(1) - Y(0) | A = 1]

on average over the treated states.

Traditional policy evaluation method turns out to be *very biased* for this estimand under staggered adoption when treatment effect is time-varying (i.e., almost always) [1]

But: it's okay when we look at one treated state at a time.



"Stacking" (Serial Trial Emulation)



Fix study periods

Anchor time at policy implementation

- Hernán MA, Robins JM. Am. J. Epidemiol. 2016. 1.
- Ben-Michael E, Feller A, Stuart EA. *Epidemiology*. 2021. 2.



"Stacking" (Serial Trial Emulation)



Relative Time (Months)

Anchor time at policy implementation

Estimate state-specific effects

Aggregate state-specific effects (using, e.g., inverse-variance weighting)

2. Ben-Michael E, Feller A, Stuart EA. *Epidemiology*. 2021.

Trial Emulation Framework: Data Collection Units

Hypothetical Target Trial

- People living in exposed & unexposed states with a chronic non-cancer pain diagnosis in the 4 years prior to policy implementation.
- Ideally people would not be allowed to move across states, wouldn't die, and would contribute complete data
 - Avoid compositional changes over time

Our Policy Trial Emulation Analogue

- People living in the treated state or one of the untreated states with a chronic non-cancer pain diagnosis in treated state's 4-year prelaw period
- Continuously enrolled in commercial health insurance for entire 7-year study period
 - Avoid compositional changes over time
 - No reason to believe enrollment is related to implementation of cannabis law













Time





Trial Emulation Framework: Analytic Strategy



Hypothetical Target Trial

- "Traditional" modeling approach for cluster-randomized trial with longitudinal outcome
- Effect estimation unconfounded due to randomization

Our Policy Trial Emulation Analogue

- Stacked effect estimation
- Must account for potential confounders
 - Idiosyncratic in "difference-indifferences" setups
- We used the augmented synthetic control method [1]

Recap



Trial emulation provides a nice framework for good study design

Careful consideration of estimand, baseline, analysis

Avoids issues with traditional kitchen-sink modeling approaches in policy evaluation

State-specific estimates are useful!

Can go further: might allow changing control pool if comparison states implement confounding policies (i.e., different controls for each treated state)

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