Heterogeneous Treatment Effects and Causal Mechanisms

Jiawei Fu and Tara Slough—NYU

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Credibility revolution → use of research designs that facilitate identification and estimation of causal effects.

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- Ultimately a question about **causal mechanisms**

Various approaches (qualitative and quantitative) to evaluating mechanisms:

- **Heterogeneous treatment effects** (HTEs) estimated by treatment $\times$ covariate interactions is very popular in applied work.

HTE and mechanisms: a survey

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AJPS (65)	61	41	0.56	0.87
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Takeaways:

1. Modal empirical article reports HTEs (treatment × covariate).
2. 87% of articles that report HTE use them to “test mechanisms.”

Known vs. under-explored problems

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- Looking at one covariate with specific relation to mechanisms.

Under-explored problem:

Under what conditions do HTEs provide evidence of mechanism activation?

Outline

Motivating example: Exogenous shocks and voting behavior

- Based on model by Ashworth et al. (2018).
- Shows that HTE can emerge when relevant mechanism is inert.

Outline

Motivating example: Exogenous shocks and voting behavior

Framework: We develop a framework to connect causal mechanisms to HTE with respect to covariates.

- Builds from causal mediation framework (Imai et al., 2010)
- New concept, assumptions necessary for the HTE setting.

Outline

Motivating example: Exogenous shocks and voting behavior

Framework: We develop a framework to connect causal mechanisms to HTE with respect to covariates.

Results: What do we learn from the existence (or non-existence) of HTE with respect to covariates?

- For continuous covariates of theoretical interest, HTE indicative of a mechanism under assumptions.
- For realizations of latent theoretical constructs, HTE are not necessarily indicative of a mechanism, even under these assumptions.

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Motivating example: Exogenous shocks and voting behavior

Framework: We develop a framework to connect causal mechanisms to HTE with respect to covariates.

Results: What do we learn from the existence (or non-existence) of HTE with respect to covariates?

Discussion: Using these results to inform research design.

Motivating Example: Exogenous Shocks and Voting

Exogenous shocks and voting

Natural experiment on effect of an exogenous shock, ω, on voter behavior:

- A natural disaster (e.g., Healy and Malhotra, 2010; Huber et al., 2012)
- An economic crisis (e.g., Wolfers, 2002)
- A pandemic (e.g., Achen and Bartels, 2004; Baccini et al., 2021)

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Example: Ashworth, Bueno de Mesquita, Friedenberg (2018):

- Assume our adaption of model is true.
- Suppose we could measure (some) model parameters directly.
  - Characterize causal estimands in terms of these parameters.
- Ask: Can HTE provide evidence of voter learning mechanism?

Model set-up

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Voters do not observe θ but may use governance outcome, g to update:

$$g = f(\theta, \omega) + \varepsilon.$$

- ω is increasing in the adversity of the shock
- ε is idiosyncratic shock drawn from symmetric, differentiable density, ϕ, that satisfies monotone likelihood ratio property relative to g.

Voter utility

Each voter's utility from a vote for politician, $p \in \{I, C\}$ is given by:

$$u_i^p = \theta^p + v_i \mathbb{I}(p = I)$$

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Variation in the population of voters:

- $v_i \sim U(-1, 1)$ is a valence shock for the incumbent.
- Heterogeneous priors about the incumbent: $\pi_i^I \sim f_\pi$ with support on $(0, 1)$.
- Common prior about the challenger: $\pi^C \in (0, 1)$.

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1. Nature reveals shock, ω, and voters observe both ω and g.
2. Voters update their beliefs about the incumbent's type.
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Voters' posteriors:

$$\beta(\overline{\theta}|\pi_i^I, \omega) = \frac{1}{1 + \frac{1-\pi_i^I}{\pi_i^I} \frac{\phi(g-f(\underline{\theta}, \omega))}{\phi(g-f(\overline{\theta}, \omega))}}$$

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A voter will vote for the incumbent if:

$$\underbrace{\beta(\overline{\theta}|\pi_i^I, \omega) + v_i}_{E[u_i^I]} \geq \underbrace{\pi^C}_{E[u_i^C]}$$

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Treatment: Binary exposure to the shock $\omega \in \{\omega', \omega''\}$

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- Voter votes for the incumbent:

$$y_{2i} \equiv \mathbb{I}[\beta(\overline{\theta}|\pi_i^I, \omega) + v_i \geq \pi^C]$$

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Mechanism: Voter learning, not valence, since ω enters through voter's posterior.

Aside: DAG representation of interactions

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The standard view

$$\begin{tikzcd} & X \arrow[d] \\ Z \arrow[r] & Y \end{tikzcd}$$

$$\frac{\partial Y}{\partial Z} \neq 0$$

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$$\frac{\partial^2 Y}{\partial Z \partial X} \stackrel{?}{=} 0$$

Our notation

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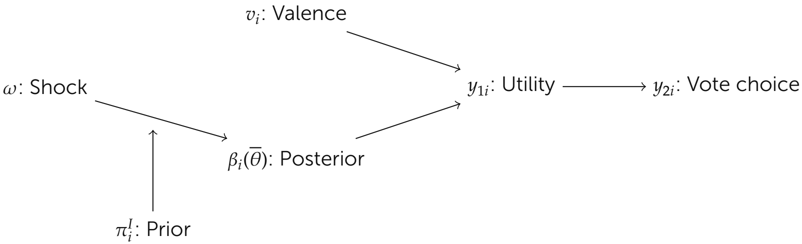

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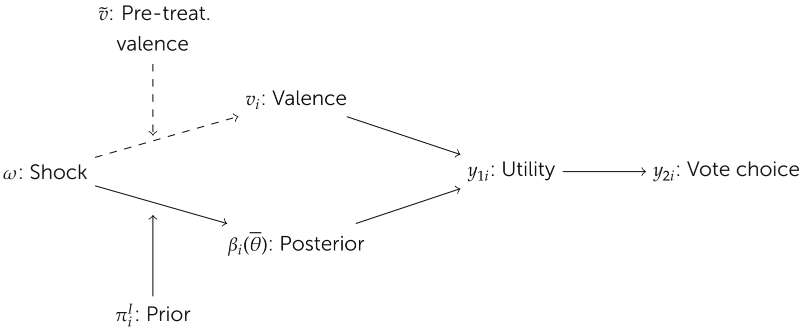

Defining HTEs

To evaluate mechanisms, the empiricist will estimate CATEs at different for different levels of the (candidate) moderators: $x \in \{\pi_i^I, \tilde{v}\}$:

$$CATE(x') = E[y|\omega = \omega'', x = x'] - E[y|\omega = \omega', x = x']$$

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We will evaluate the presence of HTE for:

- Outcomes: $y \in$ {Voter utility for I, Vote for I}
- Potential moderators: $x \in$ {Prior belief about I, Pre-treatment valence}

HTEs and mechanisms (results)

	y_1: Voter utility	y_2: Vote choice
x_1: Prior (π_i^I)	Mechanism HTE $CATE(\pi') \neq CATE(\pi'')$	
x_2: Valence ($\tilde{v}_i$)		

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HTE are not necessarily indicative of mechanism activation.

- To what extent is this general?

Framework

Three main components

A **treatment**, Z.

An **outcome**, Y.

- Continuous, we directly observe the variable of theoretical interest.
- (Latent variable case later.)

A set of pre-treatment **covariates**, X.

Causal Effects

Mediators as mechanism representations.

Several causal effects typically described wrt causal mediation.

- Total effect (TE) of Z on Y.
- Indirect effect (IE_j) of Z on Y through mediator/mechanism $j \in \{1, 2\}$.
    - Mechanism of interest will be $j = 1$.
    - Composite of all other mechanisms is $j = 2$.
- Direct (unmediated) effect (DE) of Z on Y.

At the individual/unit level:

$$TE = DE + IE_1 + IE_2$$

If a mechanism j is activated or present (for any unit), then there exists some unit for which $IE_j \neq 0$.

Estimands

Average treatment effect (ATE):

$$
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ATE &= E_X[Y(z) - Y(z')] \\
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Conditional average treatment effects (CATE): Consider pre-treatment covariate $X_k \in X$. The CATE with respect to $X_k = x$ is:

$$CATE(X_k = x) = E_{X_{\neg k}}[Y|Z = z, X_k = x] - E_{X_{\neg k}}[Y|Z = z', X_k = x].$$

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Heterogeneous Treatment Effects (HTEs): HTEs exist with respect to pre-treatment covariate $X_k \in X$ iff:

$$\text{CATE}(\text{X}_k = x) \neq CATE(X_k = x')$$

for some $x \neq x' \in X_k$.

Reformulating the question

Original statement:

Under what conditions do HTEs provide evidence of mechanism activation?

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More precise version:

Under what conditions are HTEs with respect to X_k sufficient to show that there there exists some unit for which $IE_j \neq 0$?

Relationship to mediation

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- Assumes **sequential ignorability**.
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Use of HTE:

- Does not require mediators to be **measurable**. (But we need specific measured covariates.)
- Invokes a set of **exclusion assumptions**.
- Seeks to demonstrate that $IE_j \neq 0$ for some unit.

HTEs and Mechanisms

Concept: Causal Indicator Variable (CIV)

Definition (Causal Indicator Variable)

Pre-treatment variable X_k is a causal indicator variable (CIV) for mechanism 1 if for some $x, x' \in X^k$, $IE_1(X_k = x) \neq IE_1(X_k = x')$.

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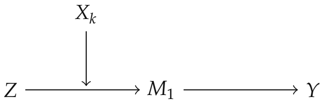
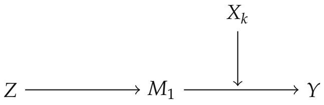
Two possibilities:

- $X_k \in X^{CIV}$ moderates the effect of treatment (Z) on mediator (M_j).
- $X_k \in X^{CIV}$ moderates the effect of the mediator (M_j) on outcome (Y).



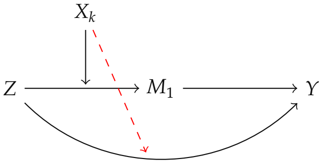


Exclusion assumption I

Assumption (Exclusion I)

For any $x, x' \in X_k$, X_k is non-linearly excluded to the direct effect such that $DE(X_k = x) = DE(X_k = x')$.

- Direct effect of Z on Y cannot depend on X_k.

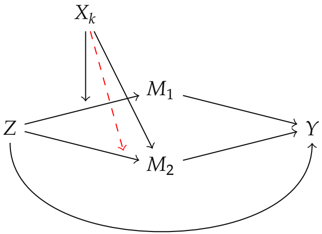


Exclusion assumption II

Assumption (Exclusion II)

For any $x, x' \in X_k$, X_k is irrelevant to the indirect effect of M_2 such that $IE_2(X_k = x) = IE_2(X_k = x')$.

- In other words, X_k is not a CIV for M_2.



HTEs as test of mechanisms (#1 of 2)

Proposition

Suppose that Y is continuous and Assumptions 1 and 2 hold. If HTE exist with respect to X_k, then $X_k \in X^{CIV}$.

Implication: By definition of CIV, HTE imply that $IE_1(X_k = x') \neq IE_1(X_k = x'')$ for some $x', x'' \in X_k$, which indicates that M_1 is active.

The usual logic for HTE, but note the assumptions.

- Implicit/unstated assumptions ≠ the absence of assumptions.

HTEs as test of mechanisms (#2 of 2)

Proposition

Suppose that Y is continuous and Assumptions 1 and 2 hold. If no HTE exist with respect to X_k, at least one of the following must true:

1. $X_k \notin X^{CIV}$
2. Mechanism 1 is not active.

Absence of observed heterogeneity often equated with an inert mechanism.

Alternate explanation: postulated relationship between X_k and M_1 is misspecified.

Absence of HTE less informative than presence of HTE.

Summary (with a conjecture)

Under Assumptions 1 and 2:

	Observed, continuous Y	Latent Y
$\exists$ HTE:	$X_k \in X^{CIV} \implies$ M_1 active	
$\nexists$ HTE:	$X_k \notin X^{CIV}$ or M_1 not active	

Latent Outcomes

Why should we care?

Many attitudinal, behavioral outcomes are realizations of latent variables.

- Example: decisions based on utility maximization.
- Vote choice vs. utility in our motivating example

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Poses challenges for the detection of mechanisms

- Through HTEs and likely other approaches.

Additional structure, concept

Suppose that Y^* is the latent variable. We observe $Y = g(Y^*)$.

- Concern emerges when $g(\cdot)$ is **non-linear**.
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Useful to define X^{Rel} as the subset of measured covariates with a non-zero effect on latent outcome Y^*. It is straightforward to see that:

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In our motivating example, for the learning mechanism:

- $X^{CIV} = \{\pi_i^I\}$
- $X^{Rel} = \{\pi_i^I, v_i\}$

Intuition and result

Mechanism test relies on additive separability of X_k from DE and IE_2 on the latent variable.

- What Assumptions 1-2 buy us.
- But a non-linear mapping from the latent implies observed outcome does not preserve additive separability on observed outcomes.

Proposition

Suppose that Y is the observed realization of the latent variable Y^* and Assumptions 1 and 2 hold. If HTE exist with respect to X_k, then $X_k \in X^{Rel}$.

Implication: Two possibilities:

- $X_k \in X^{CIV} \implies M_1$ is active.
- $X_k \notin X^{CIV} \implies M_1$ may or may not be active.

Summary

Under Assumptions 1 and 2:

	Observed, continuous Y	Latent Y
$\exists$ HTE:	$X_k \in X^{CIV} \implies$ M_1 active	$X_k \in X^{Rel}$ M_1 active or not active
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$\nexists$ HTE:	$X_k \notin X^{CIV}$ **or** M_1 not active	($X_k \notin X^{Rel}$ M_1 active or not active)

Discussion

How can we improve the use of HTE for mechanism testing?

More explicit theory in applied empirical work:

- What are the candidate mechanisms?
- How does covariate X_k relate theoretically to these mechanisms?
    - Is X_k a possible CIV for a mechanism?
    - Is Assumption 2 plausible with respect to other mechanisms?
- What from the theory is observed vs. latent?

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More explicit theory in applied empirical work.

More accurate interpretation of findings:

- If willing to make Assumptions #1 and #2, what could have been learned?
- e.g., Lack of (detected) HTE does not imply mechanism inactive.

How can we improve the use of HTE for mechanism testing?

More explicit **theory** in applied empirical work.

More accurate **interpretation** of findings.

Better **design** of studies:

- What variables are (theoretically) most likely to be in X^{CIV}? $\leftarrow$ collect them!
- Can latent outcomes be avoided? Can we measure theoretical constructs more directly?

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More explicit **theory** in applied empirical work.

More accurate **interpretation** of findings.

Better **design** of studies.

Alternate uses of HTE (besides mechanism tests):

- e.g., Targeting of subsequent interventions.
- Assessment of degree of heterogeneity in treatment effects.

Take-aways

1. Using HTEs to test for activation of a mechanism:
    - Invokes assumptions about the covariate and other possible mechanisms.
    - May not be informative even under these assumptions.

2. Analysis of theoretical issues complements statistical critiques.
    - e.g., Concerns about power assume we could learn something if we had more power.

Thank you!

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