Unpacking the Black-Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies

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Joint work with
L. Keele (Penn State)  D. Tingley (Harvard)  T. Yamamoto (MIT)
Causal inference is a central goal of scientific research. Scientists care about *causal mechanisms*, not just *causal effects*.
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Scientists care about causal mechanisms, not just causal effects.

Randomized experiments often only determine whether the treatment causes changes in the outcome, not how and why the treatment affects the outcome.
Quantitative Research and Causal Mechanisms

- Causal inference is a central goal of scientific research
- Scientists care about *causal mechanisms*, not just *causal effects*
- Randomized experiments often only determine *whether* the treatment causes changes in the outcome
- Not *how* and *why* the treatment affects the outcome
- Common criticism of experiments and statistics: black box view of causality
Causal inference is a central goal of scientific research. Scientists care about *causal mechanisms*, not just *causal effects*. Randomized experiments often only determine whether the treatment causes changes in the outcome, not how and why the treatment affects the outcome. Common criticism of experiments and statistics: a **black box** view of causality.

Qualitative research uses process tracing. **Question:** How can quantitative research be used to identify causal mechanisms?
**Goal:** Convince you that statistics can be useful for learning about causal mechanisms
Overview of the Talk

- **Goal:** Convince you that statistics *can* be useful for learning about causal mechanisms
- **Method:** Causal Mediation Analysis

\[ \text{Mediator, } M \]
\[ \text{Treatment, } T \rightarrow \text{Outcome, } Y \]

Direct and indirect effects; intermediate and intervening variables
Overview of the Talk

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  Direct and indirect effects; intermediate and intervening variables

- **New tools:** framework, estimation algorithm, sensitivity analysis, research designs, easy-to-use software
Causal Mediation Analysis in **American Politics**

- The political psychology literature on media framing
- Nelson *et al.* (*APSR*, 1998)

Popular in social psychology
Resource curse thesis

Authoritarian government

Civil war

Natural resources

Slow growth

Causal Mediation Analysis in International Relations

- The literature on international regimes and institutions
- Krasner (International Organization, 1982)

Figure 2

- Power and interests are mediated by regimes
Regression:

\[ Y_i = \alpha + \beta T_i + \gamma M_i + \delta X_i + \epsilon_i \]

- Each coefficient is interpreted as a causal effect
- Sometimes, it’s called **marginal effect**
- Idea: increase \( T_i \) by one unit while holding \( M_i \) and \( X_i \) constant

But, if you change \( T_i \), that may also change \( M_i \)

The Problem: **Post-treatment bias**

Usual advice: only include causally prior (or pre-treatment) variables

But, then you lose causal mechanisms!
Formal Statistical Framework of Causal Inference

- Units: \( i = 1, \ldots, n \)
- "Treatment": \( T_i = 1 \) if treated, \( T_i = 0 \) otherwise
- Pre-treatment covariates: \( X_i \)

Voters Contact Turnout Age Party ID

<table>
<thead>
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Causal effect: \( Y_i(1) - Y_i(0) \)

Problem: only one potential outcome can be observed per unit
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- Potential outcomes: $Y_i(1)$ and $Y_i(0)$
- Observed outcome: $Y_i = Y_i(T_i)$
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Potential Outcomes Framework for Mediation

- Binary treatment: $T_i$
- Pre-treatment covariates: $X_i$
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- Potential outcomes: \( Y_i(t, m) \)
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- Potential outcomes: $Y_i(t, m)$
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- Again, only one potential outcome can be observed per unit
Causal Mediation Effects

- Total causal effect:

\[ \tau_i \equiv Y_i(1, M_i(1)) - Y_i(0, M_i(0)) \]
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- Causal mediation (Indirect) effects:

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- Causal mediation (Indirect) effects:
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- Causal effect of the treatment-induced change in \( M_i \) on \( Y_i \)
- Change the mediator from \( M_i(0) \) to \( M_i(1) \) while holding the treatment constant at \( t \)
- Represents the mechanism through \( M_i \)
Total Effect = Indirect Effect + Direct Effect

- Direct effects:

\[ \zeta_i(t) \equiv Y_i(1, M_i(t)) - Y_i(0, M_i(t)) \]
Total Effect = Indirect Effect + Direct Effect

- Direct effects:

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- Causal effect of \( T_i \) on \( Y_i \), holding mediator constant at its potential value that would be realized when \( T_i = t \)

- Change the treatment from 0 to 1 while holding the mediator constant at \( M_i(t) \)

- Represents all mechanisms other than through \( M_i \)
Total Effect = Indirect Effect + Direct Effect

- Direct effects:

$$\zeta_i(t) \equiv Y_i(1, M_i(t)) - Y_i(0, M_i(t))$$

- Causal effect of $T_i$ on $Y_i$, holding mediator constant at its potential value that would be realized when $T_i = t$
- Change the treatment from 0 to 1 while holding the mediator constant at $M_i(t)$
- Represents all mechanisms other than through $M_i$

- Total effect = mediation (indirect) effect + direct effect:

$$\tau_i = \delta_i(t) + \zeta_i(1 - t) = \frac{1}{2} \{\delta_i(0) + \delta_i(1) + \zeta_i(0) + \zeta_i(1)\}$$
What Does the Observed Data Tell Us?

- Quantity of Interest: **Average causal mediation effects (ACME)**

\[ \bar{\delta}(t) \equiv \mathbb{E}(\delta_i(t)) = \mathbb{E}\{Y_i(t, M_i(1)) - Y_i(t, M_i(0))\} \]
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- \( Y_i(t, M_i(t)) \) is observed but \( Y_i(t, M_i(t')) \) can never be observed

- We have an identification problem
What Does the Observed Data Tell Us?

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- \(Y_i(t, M_i(t))\) is observed but \(Y_i(t, M_i(t'))\) can never be observed

- We have an identification problem

\[ \Rightarrow \text{Need additional assumptions to make progress} \]
Identification under Sequential Ignorability

- Proposed identification assumption: **Sequential Ignorability (SI)**
  \[
  \{ Y_i(t', m), M_i(t) \} \perp T_i \mid X_i = x, \quad (1)
  \]
  \[
  Y_i(t', m) \perp M_i(t) \mid T_i = t, X_i = x \quad (2)
  \]

Limitation: \( X_i \) cannot include post-treatment confounders

Under SI, ACME is nonparametrically identified:
\[
\int \int E( Y_i \mid M_i, T_i = t, X_i = x ) \left\{ dP( M_i \mid T_i = 1, X_i ) - dP( M_i \mid T_i = 0, X_i ) \right\} dP( X_i )
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- (1) is guaranteed to hold in a standard experiment
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Example: Anxiety, Group Cues and Immigration

Brader, Valentino & Suhat (2008, AJPS)

- How and why do ethnic cues affect immigration attitudes?
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- **How and why** do ethnic cues affect immigration attitudes?
- **Theory:** Anxiety transmits the effect of cues on attitudes

\[
\text{Anxiety, } M \\
\text{Media Cue, } T \\
\rightarrow \text{Immigration Attitudes, } Y
\]

**ACME** = Average difference in immigration attitudes due to the change in anxiety induced by the media cue treatment

**Sequential ignorability** = No unobserved covariate affecting both anxiety and immigration attitudes
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- Linear structural equation model (LSEM):

\[
    M_i = \alpha_2 + \beta_2 T_i + \xi_2^T X_i + \epsilon_{i2},
\]
\[
    Y_i = \alpha_3 + \beta_3 T_i + \gamma M_i + \xi_3^T X_i + \epsilon_{i3}.
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Traditional Estimation Method

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- Fit two least squares regressions separately
- Use product of coefficients \((\hat{\beta}_2 \hat{\gamma})\) to estimate ACME
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- Fit two least squares regressions separately
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- The method is valid under SI
- Can be extended to LSEM with interaction terms
- Problem: Only valid for the simplest LSEMs
Proposed General Estimation Algorithm

1. Model outcome and mediator
   - Outcome model: $p(Y_i \mid T_i, M_i, X_i)$
   - Mediator model: $p(M_i \mid T_i, X_i)$
   - These models can be of any form (linear or nonlinear, semi- or nonparametric, with or without interactions)
Proposed General Estimation Algorithm

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2. Predict mediator for both treatment values ($M_i(1), M_i(0)$)

3. Predict outcome by first setting $T_i = 1$ and $M_i = M_i(0)$, and then $T_i = 1$ and $M_i = M_i(1)$

4. Compute the average difference between two outcomes to obtain a consistent estimate of ACME
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5. Monte Carlo or bootstrap to estimate uncertainty
Example: Estimation under Sequential Ignorability

- Original method: *Product of coefficients with the Sobel test*

\[
\bar{\delta}(1) \left[ 0.146, 0.548 \right] \left[ 0.048, 0.170 \right]
\]

347.105

Decrease Immigration.

204.074

Support English Only Laws.

277.029

Request Anti-Immigration Information.

276.086

Send Anti-Immigration Message.
Example: Estimation under Sequential Ignorability

- Original method: Product of coefficients with the Sobel test
  - Valid only when both models are linear w/o $T-M$ interaction (which they are not)
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<th>Product of Coefficients</th>
<th>Average Causal Mediation Effect ($\delta$)</th>
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<tr>
<td>Decrease Immigration</td>
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<td>$\delta(1)$</td>
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<td>0.029</td>
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<td>$\delta(1)$</td>
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<td>$\delta(1)$</td>
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Need for Sensitivity Analysis

- Even in experiments, SI is required to identify mechanisms
- SI is often too strong and yet not testable
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- Need to assess the robustness of findings via sensitivity analysis
- **Question**: How large a departure from the key assumption must occur for the conclusions to no longer hold?
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- **Sensitivity analysis by assuming**

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\begin{align*}
\{ Y_i(t', m), M_i(t) \} &\perp T_i \mid X_i = x \\
\text{but not} & \quad Y_i(t', m) \perp M_i(t) \mid T_i = t, X_i = x
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- Possible existence of unobserved *pre-treatment* confounder
Parametric Sensitivity Analysis

- **Sensitivity parameter**: $\rho \equiv \text{Corr}(\epsilon_{i2}, \epsilon_{i3})$

Sequential ignorability implies $\rho = 0$

Set $\rho$ to different values and see how ACME changes

When do my results go away completely?

$\bar{\delta}(t) = 0$ if and only if $\rho = \text{Corr}(\epsilon_{i1}, \epsilon_{i2})$ where $Y_i = \alpha_1 + \beta_1 T_i + \epsilon_{i1}$

Easy to estimate from the regression of $Y_i$ on $T_i$:

Alternative interpretation based on $R^2$:

How big does the effects of unobserved confounders have to be in order for my results to go away?
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- Set $\rho$ to different values and see how ACME changes

- When do my results go away completely?
- $\bar{\delta}(t) = 0$ if and only if $\rho = \text{corr}(\epsilon_{i1}, \epsilon_{i2})$ where

\[
Y_i = \alpha_1 + \beta_1 T_i + \epsilon_{i1}
\]

- Easy to estimate from the regression of $Y_i$ on $T_i$:

- Alternative interpretation based on $R^2$:
  How big does the effects of unobserved confounders have to be in order for my results to go away?
ACME > 0 as long as the error correlation is less than 0.39 (0.30 with 95% CI)
Without sequential ignorability, standard experimental design lacks identification power.

Even the sign of ACME is not identified.
Beyond Sequential Ignorability

- Without sequential ignorability, standard experimental design lacks identification power
- Even the sign of ACME is not identified
- Need to develop alternative research design strategies for more credible inference
- New experimental designs: Possible when the mediator can be directly or indirectly manipulated
- Observational studies: use experimental designs as templates
Crossover Design

- Recall ACME can be identified if we observe $Y_i(t', M_i(t))$
- Get $M_i(t)$, then switch $T_i$ to $t'$ while holding $M_i = M_i(t)$
Crossover Design

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Crossover design:

1. Round 1: Conduct a standard experiment
2. Round 2: Change the treatment to the opposite status but fix the mediator to the value observed in the first round
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Crossover design:

1. Round 1: Conduct a standard experiment
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- Very powerful – identifies mediation effects for each subject
- Must assume no carryover effect: Round 1 doesn’t affect Round 2
- Can be made plausible by design
Bertrand & Mullainathan (2004, AER)

- **Treatment**: Black vs. White names on CVs
- **Mediator**: Perceived qualifications of applicants
- **Outcome**: Callback from employers
Example: Labor Market Discrimination Experiment

Bertrand & Mullainathan (2004, AER)
- Treatment: Black vs. White names on CVs
- Mediator: Perceived qualifications of applicants
- Outcome: Callback from employers
- Quantity of interest: Direct effects of (perceived) race
- Would Jamal get a callback if his name were Greg but his qualifications stayed the same?
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- Treatment: Black vs. White names on CVs
- Mediator: Perceived qualifications of applicants
- Outcome: Callback from employers

- Quantity of interest: Direct effects of (perceived) race
- Would Jamal get a callback if his name were Greg but his qualifications stayed the same?

- Round 1: Send Jamal’s actual CV and record the outcome
- Round 2: Send his CV as Greg and record the outcome

- Assumptions are plausible
Key difference between experimental and observational studies: treatment assignment.
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Sequential ignorability:
1. Ignorability of treatment given covariates
2. Ignorability of mediator given treatment and covariates

Both (1) and (2) are suspect in observational studies
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Search for quasi-randomized treatments: “natural” experiments
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How can we design observational studies?

Experiments can serve as templates for observational studies
Example: Incumbency Advantage

- Estimation of incumbency advantages goes back to 1960s
- Why incumbency advantage? Scaring off quality challenger
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- Use of cross-over design (Levitt and Wolfram, LSQ)
  1. 1st Round: two non-incumbents in an open seat
  2. 2nd Round: same candidates with one being an incumbent
Estimation of incumbency advantages goes back to 1960s
Why incumbency advantage? Scaring off quality challenger

Use of cross-over design (Levitt and Wolfram, LSQ)

1. 1st Round: two non-incumbents in an open seat
2. 2nd Round: same candidates with one being an incumbent

Assumption: challenger quality (mediator) stays the same
Estimation of direct effect is possible
Concluding Remarks

- Quantitative analysis can be used to identify causal mechanisms!
- Estimate causal mediation effects rather than marginal effects
- Wide applications across social and natural science disciplines
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- Under standard research designs, sequential ignorability must hold for identification of causal mechanisms
- Under SI, a general, flexible estimation method is available
- SI can be probed via sensitivity analysis
- Easy-to-use software mediation is available in R and STATA
- Credible inference is possible under alternative research designs
Concluding Remarks

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- Ongoing research: multiple mediators, instrumental variables
The project website for papers and software:

http://imai.princeton.edu/projects/mechanisms.html

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