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

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Quantitative Research and Causal Mechanisms

- Causal inference is a central goal of scientific research
- Scientists care about *causal mechanisms*, not just *causal effects*

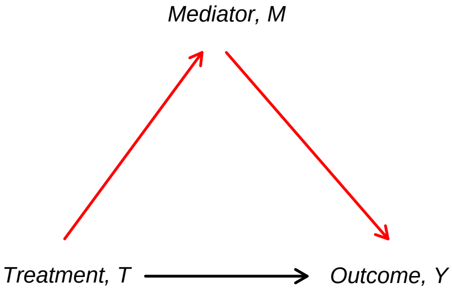
- Randomized experiments often only determine whether the treatment causes changes in the outcome
- Not how and why the treatment affects the outcome
- Common criticism of experiments and statistics:

black box view of causality

- Qualitative research uses process tracing
- **Question:** How can quantitative research be used to identify causal mechanisms?

Overview of the Talk

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

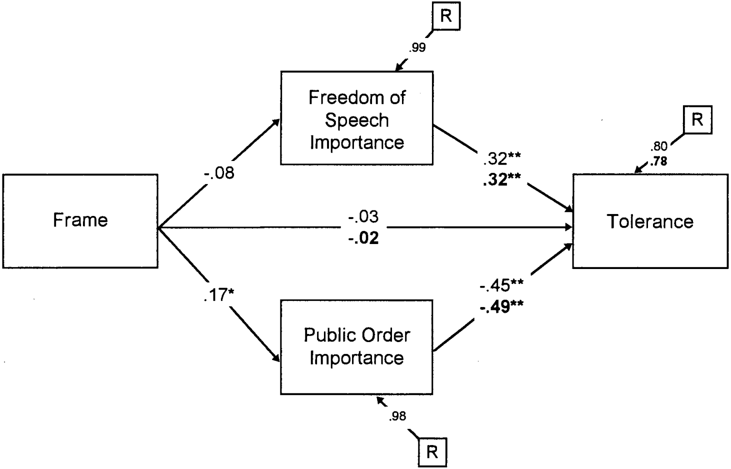


Direct and indirect effects; intermediate and intervening variables

- **New tools:** framework, estimation algorithm, sensitivity analysis, research designs, easy-to-use software

Causal Mediation Analysis in **American Politics**

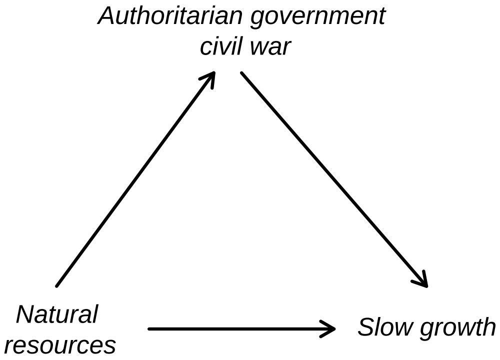
- The political psychology literature on media framing
- Nelson *et al*. (*APSR*, 1998)



- Popular in social psychology

Causal Mediation Analysis in **Comparative Politics**

- Resource curse thesis



- Causes of civil war: Fearon and Laitin (*APSR*, 2003)

Causal Mediation Analysis in **International Relations**

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

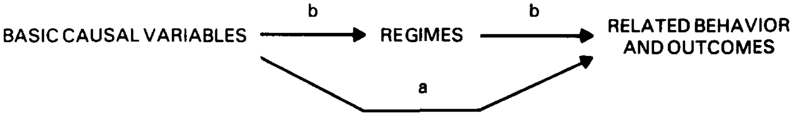


Figure 2

- Power and interests are mediated by regimes

Current Practice in **Political Science**

- 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
- Potential outcomes: $Y_i(1)$ and $Y_i(0)$
- Observed outcome: $Y_i = Y_i(T_i)$

Voters	Contact	Turnout		Age	Party ID
i	T_i	$Y_i(1)$	$Y_i(0)$	X_i	X_i
1	1	1	?	20	D
2	0	?	0	55	R
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n	1	0	?	62	D

- Causal effect: $Y_i(1) - Y_i(0)$
- Problem: **only one potential outcome can be observed per unit**

Potential Outcomes Framework for Mediation

- Binary treatment: T_i
- Pre-treatment covariates: X_i

- Potential mediators: $M_i(t)$
- Observed mediator: $M_i = M_i(T_i)$

- Potential outcomes: $Y_i(t, m)$
- Observed outcome: $Y_i = Y_i(T_i, M_i(T_i))$

- Again, **only one potential outcome can be observed per unit**

Causal Mediation Effects

- Total causal effect:

$$\tau_i \equiv Y_i(1, M_i(1)) - Y_i(0, M_i(0))$$

- Causal mediation (Indirect) effects:

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

- 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:

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

- 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)

$$\bar{\delta}(t) \equiv \mathbb{E}(\delta_i(t)) = \mathbb{E}\{Y_i(t, M_i(1)) - Y_i(t, M_i(0))\}$$

- Average direct effects ($\bar{\zeta}(t)$) are defined similarly

- $Y_i(t, M_i(t))$ is observed but $Y_i(t, M_i(t'))$ can never be observed
- We have an identification problem

$\Longrightarrow$ Need additional assumptions to make progress

Identification under Sequential Ignorability

- Proposed identification assumption: Sequential Ignorability (SI)

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i \mid X_i = x, \qquad (1)$$

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) \mid T_i = t, X_i = x \qquad (2)$$

- (1) is guaranteed to hold in a standard experiment
- (2) does **not** hold unless X_i includes all confounders
- Limitation: X_i cannot include post-treatment confounders

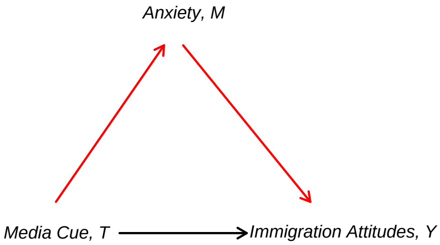
Under SI, ACME is nonparametrically identified:

$$\int \int \mathbb{E}(Y_i \mid M_i, T_i = t, X_i) \{dP(M_i \mid T_i = 1, X_i) - dP(M_i \mid T_i = 0, X_i)\} \, dP(X_i)$$

Example: Anxiety, Group Cues and Immigration

Brader, Valentino & Suhat (2008, AJPS)

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



- 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

Traditional Estimation Method

- Linear structural equation model (LSEM):

$$\begin{aligned} M_i &= \alpha_2 + \beta_2 T_i + \xi_2^\top X_i + \epsilon_{i2}, \\ Y_i &= \alpha_3 + \beta_3 T_i + \gamma M_i + \xi_3^\top X_i + \epsilon_{i3}. \end{aligned}$$

- Fit two least squares regressions separately
- Use product of coefficients ($\hat{\beta}_2 \hat{\gamma}$) to estimate ACME

- 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)
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
5. Monte Carlo or bootstrap to estimate uncertainty

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)
- Our method: Calculate ACME using our general algorithm

Outcome variables	Product of Coefficients	Average Causal Mediation Effect (δ)
Decrease Immigration	.347	.105
$\bar{\delta}(1)$	[0.146, 0.548]	[0.048, 0.170]
Support English Only Laws	.204	.074
$\bar{\delta}(1)$	[0.069, 0.339]	[0.027, 0.132]
Request Anti-Immigration Information	.277	.029
$\bar{\delta}(1)$	[0.084, 0.469]	[0.007, 0.063]
Send Anti-Immigration Message	.276	.086
$\bar{\delta}(1)$	[0.102, 0.450]	[0.035, 0.144]

Need for Sensitivity Analysis

- Even in experiments, SI is required to identify mechanisms
- SI is often too strong and yet not testable
- 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?
- Sensitivity analysis by assuming

$$\{Y_i(t', m), M_i(t)\} \perp\!\!\!\perp T_i \mid X_i = x$$

but not

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) \mid T_i = t, X_i = x$$

- Possible existence of unobserved *pre-treatment* confounder

Parametric Sensitivity Analysis

- Sensitivity parameter: $\rho \equiv \mathrm{Corr}(\epsilon_{i2}, \epsilon_{i3})$
- Sequential ignorability implies $\rho = 0$
- Set ρ to different values and see how ACME changes

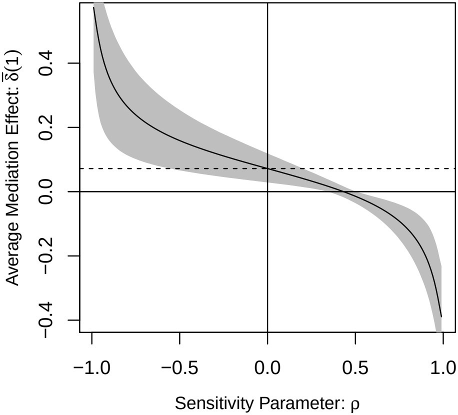
- When do my results go away completely?
- $\bar{\delta}(t) = 0$ if and only if $\rho = \mathrm{Corr}(\epsilon_{i1}, \epsilon_{i2})$ where

$$Y_i = \alpha_1 + \beta_1 T_i + \epsilon_{i1}$$

- 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?

Example: Sensitivity Analysis



- ACME $>$ 0 as long as the error correlation is less than 0.39 (0.30 with 95% CI)

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:
  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
- 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

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?

- 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

Designing Observational Studies

- Key difference between experimental and observational studies: treatment assignment
- 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

- Statistical control: matching, propensity scores, etc.
- Search for quasi-randomized treatments: “natural” experiments

- 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

- 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

- 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

- Ongoing research: multiple mediators, instrumental variables

The project website for papers and software:

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

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