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

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

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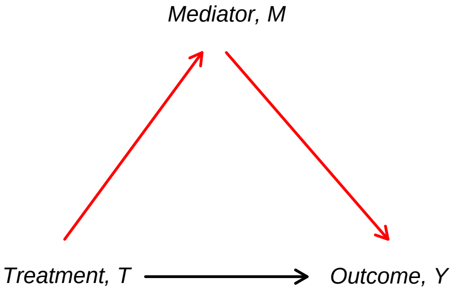

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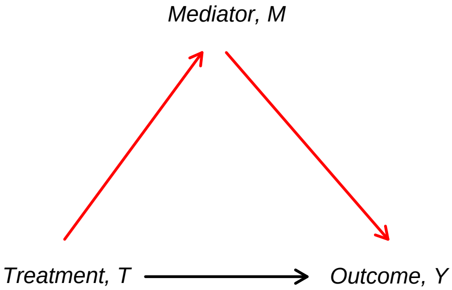
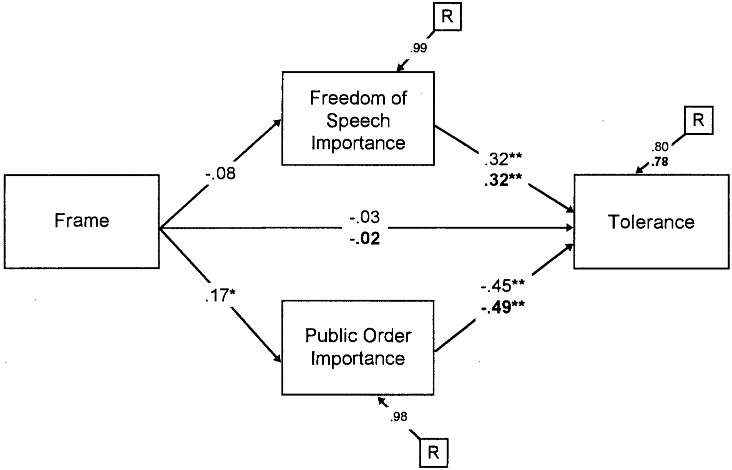


Direct and indirect effects; intermediate and intervening variables

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

Causal Mediation Analysis in **American Politics**

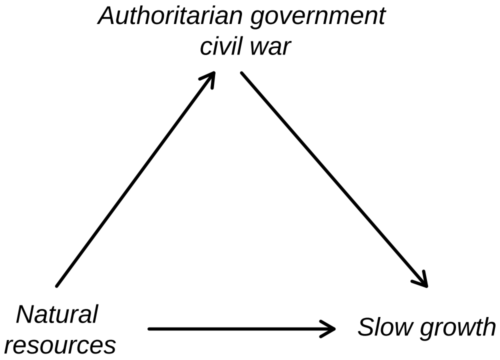
- The political psychology literature on media framing
- Nelson *et al*. (*APSR*, 1998)



- Popular in social psychology

Causal Mediation Analysis in **Comparative Politics**

- Resource curse thesis



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

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

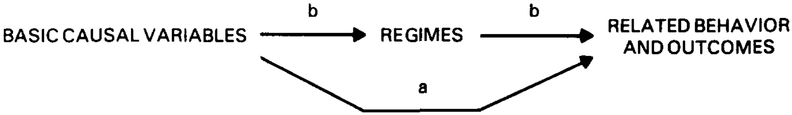


Figure 2

- 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
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1	1	1	?	20	D
2	0	?	0	55	R
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n	1	0	?	62	D

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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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- 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 $M_i(t)$
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- 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)

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$\Longrightarrow$ Need additional assumptions to make progress

Identification under Sequential Ignorability

- Proposed identification assumption: Sequential Ignorability (SI)

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

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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)

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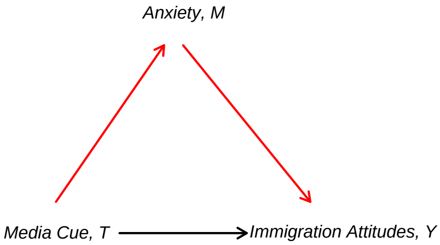

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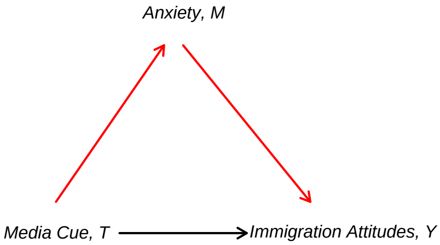

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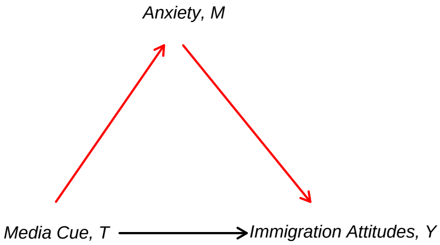

- ACME $=$ Average difference in immigration attitudes due to the change in anxiety induced by the media cue treatment
- Sequential ignorability $=$ No unobserved covariate affecting both anxiety and immigration attitudes

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}.
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- Problem: Only valid for the simplest LSEMs

Proposed General Estimation Algorithm

1. Model outcome and mediator
   - Outcome model: $p(Y_i \mid T_i, M_i, X_i)$
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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 $M_i = M_i(1)$
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5. Monte Carlo or bootstrap to estimate uncertainty

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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]

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- Possible existence of unobserved *pre-treatment* confounder

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- $\bar{\delta}(t) = 0$ if and only if $\rho = \mathrm{Corr}(\epsilon_{i1}, \epsilon_{i2})$ where

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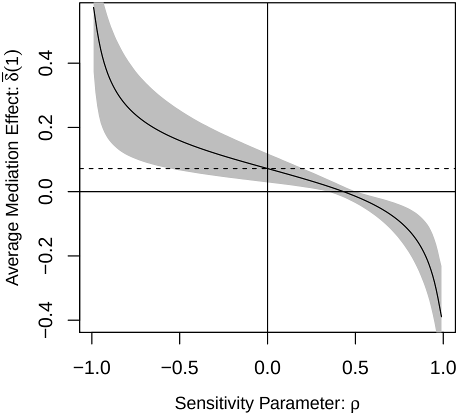
- Alternative interpretation based on R^2:
  How big does the effects of unobserved confounders have to be in order for my results to go away?

Example: Sensitivity Analysis



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

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- 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

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- 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 $M_i = M_i(t)$

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  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
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- 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

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- How can we design observational studies?
- Experiments can serve as templates for observational studies

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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

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

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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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