Weighting Methods for Causal Mediation Analysis

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The University of Chicago

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Agenda

- Concepts of causal mediation
- Brief review of existing methods

-- Break –

- Rationale of the RMPW strategy

-- Lunch –

- Parametric and nonparametric procedures and simulation results
- Hands-on practice with free RMPW software; Stata, SAS, and R code

-- Break --

- Multisite causal mediation analysis

- Wrapup: Q&A wrt causal mediation analysis and its distinctions from and connections with other methods

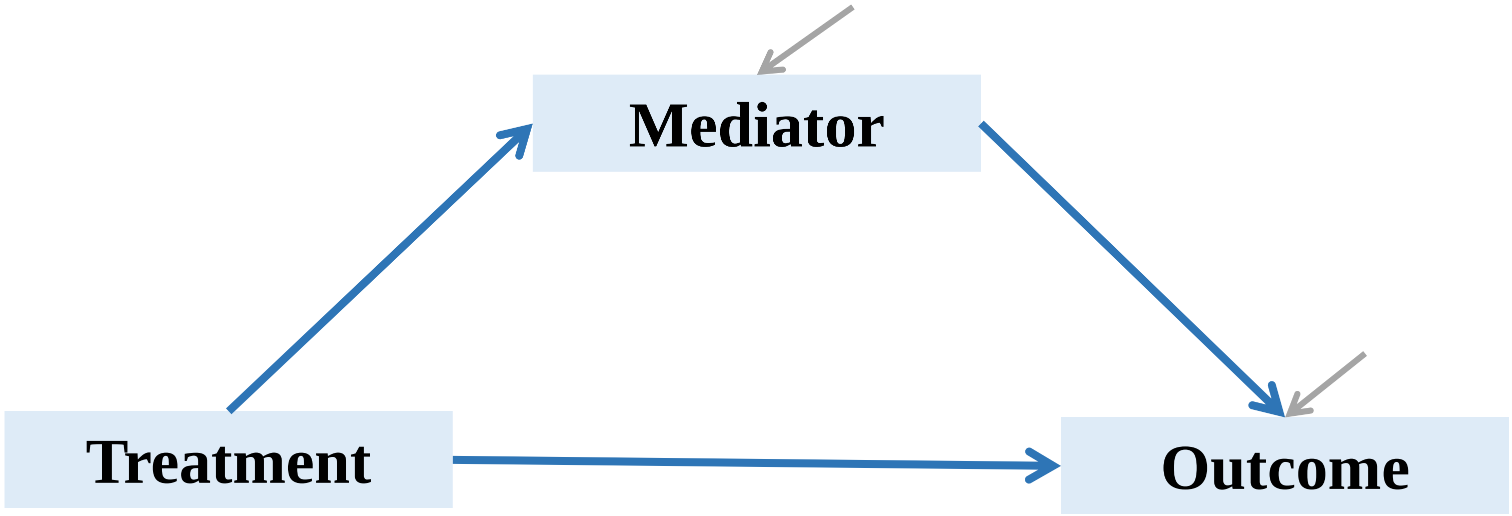
Concepts of Causal Mediation

Introduction

- Intervention Theory: Hypothesis of a causal mechanism operating through a focal mediator

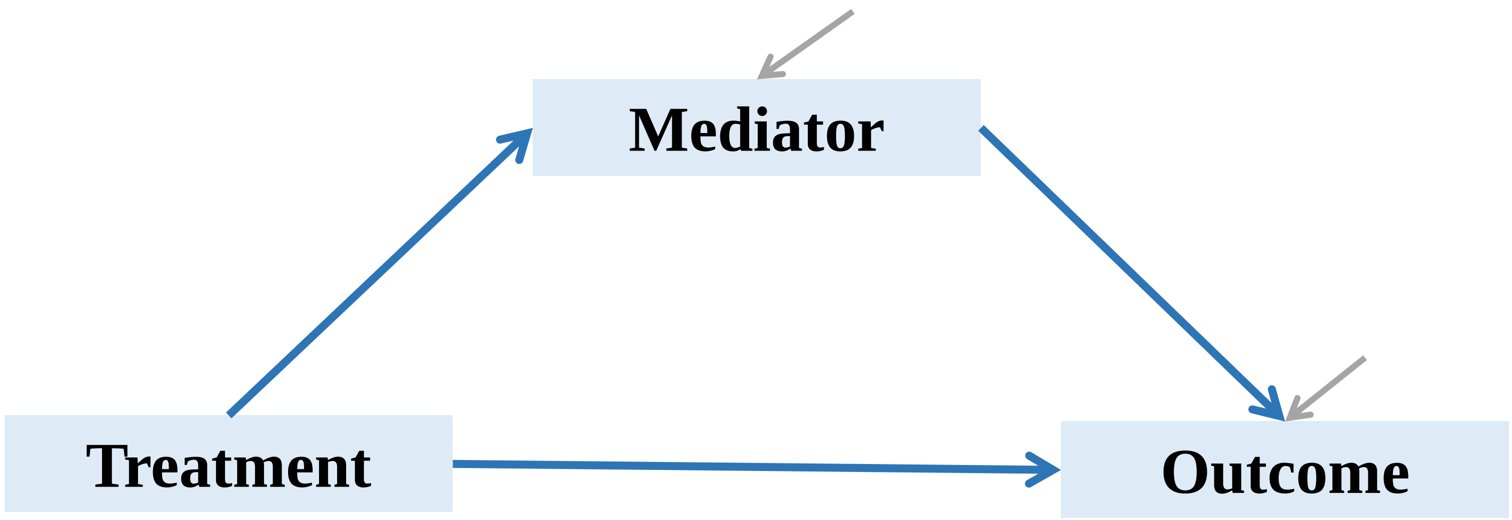
- Total Effect = Indirect Effect + Direct Effect
  - *Indirect Effect*: Expected change in the outcome due to an intervention-induced change in the focal mediator
  - *Direct Effect*: Expected change in the outcome caused by the intervention through other unspecified mechanisms without affecting the mediator

Indirect and Direct Effects



e.g., Treatment: Encouragement to study
Mediator: Time spent on studying
Outcome: Test score

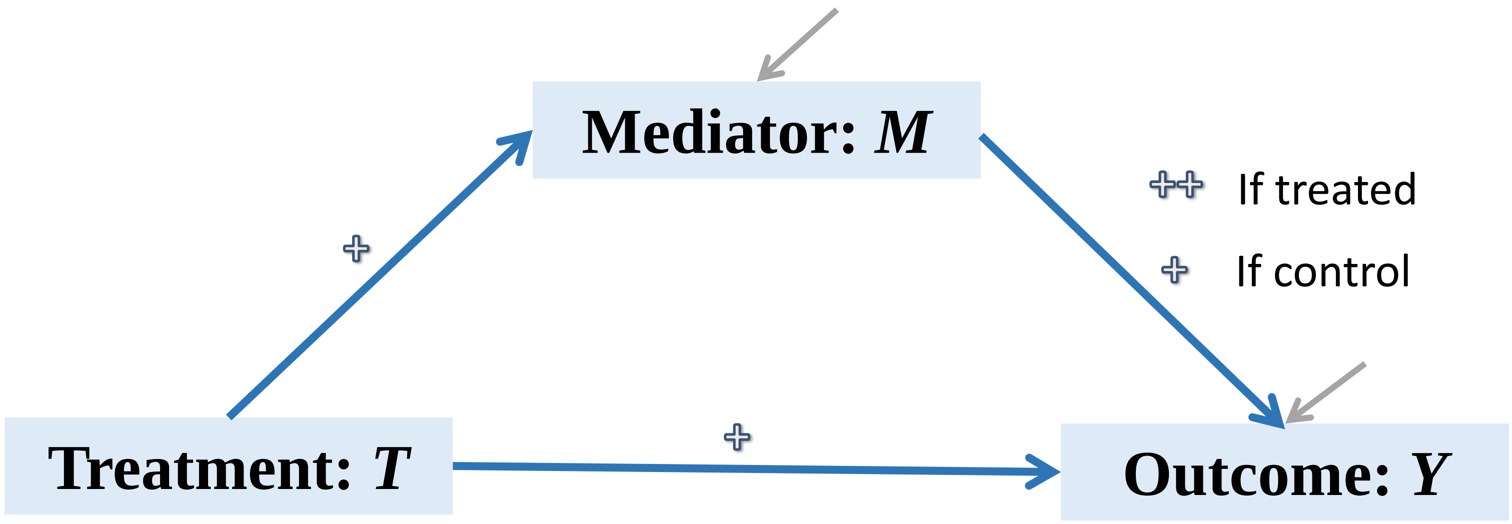
Indirect and Direct Effects



Explicate your *theoretical hypotheses*:

- How would encouragement affect hours of study?
- How would encouragement affect test score through changing hours of study?
- Would encouragement affect test score without changing hours of study?
  - Would encouragement change the effectiveness of study?
  - Would encouragement change test-taking behavior?

Treatment-by-Mediator Interaction



The treatment may change (1) an individual's mediator values, and (2) the mediator-outcome relationship.

(Judd & Kenny, 1981)

NEWWS Riverside Experiment

$\boldsymbol{LFA}\colon \boldsymbol{T = 1}$

$\boldsymbol{Control}\colon \boldsymbol{T = 0}$

Labor force attachment program (LFA) vs. the Control condition

Policy Context: Welfare-to-Work

- Change in Legislation
  - Replacing AFDC with TANF in the late 1990s
  - Employment-focused incentives and services

- Population
  - Welfare applicants/recipients with preschool-age children (mostly single mothers, disproportionately depressed)

- Public Concern
  - How would the policy affect maternal depression? What is the mediating role of employment?

Labor Force Attachment

Features of the LFA program

- provided encouragement, support, and emphasis on seeking and securing jobs
- threatened sanctions
- no guaranteed employment

Mediation Mechanisms

Under LFA

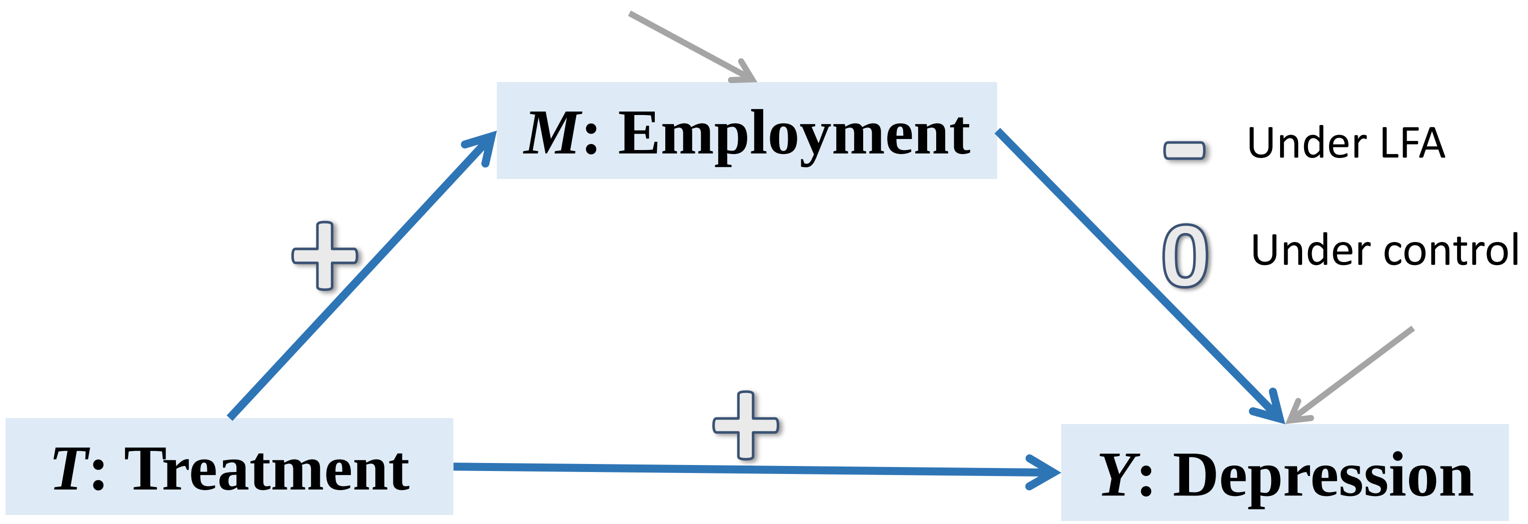
- Employment might boost self-efficacy and reduce depression
- Anticipated sanctions if unemployed might add stress and increase depression

Under the control condition

(with guaranteed cash assistance)

- Employment might not be as beneficial
- Unemployment might not be as detrimental to psychological well-being

Theoretical Hypotheses



Data

	LFA	Control	Total
Sample Size	208	486	694

- *Y*: Depressive symptoms measured at the 2-year follow-up
  - A 12-item battery (CES-D) (e.g., I could not get going in the past week)
  - Item responses on a scale from “rarely” to “most of the time”
  - Summary score ranging from 0 to 34

    Mean = 7.49; SD = 7.74

- *M*: Quarterly employment data maintained by the state

Potential Mediators and Potential Outcomes under SUTVA

Individual Unit	Treatment	Potential Mediators		Potential Outcomes	
	T	$M(1)$	$M(0)$	$Y(1)$	$Y(0)$
1	1	1	1		
2	1	1	0		
3	1	0	0		
4	0	1	1		
5	0	1	0		
6	0	0	0		
Population Average		$E[M(1)]$	$E[M(0)]$	$E[Y(1)]$	$E[Y(0)]$

Intention-to-Treat (ITT) Effects

- Sample estimate of $E[Y(1) - Y(0)]$: 0.11 (SE=0.64, t=0.18, p=0.86)
- Sample estimate of $E[M(1) - M(0)]$: 0.26 ($p < .05$)

	LFA	Control
Employment Rate	***.654***	***.395***

Null ITT Effect = No Mediation?

Or

Are There Counteracting Mechanisms?

Challenges to Causal Mediation Analysis

- The treatment may change the mediator-outcome relationship, key to understanding the causal mechanism
  - How to decompose the total effect then?
- Individuals select mediator values in randomized experiments
  - How to adjust for selection bias?

Notation

Potential Outcomes:

- $Y(1,M(1))$: depression score if assigned to LFA—i.e., $Y(1)$
- $Y(0,M(0))$: depression score if assigned to the control condition—i.e., $Y(0)$
- $Y(1,M(0))$: depression score if assigned to LFA yet counterfactually experiencing employment associated with the control condition
- $Y(0,M(1))$: depression score if assigned to the control condition yet counterfactually experiencing employment associated with LFA

Potential Mediators and Potential Outcomes

Unit	Treatment	Potential Mediators		Potential Outcomes
	T	$M(1)$	$M(0)$	$Y(1,M(1))$
1	1	1	1	$Y(1,1)$
2	1	1	0	$Y(1,1)$
3	1	0	0	$Y(1,0)$
4	0	1	1	$Y(1,1)$
5	0	1	0	$Y(1,1)$
6	0	0	0	$Y(1,0)$
Population Average		$E[M(1)]$	$E[M(0)]$	$E[Y(1,M(1))]$

Treatment Effect Decomposition

Total effect
(Policy impact on depression)

$$E\left[Y\left(1, M\left(1\right)\right) - Y\left(0, M\left(0\right)\right)\right]$$

Natural indirect effect
(Policy impact on depression
through changing employment)

$$= E\left[Y\left(1, M\left(1\right)\right) - Y\left(1, M\left(0\right)\right)\right]$$

Natural direct effect
(Policy impact on depression
if leaving employment unchanged)

$$+ E\left[Y\left(1, M\left(0\right)\right) - Y\left(0, M\left(0\right)\right)\right]$$

(Robins & Greenland, 1992; Pearl, 2001)

Further Decomposition

Natural indirect effect $$E\left[Y\left(1, M\left(1\right)\right) - Y\left(1, M\left(0\right)\right)\right]$$

(Impact of policy-induced change in employment on depression if treated)

Pure indirect effect $$= E\left[Y\left(0, M\left(1\right)\right) - Y\left(0, M\left(0\right)\right)\right]$$

(Impact of policy-induced change in employment on depression if untreated)

Treatment-by-mediator interaction effect

(Policy impact on depression through changing the mediator-outcome relationship)

$$+ E\left[\left\{Y\left(1, M\left(1\right)\right) - Y\left(1, M\left(0\right)\right)\right\} - \left\{Y\left(0, M\left(1\right)\right) - Y\left(0, M\left(0\right)\right)\right\}\right]$$

Brief Review of Existing Methods

Path Analysis and SEM

- *Mediator Model* $$M = \pi_M + \alpha T + \varepsilon_M$$
- *Outcome Model* $$Y = \pi_Y + \beta M + \lambda T + \varepsilon_Y.$$

$\alpha\beta$ identifies the natural indirect effect while λ identifies the natural direct effect under the following assumptions (possibly within levels of covariates):

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The Instrumental Variable Method

- *Mediator Model* $$M = \gamma_M + \alpha T + \varepsilon_M$$

- *Outcome Model* $$Y = \pi_Y + \beta M + \varepsilon_Y .$$

The ITT effect of T on Y is equivalent to the natural indirect effect $\alpha\beta$; hence β identifies the mediator effect on the outcome under the following assumptions (possibly within levels of covariates):

Marginal Structural Models

- *Weighted Mediator Model* $$M = \pi_M + \alpha T + \varepsilon_M$$
- *Weighted Outcome Model* $$Y = \pi_Y + \beta M + \lambda T + \varepsilon_Y.$$

$\alpha\beta$ identifies the natural indirect effect while λ identifies the natural direct effect under the following assumptions:

New Strategies Allowing for Treatment-by-Mediator Interaction

- Modified regression approaches (Pearl, 2010; Petersen, Sinisi, & van der Laan, 2006; Preacher, Rucker, & Hayes, 2007; Valeri & VanderWeele, 2013; VanderWeele, 2013; VanderWeele & Vansteelandt, 2009, 2010)

Identification Assumptions:

- Sequential Ignorability (within levels of covariates)
  - The treatment assignment is independent of all the potential mediators and the potential outcomes
  - The mediator value assignment under each treatment is independent of all the potential outcomes
- Both the mediator model and the outcome model are correctly specified

New Strategies Allowing for Treatment-by-Mediator Interaction

- Resampling approach (Imai, Keele, and Yamamoto, 2010; Imai, Keele, & Tingley, 2010)

Identification Assumptions:

- Sequential Ignorability (within levels of covariates)
  - The treatment assignment is independent of all the potential mediators and the potential outcomes
  - The mediator value assignment under each treatment is independent of all the potential outcomes with
- Both the mediator model and the outcome model are correctly specified

Rationale of the RMPW Strategy

Rationale for RMPW

- Obtain consistent estimates of

$$E[Y(0,M(0))]$$

$$E[Y(1,M(1))]$$

$$E[Y(1,M(0))]$$

$$E[Y(0,M(1))]$$

Rationale for RMPW

$\boxed{E[Y(0,M(0))]}$

$E[Y(1,M(1))]$

$\boxed{E[Y(1,M(0))]}$

$E[Y(0,M(1))]$

$$\text{Direct Effect}:$$
$$E\left[Y\left(1,M\left(0\right)\right)-Y\left(0,M\left(0\right)\right)\right]$$

Rationale for RMPW

$E[Y(0,M(0))]$

$\boxed{E[Y(1,M(1))]}$

$\boxed{E[Y(1,M(0))]}$

$E[Y(0,M(1))]$

Indirect Effect :

$$E[Y(1,M(1)) - Y(1,M(0))]$$

Rationale for RMPW

$\boxed{E[Y(0,M(0))]}$

$E[Y(1,M(1))]$

$E[Y(1,M(0))]$

$\boxed{E[Y(0,M(1))]}$

Pure Indirect Effect :

$$E\left[Y\left(0,M\left(1\right)\right)-Y\left(0,M\left(0\right)\right)\right]$$

Rationale for RMPW

$\boxed{E[Y(0,M(0))]}$

$\boxed{E[Y(1,M(1))]}$

$\boxed{E[Y(1,M(0))]}$

$\boxed{E[Y(0,M(1))]}$

Treatment-by-Mediator Interaction Effect:

$$E\{[Y(1,M(1))-Y(1,M(0))]-[Y(0,M(1))-Y(0,M(0))]\}$$

How to Identify $E[Y(1, M(0))]$?

Hypothetical Sequential Randomized Experiment

$$T = 0$$

Employment Rate: $pr(M = 1 \mid T = 0) = .4$
Unemployment Rate: $pr(M = 0 \mid T = 0) = .6$

$$E[Y(0, M(0))]$$

Hypothetical Sequential Randomized Experiment

$T = 0$

Employment Rate:
$pr(M = 1 | T = 0) = .4$

Unemployment Rate:
$pr(M = 0 | T = 0) = .6$

$E[Y(0, M(0))]$

$T = 1$

Employment Rate:
$pr(M = 1 | T = 1) = .7$

Unemployment Rate:
$pr(M = 0 | T = 1) = .3$

$E[Y(1, M(1))]$

Hypothetical Sequential Randomized Experiment

$T = 0$

Employment Rate:
$pr(M = 1 \mid T = 0) = .4$

Unemployment Rate:
$pr(M = 0 \mid T = 0) = .6$

$E[Y(0, M(0))]$

$T = 1$

Employment Rate:
$pr(M = 1 \mid T = 1) = .7$

Unemployment Rate:
$pr(M = 0 \mid T = 1) = .3$

$E[Y(1, M(1))]$

$\omega = \frac{0.4}{0.7} = \frac{4}{7}$

$\omega = \frac{0.6}{0.3} = 2$

$T = 1$

Employment Rate:
$pr(M = 1 \mid T = 0) = .4$

Unemployment Rate:
$pr(M = 0 \mid T = 0) = .6$

$E[Y(1, M(0))]$

$$\omega = \frac{pr(M = m \mid T = 0)}{pr(M = m \mid T = 1)} = \frac{\theta_{M(0)}}{\theta_{M(1)}}$$

Outcome Model

- Unweighted Control Group ($T = 0$)

Treatment (T)	**Duplicate ($D1$)**	**RMPW**	**Estimate**
0	0	1	$E[Y(0,M(0))]$

Outcome Model

- Weighted LFA Group ($T = 1$)

Treatment (T)	Duplicate ($D1$)	RMPW	Estimate
0	0	1	$E[Y(0,M(0))]$
1	0	$\theta_{M(0)}/\theta_{M(1)}$	$E[Y(1,M(0))]$

Direct Effect

Outcome Model

- Unweighted LFA Group ($T = 1$), a duplicate ($D1 = 1$)

Treatment (T)	**Duplicate ($D1$)**	**RMPW**	**Estimate**
0	0	1	$E[Y(0,M(0))]$
1	0	$\theta_{M(0)}/\theta_{M(1)}$	$E[Y(1,M(0))]$
1	1	1	$E[Y(1,M(1))]$

Indirect Effect

Outcome Model

- Merge the original sample with a duplicate LFA group

Treatment (T)	Duplicate ($D1$)	RMPW	Estimate
0	0	1	$E[Y(0,M(0))]$
1	0	$\theta_{M(0)}/\theta_{M(1)}$	$E[Y(1,M(0))]$
1	1	1	$E[Y(1,M(1))]$

Direct Effect

Indirect Effect

- Weighted outcome model:

$$Y = \gamma_0 + \gamma^{(DE)}T + \gamma^{(IE.1)}D1 + e$$

Direct Effect

Indirect Effect

Randomization of Treatment Only

Assume sequential randomization within levels of $\mathbf{X}$

For an employed LFA unit,

$$\omega = \frac{pr(M = 1 \mid T = 0, \mathbf{X} = \mathbf{x})}{pr(M = 1 \mid T = 1, \mathbf{X} = \mathbf{x})} = \frac{\theta_{M(0)=1}(\mathbf{x})}{\theta_{M(1)=1}(\mathbf{x})}$$

Propensity of employment under the control condition

Propensity of employment under LFA

For an unemployed LFA unit,

$$\omega = \frac{pr(M = 0 \mid T = 0, \mathbf{X} = \mathbf{x})}{pr(M = 0 \mid T = 1, \mathbf{X} = \mathbf{x})} = \frac{\theta_{M(0)=0}(\mathbf{x})}{\theta_{M(1)=0}(\mathbf{x})}$$

Propensity of unemployment under the control condition

Propensity of unemployment under LFA

86 Pretreatment Covariates *X*

- **Psychological well-being** at the time of randomization
- Personal history of employment and history of welfare dependence
- Human capital, employment status, earnings, income at randomization
- Preference to work, willingness to accept a low-wage job, ashamed to be on welfare, perceived social support, and perceived barriers to work
- Household composition (e.g., number of children, age of children, living with an extended family, living with a partner, marriage status; ever been a teen mother)
- Childcare arrangement, extra family burden (e.g., physical health or mental health problem of a family member), public housing residence, and residential mobility
- Demographic features (age and race/ethnicity)

Identification Assumptions

- Sequential Ignorability

  When only the treatment is randomized, we assume sequential randomization within levels of pretreatment covariates **X** = **x**, that is,

  - No confounding of treatment-mediator relationship and treatment-outcome relationship
  - No confounding of mediator-outcome relationship within a treatment and across treatments (the latter implies no posttreatment confounders)

We Do Not Assume…

Unlike the existing methods reviewed earlier, we do not assume:

- No treatment-by-mediator interaction
- The exclusion restriction
- Functional form of the outcome model

How to Identify $E[Y(0, M(1))]$?

Hypothetical Sequential Randomized Experiment

$T=0$	$T=1$		$T=0$
Employment Rate: $pr(M=1 \mid T=0)=.4$	Employment Rate: $pr(M=1 \mid T=1)=.7$	$\omega=$ ______	Employment Rate: $pr(M=1 \mid T=1)=.7$
Unemployment Rate: $pr(M=0 \mid T=0)=.6$	Unemployment Rate: $pr(M=0 \mid T=1)=.3$	$\omega=$ ______	Unemployment Rate: $pr(M=0 \mid T=1)=.3$
$E[Y(0,M(0))]$	$E[Y(1,M(1))]$		$E[Y(0,M(1))]$

$\omega=$ ____________

Outcome Model

Weighted Control Group ($T = 0$), a duplicate ($D0 = 1$)

Treatment (T)	**Duplicate ($D1$)**	**Duplicate ($D0$)**	**RMPW**	**Estimate**
0	0	0	1	$E[Y(0,M(0))]$
0	0	1	$\theta_{M(1)}/\theta_{M(0)}$	$E[Y(0,M(1))]$
1	0	0	$\theta_{M(0)}/\theta_{M(1)}$	$E[Y(1,M(0))]$
1	1	0	1	$E[Y(1,M(1))]$

Pure Indirect Effect

Outcome Model

Weighted outcome model:

$$Y = \gamma_0 + \gamma^{(DE)}T + \gamma^{(IE.1)}D1 + \gamma^{(IE.0)}D0 + e$$

Direct Effect

Indirect Effect

Pure Indirect Effect

$\gamma^{(IE.1)} - \gamma^{(IE.0)}$ identifies

the natural treatment - by - mediator interaction effect

More to Follow on Estimation

- Weighted least squares equivalent to weighted method-of-moments analysis
- Two-step estimation complicates the estimation of standard errors
  - Step 1: propensity score estimation
  - Step 2: causal effect estimation

LUNCH BREAK

Parametric and Nonparametric Procedures and Simulation Results

Analytic Procedure

1. Estimating/predicting the propensity scores
2. Parametrically or nonparametrically estimating the weight
3. Parametrically or nonparametrically checking balance
4. Estimating the causal effects under weighting

1. Estimating/Predicting the Propensity Scores of (Un)Employment

For each participant in the LFA program, the propensity of being employed under LFA

$$\theta_{M(1)=1}(\mathbf{x}) = pr(M = 1 | T = 1, \mathbf{X} = \mathbf{x})$$

The propensity of being unemployed under LFA

$$\theta_{M(1)=0}(\mathbf{x}) = 1 - \theta_{M(1)=1}(\mathbf{x})$$

1. Estimating/Predicting the Propensity Scores of (Un)Employment

For each member of the control group, the propensity of being employed under the control condition:

$$\theta_{M(0)=1}(\mathbf{x}) = pr(M = 1|T = 0, \mathbf{X} = \mathbf{x})$$

The propensity of being unemployed under the control condition

$$\theta_{M(0)=0}(\mathbf{x}) = 1 - \theta_{M(0)=1}(\mathbf{x})$$

Apply this prediction function to members of the LFA group, we predict their propensity of employment (or unemployment) **had they counterfactually been assigned in the control group.**

2a. Parametric Estimation of RMPW Weights

For an **employed** LFA unit,

$$\hat{\omega} = \frac{\hat{\theta}_{M(0)=1}(\mathbf{x})}{\hat{\theta}_{M(1)=1}(\mathbf{x})}$$

For an **unemployed** LFA unit,

$$\hat{\omega} = \frac{\hat{\theta}_{M(0)=0}(\mathbf{x})}{\hat{\theta}_{M(1)=0}(\mathbf{x})}$$

2a. Parametric RMPW Adjustment

	Control	LFA Unweighted	LFA Weighted
Never Employed	.605	.346	.624
Ever Employed	.395	.654	.376

3a. Parametric Balance Checking

- IF the sequential ignorability assumption holds, and
- IF the propensity score models are correctly specified,

propensity score-based parametric weighting (e.g., IPTW) is expected to balance the covariate distribution across the treatment-by-mediator combinations

	T=1		T=2		Standardized Difference	Global Test
	M=1	M=2	M=1	M=2		
X1						
X2						
. . .						

4. Weighted Estimation of Causal Effects

$$Y = \gamma_0 + \gamma^{(DE)}T + \gamma^{(IE.1)}D1 + e$$

In Stata, one may use weighted regression with *cluster-robust standard errors*, clustering the original observations and their duplicates by the individual ID. This is because the duplicate observations create correlated errors.

Later we will discuss a *two-step estimation* procedure (equivalent to a *GMM procedure* in Stata) that estimates the asymptotic standard errors fully accounting for the fact that the weight is unknown and must be estimated.

Total Effect Decomposition

	Parametric RMPW
Natural Direct Effect	1.29 SE = 0.87, t = 1.48, p = .11
Natural Indirect Effect	-0.87 SE = 0.47, t = -1.89, p = .06

Further Decomposition

	Parametric RMPW
Natural Direct Effect	1.29 $SE = 0.87$, $t = 1.48$, $p = .11$
Natural Indirect Effect	-0.87 $SE = 0.47$, $t = -1.89$, $p = .06$
Pure Indirect Effect	0.32 $SE = 0.27$, $t = 1.48$, $p = .14$
Natural Treatment-by-Mediator Interaction Effect	-1.19 $SE = 0.53$, $t = -2.26$, $p < .05$

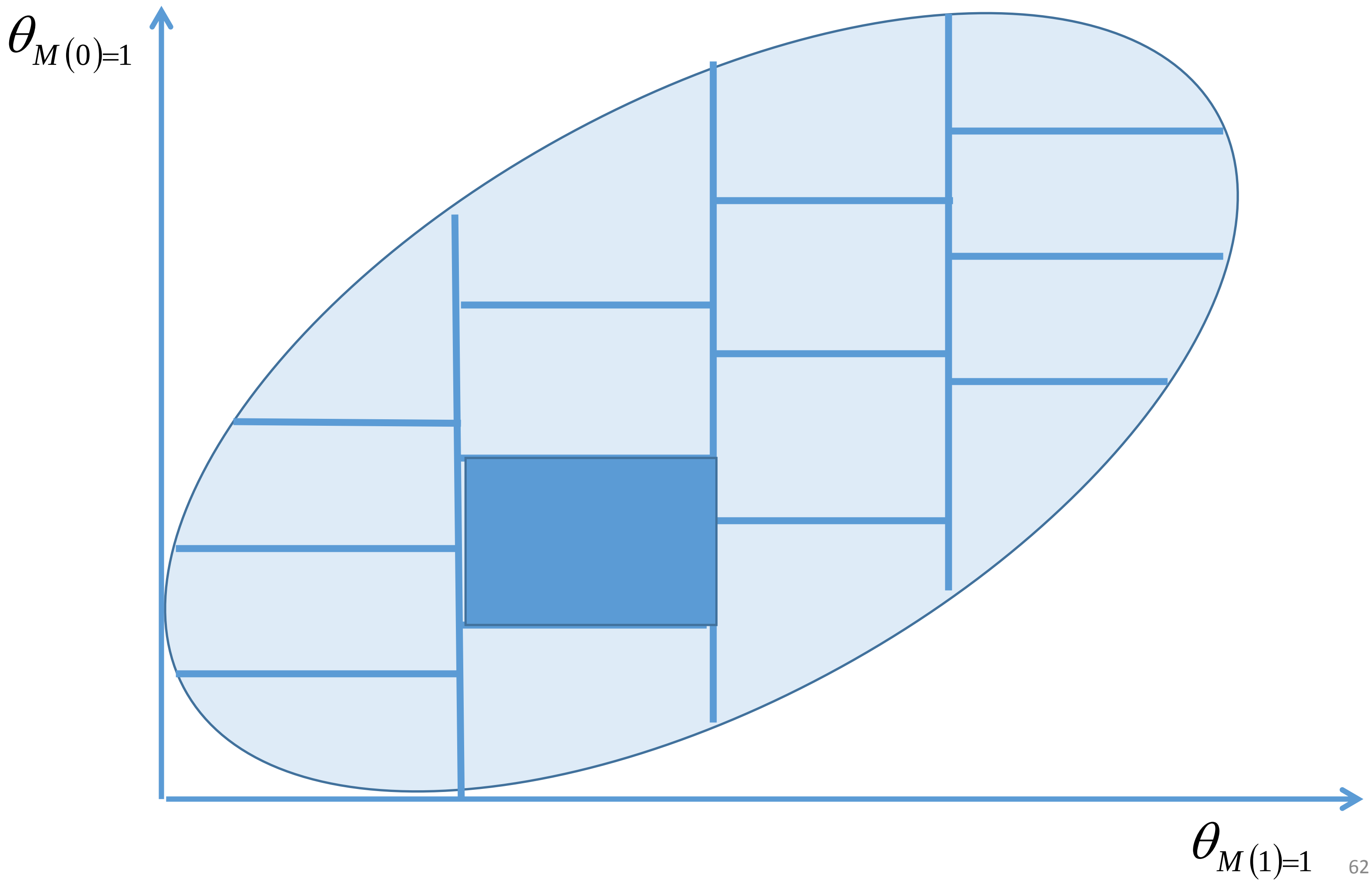
2b. Nonparametric Estimation of RMPW Weights

Each observation, whether in the LFA group or the control group, has $\hat{\theta}_{M(1)=1}(\mathbf{x})$ and $\hat{\theta}_{M(0)=1}(\mathbf{x})$.

In the nonparametric procedure,

i. Group observations into quartiles by their values of $\hat{\theta}_{M(1)=1}(\mathbf{x})$.
ii. Separately within each of these quartiles, further group observations into quartiles by their values of $\hat{\theta}_{M(0)=1}(\mathbf{x})$
iii. After steps 1 and 2, each observations has been grouped into 1 of 16 strata

2b. Nonparametric Estimation of RMPW Weights



2b. Nonparametric Estimation of RMPW Weights

Within each stratum, re-estimate each individual's propensity scores on the basis of the cell counts:

	$T = 1$	$T = 0$	
$M(1) = 1$	$\hat{\theta}_{M(1)=1} = .5$	$\hat{\theta}_{M(0)=1} = .3$	$M(0) = 1$
$M(1) = 0$	$\hat{\theta}_{M(1)=0} = .5$	$\hat{\theta}_{M(0)=0} = .7$	$M(0) = 0$

2b. Nonparametric Estimation of RMPW Weights

For an **employed** LFA unit:

$$\hat{\omega} = \frac{pr(M = 1|T = 0, S = s)}{pr(M = 1|T = 1, S = s)}$$

For an **unemployed** LFA unit:

$$\hat{\omega} = \frac{pr(M = 0|T = 0, S = s)}{pr(M = 0|T = 1, S = s)}$$

For example, $pr(M = 1|T = 0, S = s)$ is simply the proportion of the control group members in strata *s* who are employed, which re-estimates the propensity of employment under the control condition for individuals in this same stratum.

3b. Nonparametric Balance Checking

- IF the sequential ignorability assumption holds,

propensity score-based nonparametric weighting (e.g., marginal mean weighting through stratification, MMWS, see Hong, 2010, 2012, 2015) is expected to balance the covariate distribution across the treatment-by-mediator combinations

(Nonparametric weighting tends to have robust results despite misspecifications of functional forms of the propensity score models.)

Total Effect Decomposition

	Parametric RMPW	Nonparametric RMPW
Natural Direct Effect	1.29 $SE = 0.87$, $t = 1.48$, $p = .11$	1.34 $SE = 0.79$, $t = 1.70$, $p = .09$
Natural Indirect Effect	-0.87 $SE = 0.47$, $t = -1.89$, $p = .06$	-0.93 $SE = 0.38$, $t = -2.43$, $p < .05$

Further Decomposition

	Parametric RMPW	Nonparametric RMPW
Natural Direct Effect	1.29 SE = 0.87, t = 1.48, p = .11	1.34 SE = 0.79, t = 1.70, p = .09
Natural Indirect Effect	-0.87 SE = 0.47, t = -1.89, p = .06	-0.93 SE = 0.38, t = -2.43, $p < .05$
Pure Indirect Effect	0.32 SE = 0.27, t = 1.48, p = .14	0.45 SE = 0.30, t = 1.50, p = .13
Natural Treatment-by-Mediator Interaction Effect	-1.19 SE = 0.53, t = -2.26, $p < .05$	-1.38 SE = 0.49, t = -2.85, $p < .01$

Summary of Simulation Results

- Parametric and nonparametric RMPW perform generally well
  - Parametric RMPW removes nearly 100% of the bias
  - Nonparametric RMPW with 4×4 stratification removes 90% of the bias
- Advantages of nonparametric RMPW in comparison with parametric RMPW
  - Tends to be relatively more *efficient*
  - Is relatively *robust* to propensity score model misspecification

Two-Step Estimation

Step 1

Estimation of the propensity scores used to compute RMPW

Step 2

Weighted estimation of the causal effects

The free stand-alone RMPW software implements an M-estimation procedure that generates asymptotic standard errors correctly capturing the estimation uncertainty in both steps. Equivalent results can be obtained by applying the GMM command in Stata (Bein et al, 2015).

RMPW Software
&
Stata, SAS, and R Code

RMPW Software

http://hlmsoft.net/ghong/

RMPW

Click **here** to get RMPW.
For a sample RMPW data set, Click **here**

For details of features, please refer to "RMPW program manual.pdf".

Please report problems with the software by sending email to Richard Congdon (richard@hlmsoft.net) and copying Guanglei Hong (ghong@uchicago.edu)

Data Set for Exercise

Save "NEWWS_Riverside_class use_rv.dta"

Save rmpw.exe

Run rmpw.exe

In the "Data Selection and Preparation" window,

Click the radio button for "Stata" under "Input Data Type"

Browse the data file on your computer

Data Set for Exercise

idnumber

Outcome: **dep12sm2**

Treatment: **treat**

Mediator: **emp**

Categorical pretreatment covariates: **AGE, race, nohsdip, lowscores, teen_parent, nevmar, chcnt, ONAFDC, emp_prior**

Continuous pretreatment covariates: **Barriers, depress_t0, EARN1000_yr_prior**

Data Set for Exercise

Variable	Obs	Mean	Std. Dev.	Min	Max
treat	694	.2997118	.4584621	0	1
dep12sm2	661	7.443268	7.753115	0	34
emp	694	.4726225	.49961	0	1
AGE	694	.5	.5976143	0	2
race	694	.8948127	.9392218	0	3
nohsdip	694	.4769452	.4998284	0	1
lowscores	694	1.299712	.730356	0	3
teen_parent	694	.370317	.4832378	0	1
nevmar	694	.4279539	.495139	0	1
chcnt	694	1.998559	.8173785	1	3
Barriers	416	2.009615	1.447858	0	6
depress_t0	430	3.52093	3.373872	0	12
ONAFDC	694	1.059078	.9703972	0	3
emp_prior	694	.4927954	.7890521	0	2
EARN1000_y~r	694	1.513833	3.978319	0	39.4

Data Set for Exercise

Class Discussion

- Which covariates were not balanced after parametric propensity score-based weighting?
- How do you interpret the coefficients in the table "IPTW Adjusted Estimation of the Mediator Effect on the Outcome?"
- How do you interpret the coefficients in the table "Estimated Direct Effect and Indirect Effect of the Treatment on the Outcome (First set of decomposition)" averaged across 5 imputations?
- Are there any notable differences between the parametric results and the nonparametric results?

Stata, SAS, and R Code

(Standard Errors Maybe Incorrect)

Save the following files in

C:\NCME 2016\RMPW

- **Stata**

  Data file: “Riverside.dta"

  Do file: “Riverside.do” (Prepared by Jonah Deutsch)

- **SAS**

  Data file: “Riverside.sas7bdat”

  program file: “Riverside_SAS.sas” (Prepared by Yihua Hong)

- **R**

  Data file: “Riverside.dta"

  Command file: “Riverside_R.R” (Prepared by Xu Qin)

Extension: Moderated Mediation

- Two subpopulations (or two experimental sites):

  $V = 1$ vs. $V = 0$

- Propensity score analysis and RMPW computation within each subpopulation

- Outcome Model:

$$Y = V\left(\gamma_{V1}^{(0)} + \gamma_{V1}^{(DE)}T + \gamma_{V1}^{(IE)}D1\right) + \left(1 - V\right)\left[\gamma_{V0}^{(0)} + \gamma_{V0}^{(DE)}T + \gamma_{V0}^{(IE)}D1\right] + e$$

Extension: Multivalued Mediators

- Three-category mediator:

  M = 0, unemployment

  M = 1, low employment

  M = 2, high employment

- Propensity scores: $\theta_{M(1)=0}, \theta_{M(1)=1}, \theta_{M(1)=2};$

  $\theta_{M(0)=0}, \theta_{M(0)=1}, \theta_{M(0)=2}.$

- Outcome Model: Same as before

Summary:
Strengths of the RMPW Method

- Does not assume no treatment-by-mediator interaction
- Does not make assumptions about the functional form of the outcome model
- Unconstrained by the distribution of the outcome or the distribution of the mediator
- Directly estimates the natural direct and indirect effects and their standard errors
- Further decomposes the indirect effect or the direct effect and estimates the impact of treatment-induced change in the mediational process
- Easy to implement with standard software or the specialized RMPW software

Summary: Limitations of the RMPW Method

- Untestable sequential ignorability assumption!!!
  - Unmeasured pretreatment confounders
  - Unmeasured post-treatment confounders
- Correct specification of the propensity score models remains crucial especially when applying the parametric RMPW method

Most Relevant Readings

- Hong, G., Deutsch, J., & Hill, H. D. (2015). Ratio-of-mediator-probability weighting for causal mediation analysis in the presence of treatment-by-mediator interaction. *Journal of Educational and Behavioral Statistics*, *40*(3), 307-340.

- Hong, G. (2015). *Causality in a social world: Moderation, mediation, and spill-over*. West Sussex, UK: John Wiley & Sons.

Other Related Publications

- Bein, E., Deutsch, J., Porter, K., Qin, X., Yang, C., & Hong, G. (2015). *Technical report on two-step estimation in RMPW analysis*. MDRC.

- Hong, G. (2010). Ratio of mediator probability weighting for estimating natural direct and indirect effects. In *JSM Proceedings*, Biometrics Section. Alexandria, VA: American Statistical Association, pp.2401-2415.

- Hong, G., Deutsch, J., & Hill, H. (2011). Parametric and non-parametric weighting methods for estimating mediation effects: An application to the National Evaluation of Welfare-to-Work Strategies. In *JSM Proceedings*, Social Statistics Section. Alexandria, VA: American Statistical Association, pp.3215-3229.

- Hong, G., & Nomi, T. (2012). Weighting methods for assessing policy effects mediated by peer change. *Journal of Research on Educational Effectiveness* special issue on the statistical approaches to studying mediator effects in education research, *5*(3), 261-289.

Other Related Publications

- Huber, M. (2014). Identifying causal mechanisms (primarily) based on inverse probability weighting. *Journal of Applied Econometrics*, *29*(6), 920-943.

- Lange, T., Vansteelandt, S., & Bekaert, M. (2012). A simple unified approach for estimating natural direct and indirect effects. *American journal of epidemiology*, *176* (3), 190–195.

- Lange, T., Rasmussen, M., & Thygesen, L. (2014). Assessing natural direct and indirect effects through multiple pathways. *American journal of epidemiology*, *179* (4), 513-518.

- Tchetgen Tchetgen, E. J., & Shpitser, I. (2012). Semiparametric theory for causal mediation analysis: Efficiency bounds, multiple robustness and sensitivity analysis. *The Annals of Statistics*, *40*(3), 1816-1845.

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