Applying Propensity Score and Mediation Analysis to Program and Policy Evaluation

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Agenda for the Day

8:00-8:40  Overview of Methodological Issues

8:40-12:00 Propensity Score Analysis

with a break at approx. 10:15

12:00-1:00 LUNCH

1:00-4:20 Mediation Analysis

with a break at approx. 2:45

4:20-5:00 Summary and Final Comments

Discussion throughout
Applying Propensity Score and Mediation Analysis to Program and Policy Evaluation

Overview of Methodological Issues

Deb Rosenberg
The Epidemiologic Context for Evaluating Programs and Policies

Programs and policies are intended to interrupt a causal sequence that leads to an adverse outcome or to promote a causal sequence leading to a positive outcome.

The mechanism(s) of action are likely to be complex and may be aimed at differing points along a causal pathway.
The Epidemiologic Context for Evaluating Programs and Policies

The mechanisms of action and evaluating effectiveness are particularly difficult when looking at public health programs that have multiple components delivered in varying ways and with varying intensity. Some examples:

- prenatal care
- medical home
- home visiting
- Medicaid expansion
- workplace breastfeeding

What are the hypotheses about these programs and policies?
How do they operate along a causal pathway?
The Epidemiologic Context for Evaluating Programs and Policies

Is there an association between a program and an outcome? How much of that association operates through affecting a specific factor and how much operates through other pathways?

Here the program takes on the role of an exposure ("treatment") along the causal pathway.
The Epidemiologic Context for Evaluating Programs and Policies

Is there an association between a factor and an outcome? How much of that association operates through access to a specific program and how much operates through other pathways?

Here the program takes on the role of a mediator along the causal pathway.
Methodological Approaches to Test Hypotheses about Programs or Policies

The Counterfactual Framework

The only way we would truly know if a program, policy, or other "exposure" causes an outcome is if we could consider each individual under both conditions of experiencing the program or policy and of not experiencing the program or policy.

Since this is never possible, we aim to choose study designs and methodological approaches that can get us as close as feasible to what the counterfactual results would be.
Methodological Approaches to Test Hypotheses about Programs or Policies

Study Design and Sample Selection

• **Experimental design** with random assignment, subjects are recruited to study and then randomly assigned to receive the treatment / program / exposure

• **Quasi-experimental design**—no randomization, but some control over the program and subject selection

• **Observational design**—no randomization and no specific control over the program
Methodological Approaches to Test Hypotheses about Programs or Policies

It is often not feasible or ethical to conduct a randomized controlled trial for estimating the causal effect of a program on health outcomes. In addition, even quasi-experimental designs may not be possible for public health programs.

In observational studies, study bias—in particular selection bias—and confounding cannot be addressed prior to analysis, so methods are needed in order to obtain a precise estimate of program effect or its mechanisms of action.
Bias and Confounding

Biases—selection bias and information bias (misclassification, reporting) are related to an aspect of the analytic process itself: participant recruitment / retention, data collection or data analysis, resulting in an invalid estimate of effect.

Confounding—the distortion of the estimate of effect by another factor not explicitly related to an aspect of the analytic process.
Selection Bias

For evaluation of programs and policies, selection bias is particularly important because it results in a non-random sample for use in testing hypotheses.

Specific selection forces may operate singly or in combination to produce bias in program participation—that is, program participation reflects a systematic, non-random process.

Depending on which selection forces are operating, the effect of a program might be either over-estimated or under-estimated.
Selection Bias

**Over-estimation of program effect:**

1. Favorable selection: those at low risk, with better access to care generally, potentially more health conscious are *over*-represented in the program.

2. Estrangement selection: those at high risk, with life circumstances which generally distance them from the health care system are *under*-represented in the program.

*Methodological Note:* Selection Bias in Prenatal Care Use by Medicaid Recipients
Janice F. Bell, MN, MPH1, and Frederick J. Zimmerman, PhD,
Selection Bias

Underestimation of program effect:

3. Adverse selection: those at high risk spurred by symptoms, prior experience, or family history are over-represented in the program

4. Confidence selection: those at low risk who do not perceive a need based on prior experience, general good health status are under-represented in the program
Addressing selection bias and confounding—defining comparison groups

The counterfactual *a priori* achieves equivalence, as each individual is compared to his/herself. Statistical approaches aim to approach this at the population level.

- In experimental studies, the process of random assignment achieves equivalence, *on average*, between groups.
- In non-experimental studies, use matching or adjustment to achieve *on average* equivalence.
# Bias and Confounding

For each of the following research designs, the checkmarks indicate possible threats to internal validity. Where there are comparison groups, assume they have not been randomly assigned.

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Regression Modeling Approaches

Traditional multivariable regression involves specifying a single model for estimating the association between a program or policy—the "exposure"—and an outcome, addressing potential selection, effect modification and/or confounding:

\[ \text{Outcome} = \text{Program} + \text{covariates, inc. inter. terms} \]

The number and complexity of covariate adjustment will be constrained by sample size
Regression Modeling Approaches

Propensity Score Analysis and Mediation Analysis use more complex regression approaches than the usual linear model.

Each method uses a multi-step process, employing two regression equations.
Regression Modeling Approaches

Propensity Score Analysis

• A tool for approximating a randomized trial and reducing selection bias in observational studies

• On average, individuals with the same propensity score are balanced on a wide array of covariates, achieving close equivalence between the exposed and unexposed groups (participants and non-participants in a program).
Regression Modeling Approaches

Multi-step process for Propensity Score Analysis:

1. **Model I**: Program = pool of covariates
   (using entire sample to compute Pscores)

2. Use matching, stratification, or weighting

3. Check covariate balance

4. **Model II**: Outcome = Program
   (using only individuals successfully matched on propensity scores, or using entire sample stratified or weighted by propensity score)
Regression Modeling Approaches

Mediation Analysis:

• Explicitly addresses questions of causal processes and a chain of events; often addresses selection forces as part of that chain

• Provides a conceptual framework and accompanying analytic methods

• Decomposes the total effect of an exposure on an outcome (TE) into a natural direct effect (NDE) and a natural indirect effect (NIE) which involves a pathway through a specific mediator
Regression Modeling Approaches

Mediation analysis focuses on the role the program or policy plays as part of the causal pathway to the outcome.

The goal is to identify both direct and indirect pathways, either from the program through another factor to the outcome or direct and indirect pathways from a factor through the program to an outcome.

The direct and indirect pathways estimate counterfactual results.
Regression Modeling Approaches

Multi-step process for Mediation Analysis:

1. **Model I:** Outcome = \( E_{\text{posure}} + M_{\text{ediator}} + E \times M \)
   + pool of covariates

2. **Model II: Mediator =** \( E_{\text{posure}} \)
   + pool of covariates

3. Combine the coefficients from these models to calculate Natural Direct and Natural Indirect Effects
Examples and Interpretation

Among children with asthma:

Medical Home → Reduced Unmet Healthcare Needs → Fewer ER visits

*Note the directionality of all three variables*

The associations between a medical home and fewer ER visits, a medical home and unmet healthcare needs, and unmet healthcare needs and fewer ER visits may all be of interest.

The primary association is between the medical home—the program—and fewer ER visits among children with asthma. Other covariates farther back in the causal chain may be imposing selection bias on this association—which children receive care in the medical home model may not be random.
Examples and Interpretation

With medical home—the "program"—as the exposure / treatment and reduced unmet healthcare needs as the mediator, we may want to ask questions like the following:

1. What is the effect of the medical home on the number of ER visits among children with asthma through any mechanism – through all pathways?

2. What is the effect of the medical home on the number of ER visits among children with asthma if these children all had the same prevalence of unmet health care needs?

3. As one specific mechanism of the medical home, how important is reducing unmet healthcare needs in decreasing ER visits among asthmatic children?
Examples and Interpretation

**Typical regression: asthmatic children**

1. **Estimate the association between having a medical home and number of ER visits**

Estimate the association using the full sample, after adjusting for a small set of covariates, but **not** adjusting for unmet needs since hypothesized to be in the causal pathway.

2. **Estimate the association between unmet needs and the number of ER visits**

Estimate the association using the full sample, after adjusting for a small set of covariates, **including the medical home**
Examples and Interpretation

Propensity Score Analysis: asthmatic children

1. Estimate the association between having a medical home and number of ER visits
   • Estimate the association using only those children individually matched on their propensity for having a medical home, or using the full sample, stratifying or weighting by the propensity score.
   • The propensity score will include a wide array of covariates, but will not include unmet needs.
   • By more complete control for selection forces and confounding, the estimated association between having a medical home and ER visit should be close to unbiased.
Examples and Interpretation

Mediation Analysis:

2. Estimate the association between having a medical home and number of ER visits

Estimate the association using the full sample, adjusting for a small set of covariates and considering reduced unmet healthcare needs as a mediator.

By then calculating the Natural Direct Effect and Natural Indirect Effect, the results will inform an understanding of the extent to which the medical home does and does not operate through reduction in unmet healthcare needs.
Examples and Interpretation

Mediation Analysis: asthmatic children

**Estimate the Natural Direct Effect:** the association between a medical home and ER visits while fixing the prevalence of reduced unmet needs to that seen among asthmatic children without a medical home.

The NDE indicates the magnitude of the association between having a medical home and ER visits that exists even with equal prevalence of unmet needs. This reflects the extent to which the medical home operates through pathways other than reducing unmet needs (has other mechanisms of action).
Examples and Interpretation

Mediation Analysis: asthmatic children

**Estimate the Natural Indirect Effect:** the expected change in the odds of fewer ER visits among asthmatic children with a medical home, if the prevalence of reduced unmet needs in this group instead mirrored that seen among asthmatic children without a medical home.

The NIE indicates the importance of reduction of unmet healthcare needs as one way having a medical home works to decrease ER visits among asthmatic children.

**Estimate the Total Effect (TE):** the association between having a medical home and ER visits through all pathways—the product (on the log scale) of the NDE and NIE.
Examples and Interpretation

Intention to BF → BF Support in hospital → Exclusive BF at discharge

*Note the directionality of all three variables*

The associations between intention to breastfeed and BF support, intention to BF and exclusive breastfeeding at discharge, and BF support and exclusive BF at discharge may all be of interest.

Intention to breastfeed may impose selection bias when estimating the association between BF hospital support and BF at discharge since hospital staff may differentially provide support and women may differentially report support depending on their stated intentions.
Examples and Interpretation

With intention to BF as the exposure and the "program" of BF support in the hospital as the mediator, we may ask questions like the following:

1. What is the effect of BF support in the hospital on exclusive BF at discharge after accounting for selection bias and confounding, particularly that imposed by intention to BF?
2. What is the effect of intention to BF on exclusive BF at discharge if women had equal access to BF support in the hospital?
3. Would increasing access to BF support in the hospital for women not initially intending to BF improve the odds that these women will exclusively BF at discharge?
Examples and Interpretation

**Typical regression:**

1. Estimate the association between BF support in the hospital and exclusive BF at discharge

   Estimate the association using the full sample, adjusting for a *small set of covariates*, **including** intention to BF.

2. Estimate the association between intention to BF and exclusive BF at discharge

   Estimate the association using the full sample, adjusting for a *small set of covariates*, **not** including BF in the hospital since hypothesized to be in the causal pathway.
Examples and Interpretation

Propensity Score Analysis:

1. Estimate the association between BF support in the hospital and exclusive BF at discharge

   • Estimate the association using only those women individually matched on their propensity for receiving BF support, or using the full sample, stratifying or weighting by the propensity score

   • The propensity score will include intention to BF along with a wide array of other covariates

   • By more complete control for selection forces and confounding, the estimated association between BF support and exclusive BF at discharge should be close to unbiased.
Examples and Interpretation

Mediation Analysis:

2. Estimate the association between intention to BF and exclusive BF at discharge

Estimate the association using the full sample, adjusting for a small set of covariates, considering BF support in the hospital as a mediator.

By then calculating the Natural Direct Effect and the Natural Indirect Effect, the results will inform an understanding of the extent to which the relationship between intention to BF and exclusive BF at discharge may or may not be altered by improved access to BF support in the hospital.
Examples and Interpretation

**Mediation Analysis:**

**Estimate the Natural Direct Effect:** the association between BF intention and exclusive BF at discharge while **fixing** the prevalence of bf support in the hospital to that seen among women **not** intending to bf.

The NDE indicates the magnitude of association between intention and exclusively BF at discharge that exists even with equal prevalence of BF support. This reflects the extent to which intention operates through pathways other than receiving the "program".
Examples and Interpretation

Mediation Analysis

**Estimate the Natural Indirect Effect:** the expected change in the odds of exclusive BF at discharge among women intending to BF, if the prevalence of receiving BF support in this group instead mirrored that seen among women not intending to BF.

The NIE indicates the importance of BF support in the hospital as one way to ameliorate the effect of intention to breastfeed on exclusively breastfeeding at discharge.

**Estimate the Total Effect (TE):** the association between intention to BF and exclusive BF at discharge through all pathways—the product (on the log scale) of the NDE and NIE.
Asking Appropriate Questions; Applying Appropriate Methods

Public health programs and policies are often multi-faceted and complex. There are many questions to be asked and hypotheses to be tested in order to understand program effectiveness.

Typical multivariable regression, propensity score analysis, and mediation analysis are all appropriate analytic approaches depending on the study design and the hypotheses being tested.