# PH784 Advanced Social Epidemiology: Methods

*Week 7: Mediation & Review*

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# Today's Plan

1. Simulating disparities
2. Mediation
    - Basics
    - Applications in social epi
    - Connecting back to 1
3. High-level Review

# Let's Step Back: Anatomy of Causal Estimand

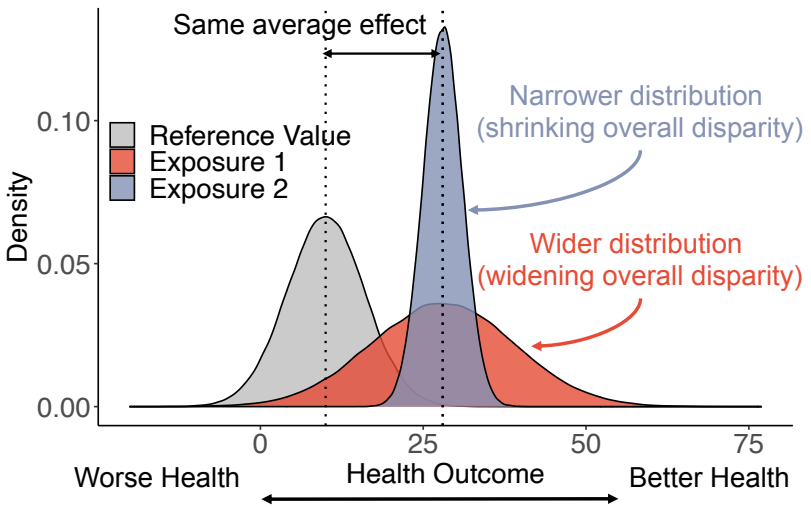
$$E[Y^{a=1}] - E[Y^{a=0}]$$

**This comparison is defined based on the choice of:**

1. Hypothetical interventions to define potential outcomes
    - Well-defined treatment, directionality, regimen (time-varying, dynamic, stochastic)
2. Study population (e.g., mean among whom?)
    - Subpopulation: ATE vs CATE, ATT, ATC, etc
3. Reference (e.g., $a = 0$)
    - vs natural course
4. **Summary measure** (e.g., mean difference)

# Summarizing Changes in Population Health

*Distribution beyond mean*




- Hypothetical interventions may have:
  - → Same "effect" on average population health
  - → Different implications for distributions
    - i.e., health disparities

## Shifting the definition of "causal effect"

- "How would the hypothetical intervention change health disparities?"
  - → e.g., $(E[Y^{A^g}|SES = high] - E[Y^{A^g}|SES = low]) - (E[Y|SES = high] - E[Y|SES = low])$
    - for stochastic intervention $A^g$
  - → "The gap-closing estimand" (Lundberg 2024)
  - → Example: Social isolation and social inequalities in all-cause mortality (Lunar et al. 2025)

# Population Interventions and Health Disparity

- Interventions may alter health disparities across social groups via:
  - → **Socially patterned effect heterogeneity**
    - $E[Y^{a=1} - Y^{a=0}|L = l] \neq E[Y^{a=1} - Y^{a=0}|L = l^*]$
    - Narrow disparities if more beneficial among minoritized groups
    - Widen disparities if less beneficial among minoritized groups
  - → **Disproportionate change in exposure distribution**
    - If minoritized groups experienced greater changes in exposure, they benefit more
    - Ignored in the “all treated” scenario of CATE

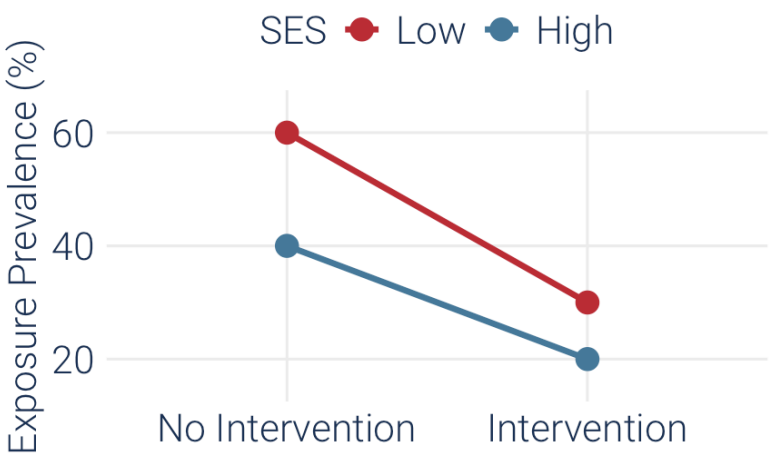
**(!) Estimating CATEs alone is inadequate**

When do interventions result in disproportionate change in exposure?

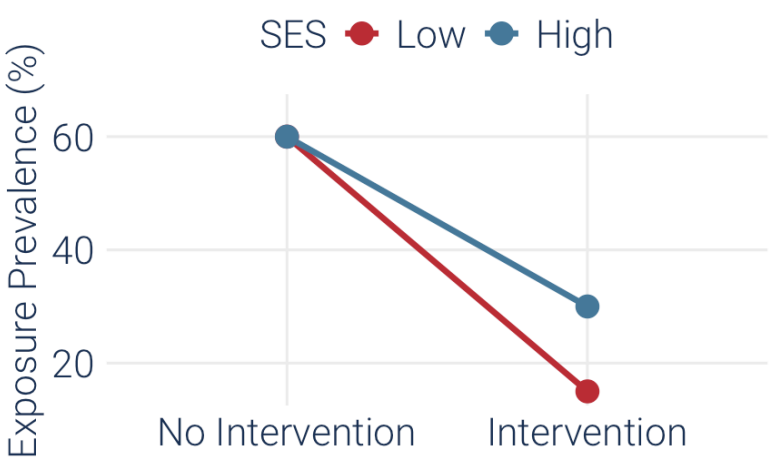
# Population Interventions and Health Disparity

*When do interventions disproportionately change exposure distributions?*

- **Existing exposure disparity**
  - → More prevalent among the low SES group
  - → Even the same relative reduction would result in greater absolute reduction
    - e.g., reducing exposure by half
      - 60% to 30% (30 percentage points reduction)
      - 40% to 20% (20 percentage points reduction)




- **Disproportionate reduction in the exposure**
  - → Even when there is no exposure disparity
    - Exposure prevalence 60% in both SES groups
      - 60% to 15% (quarter)
      - 60% to 30% (half)
    - Distinguish this from effect heterogeneity
  - → *Example?*
    - Water fluoridation



# Population Interventions and Health Disparity

*How do we simulate effects on health disparities rather than average health?*

- Key ingredients of health disparities
  - → **Effect heterogeneity**
    - $E[Y^{a=1} - Y^{a=0}|L = l] \neq E[Y^{a=1} - Y^{a=0}|L = l^*]$
  - → **Disproportionate changes in exposure**
    - How do we incorporate disproportionate changes in exposure in causal estimand?
    - Stochastic intervention
      - Various estimators (e.g., Muñoz and Van Der Laan 2012)
        - e.g., Standardization (as in Ahern et al. 2016)

# Population Interventions and Health Disparity

*How do we simulate effects on health disparities rather than average health?*

| $ID$ | $Y$ | $A$ | $L$ | $\tau(L)$ | $a=1$ | $a=0$ | $Y^{a=1}$ | $Y^{a=0}$ |
|---|---|---|---|---|---|---|---|---|
| 1 | $Y_1$ | 1 | $\ell_1$ | $\tau_1$ | 1 | 0 | $Y_1$ | $Y_1 - \tau_1$ |
| 2 | $Y_2$ | 0 | $\ell_2$ | $\tau_2$ | 1 | 0 | $Y_2 + \tau_2$ | $Y_2$ |
| 3 | $Y_3$ | 0 | $\ell_3$ | $\tau_3$ | 1 | 0 | $Y_3 + \tau_3$ | $Y_3$ |
| $\dots$ | $\dots$ | $\dots$ | $\dots$ | $\dots$ | $\dots$ | $\dots$ | $\dots$ | $\dots$ |
| n | $Y_n$ | $A_n$ | $\ell_n$ | $\tau_n$ | 1 | 0 | $Y_n + (1 - A_n)\tau_n$ | $Y_n - A_n\tau_n$ |

- **Simple standardization for static interventions**
  - → #1 Assign everyone to be treated $a = 1$ (6th column) and untreated $a = 0$ (7th column)
  - → #2 Predict potential outcome under each scenario ($Y^{a=1}$ & $Y^{a=0}$)
    - Based on estimated effects $\tau_i$
  - → #3 Calculate mean of $Y^{a=1}$ and mean of $Y^{a=0}$ across all individuals
  - → #4 Calculate the difference between the two means & bootstrap
    - ATE: $E[Y^{a=1}] - E[Y^{a=0}]$

# Population Interventions and Health Disparity

*How do we simulate effects on health disparities rather than average health?*

| $ID$ | $Y$ | $A$ | $L$ | $\tau(L)$ | $A^g$ | $Y^{A^g}$ |
|---|---|---|---|---|---|---|
| 1 | $Y_1$ | 1 | $\ell_1$ | $\tau_1$ | 1 | $Y_1$ |
| 2 | $Y_2$ | 0 | $\ell_2$ | $\tau_2$ | 0 | $Y_2$ |
| 3 | $Y_3$ | 0 | $\ell_3$ | $\tau_3$ | 1 | $Y_3 + \tau_3$ |
| … | … | … | … | … | … | … |
| n | $Y_n$ | $A_n$ | $\ell_n$ | $\tau_n$ | $A_i^g$ | $Y_n + (A_i^g - A_n)\tau_n$ |

- **Standardization for stochastic interventions**
  - → #1 Assign exposure distributions under a stochastic intervention of interest
    - e.g., randomly removing exposure by 50%
    - e.g., lowering propensity scores by 50%
  - → #2 Predict potential outcome $Y^{A^g}$ based on estimated effects $\tau_i$
  - → #3 Calculate mean of $Y^{A^g}$ and mean of observed outcome $Y$ across all individuals
  - → #4 Calculate the difference between the two means & bootstrap
    - Stochastic intervention effect: $E[Y^{A^g}] - E[Y]$
      - compared to “no intervention”

# Population Interventions and Health Disparity

*How do we simulate effects on health disparities rather than average health?*

| $ID$ | $Y$ | $A$ | $L$ | $\tau(L)$ | $A^g$ | $Y^{A^g}$ |
|---|---|---|---|---|---|---|
| 1 | $Y_1$ | 1 | $\ell_1$ | $\tau_1$ | 1 | $Y_1$ |
| 2 | $Y_2$ | 0 | $\ell_2$ | $\tau_2$ | 0 | $Y_2$ |
| 3 | $Y_3$ | 0 | $\ell_3$ | $\tau_3$ | 1 | $Y_3 + \tau_3$ |
| ... | ... | ... | ... | ... | ... | ... |
| n | $Y_n$ | $A_n$ | $\ell_n$ | $\tau_n$ | $A_i^g$ | $Y_n + (A_i^g - A_n)\tau_n$ |

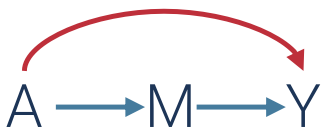
- **Standardization for stochastic interventions on health disparities**
  - → #1 Assign exposure distributions under a stochastic intervention of interest
  - → #2 Predict potential outcome $Y^{A^g}$ based on estimated effects $\tau_i$
  - → #3 Calculate disparities in $Y^{A^g}$ and disparities in observed outcome $Y$
  - → #4 Calculate the difference between the two disparities & bootstrap
    - e.g., $(E[Y^{A^g}|SES = high] - E[Y^{A^g}|SES = low]) - (E[Y|SES = high] - E[Y|SES = low])$
      - "How would the hypothetical intervention change SES-based health disparities?"
    - "The Gap-closing Estimand" (Lundberg 2024) or "Disparity Treatment Effect" (Shiba)
      - Example: Social isolation and social inequalities in all-cause mortality (Lunar et al. 2025)

# Summary 1

- **Two key ingredients of health disparities**
  - → **Effect heterogeneity**
  - → **Exposure disparities**
    - Often ignored by considering the “all exposed vs unexposed” scenarios
- Standardization to predict potential outcome distributions under hypothetical stochastic interventions
  - → Consider estimand that explicitly captures changes in disparities
  - → Disparity effect

# Mediation Analysis

*Two effects in mediation analyses*




- **Indirect Effect**
  - → Effect of exposure $A$ through mediator $M$
- **Direct effect**
  - → Effect of exposure $A$ that is independent of mediator $M$
    - Various definitions depending on the motivation
    - Should be chosen based on causal estimand of interest.

### Motivation for Causal Mediation Analysis

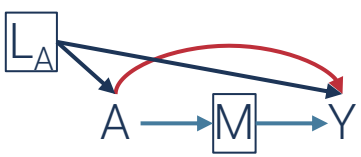
- **#1 Target of interventions**
  - → Particularly useful when “exposure” is hard to manipulate
- **#2 Effect decomposition**
  - → Explaining what explains the effect that we are observing
  - → Strengthening theory and generating hypotheses

# Naive Approach: Difference Method

*Example: Linear regression of outcome $Y$ on exposure $A$ adjusting for confounders $L_A$*




- Model 1: $E[Y|A, L_A] = \beta_0 + \beta_1 A + \beta L_A$
  - → $\beta_1$: Total effect of $A$ on $Y$ (within strata of $L_A$)
    - Assuming exchangeability conditional on $L_A$

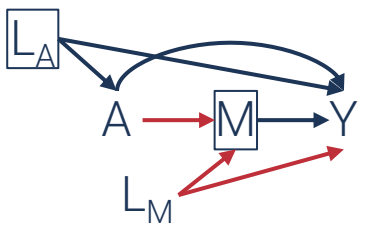



- Model 2: $E[Y|A, M, L_A] = \gamma_0 + \gamma_1 A + \gamma_2 M + \gamma L_A$
  - → Additionally adjust for mediator $M$
    - Attenuation as "evidence of mediation"
  - → $\gamma_1$: Effect of $A$ conditional on $M$
    - Effect that is independent of $M$
    - Direct effect
  - → $\beta_1 - \gamma_1$: Effect of $A$ through $M$
    - Indirect Effect

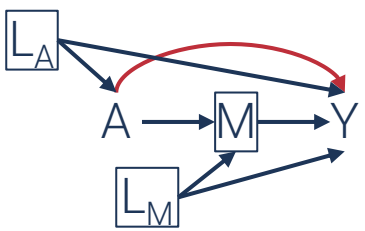
**⚠Any potential issue?**

# Naive Approach: Difference Method

*Example: Linear regression of outcome $Y$ on exposure $A$ adjusting for confounders $L_A$*




- Model 2: $E[Y|A, M, L_A] = \gamma_0 + \gamma_1 A + \gamma_2 M + \gamma L_A$
  - → $\gamma_1$: Association between $A$ and $Y$ conditional on $M$
    - $M$ as a collider
      - Selection bias through mediator-outcome confounders $L_M$
    - Ignored exposure-mediator interaction $A \times M$




- Model 3:
  $E[Y|A, M, L_A, L_M] = \theta_0 + \theta_1 A + \theta_2 M + \theta_3 A \times M + \theta L_A + \delta L_M$
  - → $\theta_1 : E[Y|A = 1, M = 0, L_A, L_M] - E[Y|A = 0, M = 0, L_A, L_M]$

**Corresponding causal estimand?**

- $E[Y^{a=1,m=0} - Y^{a=0,m=0}|L_A, L_M]$ under conditional exchangeability for BOTH $A$ and $M$
  - → "The effect of $A$ while fixing the mediator to $m = 0$"
    - Joint intervention for both $A$ and $M$
    - Controlled Direct Effect

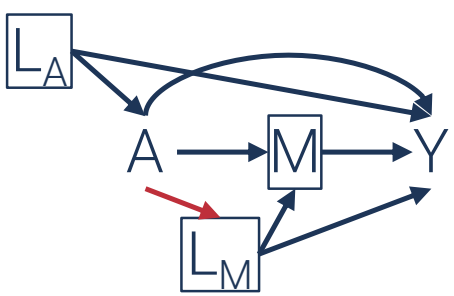
# Causal Mediation Analysis

- Naive regression analysis is often:
  - → Based on strong and potentially incorrect assumptions
  - → Vague or potentially irrelevant causal estimand

- **Causal mediation analysis**
  - → First, define Direct/Indirect Effects based on potential outcomes
    - CDE, NDE, IDE, etc
  - → Second, consider identification assumptions
  - → Third, estimate the target statistical estimand
    - Can be regular outcome regression
      - if assumptions are valid and corresponding estimand is of interest
    - But also flexible estimation via weighting, machine learning, etc

# Controlled Direct Effect

- **Total Effect**: $TE = E[Y^{a=1} - Y^{a=0}]$
- **Controlled Direct Effect**: $CDE(m) = E[Y^{a=1,m} - Y^{a=0,m}]$
  - → Function of a specific mediator value $m$
- "Proportion eliminated": $(TE - CDE(m))/TE$
  - → How much of the total effect of $A$ would be eliminated if we intervened and fixed mediator value to $m$ for everyone?




- CDE as a joint intervention for $A$ and $M$
  - → Can be viewed as time-varying treatment analysis
  - → CDE can be identified in the presence of exposure-induced confounding: $A \to L_M$
    - Adjusting for time-dependent confounding via g-methods
    - e.g., "Causal mediation via marginal structural model" (Nandi et al. 2012)

# “Hypothetical Mediator Intervention”

- Controlled Direct Effect: $CDE(m) = E[Y^{a=1,m} - Y^{a=0,m}]$
  - → Joint intervention that also fixes mediator to a specific value $m$
    - Deterministic intervention for $M$
    - Different $CDE(m)$ estimates across $m$ values with the exposure-mediator interaction
  - → How do we choose a meaningful $m$ value?
    - Policy relevance (might be feasible with a binary $M$)
    - But hard to pick a single value for $M$ with numerous levels
      - e.g., fixing PM2.5 to $9\mu g/m^3$ for everyone

**Alternative hypothetical mediator intervention**

- A random draw from a distribution of mediator values $\mathcal{M}$
  - → e.g., $\mathcal{M}(a|L)$
  - → “Distribution of mediator values that would have been observed among people like you (in terms of covariates $L$) had they received treatment $a$”

# “Hypothetical Mediator Intervention” for a Mediator Distribution

- **Interventional Direct Effect**
  - → $IDE = E[Y^{a=1,\mathcal{M}(0|L)} - Y^{a=0,\mathcal{M}(0|L)}]$
    - Exposure effect that would be observed while fixing the *distribution* of mediator values
      - Distribution under $a = 0$ conditional on $L$
      - Additionally require no A-M confounding assumption
    - Can also be defined as $IDE = E[Y^{a=1,\mathcal{M}(1|L)} - Y^{a=0,\mathcal{M}(1|L)}]$
  - → Non-zero $IDE$
    - Suggests the presence of effect of $A$ that is independent of $\mathcal{M}$
      - Hence, direct effect

- Extending causal inference for distributional interventions (see Lecture 5) to mediation
  - → Stochastic interventional effect (Rudolph et al. 2018)
    - aka interventional effects, randomized interventional analogs
  - → Flexible specification of $\mathcal{M}$

# Extension to Health Disparity Research




- Example in Nguyen et al. (2021)
  - → Y: Wellbeing
  - → M: Bullying
  - → A: Sexual minority
- Observed disparity:
  - → $\mathcal{D} = E[Y|A=1] - E[Y|A=0]$

- Counterfactual disparity under a hypothetical intervention ($A^g$) equalizing the level of bullying $\mathcal{M}$ among sexual minority to the level experienced by majority (i.e., $\mathcal{M}(0)$)
  - → $\mathcal{D}^{A^g} = E[Y^{\mathcal{M}(0)}|A=1] - E[Y|A=0]$
- **"Decomposing" disparity**
  - → $\mathcal{D} = E[Y|A=1] - E[Y|A=0]$
    - $= E[Y|A=1] - E[Y^{\mathcal{M}(0)}|A=1] + E[Y^{\mathcal{M}(0)}|A=1] - E[Y|A=0]$
    - $= E[Y|A=1] - E[Y^{\mathcal{M}(0)}|A=1] + \mathcal{D}^{A^g}$

Nguyen et al. (2021) used the notation $E[Y^{1,\mathcal{M}(0,C)}|A=1,C] - E[Y|A=0,C]$ for $\mathcal{D}^{A^g}$, which I think is a typo because they conceptualized no hypothetical intervention for sexual minority status. Also note that their estimand is conditional on covariates $C$. A marginal rather than conditional distribution $\mathcal{M}$ may

# Extension to Health Disparity Research

- "Decomposing" disparity
  - → $\mathcal{D} = E[Y|A=1] - E[Y^{\mathcal{M}(0)}|A=1] + \mathcal{D}^{A^g}$
    - Observed disparity = "Disparity-removed" + Remaining disparity under an intervention

- Causal inference for health disparity
  - → Often viewed as an extension of effect decomposition/mediation
  - → But the causal estimand involves no counterfactual for the "exposure"
    - e.g., no conceptualization of "race effect"
      - Avoid the potential consistency concern for the "exposure"
        - No components corresponding to "direct/indirect effects"
      - (My view) a more general extension of stochastic intervention effect rather than mediation

**! Which is more relevant?**

- The decomposition?
- The expected change in disparity (i.e., $\mathcal{D} - \mathcal{D}^{A^g}$)?
  - → The "Gap-closing Estimand" (Lundberg 2024) or "Disparity (Treatment) Effect" (Shiba)

# Disparity Effect and Effect Decomposition

- Example from this slide
- "Disparity effect"
  - → $(E[Y^{A^g}|SES = high] - E[Y^{A^g}|SES = low]) - (E[Y|SES = high] - E[Y|SES = low])$
    - "How would the hypothetical intervention change SES-based health disparities?"
    - e.g., what if the distribution of $A$ among $SES = low$ is identical to that of $SES = high$
      - Can conceptualize alternative interventions more flexibly
      - Simulating how interventions may change "exposure disparities" (see this slide)

**Different notation/estimand but same idea**

- Mediation would have conceptualized SES as an "exposure"
  - → Here, the "exposure" is what mediation would conceptualize as a mediator ($M$)
    - Correspond better to conceptualized hypothetical interventions ($A^g$)
      - Manipulating the distribution of $A$ while conducting no explicit intervention for SES
- More explicit focus on consequence rather than explanation
- Can incorporate "allowability" (Jackson 2021)

# Disparity Effect and Effect Decomposition

- Framing & terminology do not matter as long as you are:
  - → Explicit about causal estimand of interest
  - → Explicit about a hypothetical intervention under consideration
    - Social identity as a factor that defines disparity rather than an interventional target
- Many estimators
  - → Standardization
    - Explicit focus on the two key ingredients of disparity
      - Effect heterogeneity & exposure disparities
      - Potentially different insights depending on which is the primary driver
  - → IPW
  - → Doubly-robust
    - Modeling of the ingredients tended to be avoided or treated implicitly as intermediate estimation steps

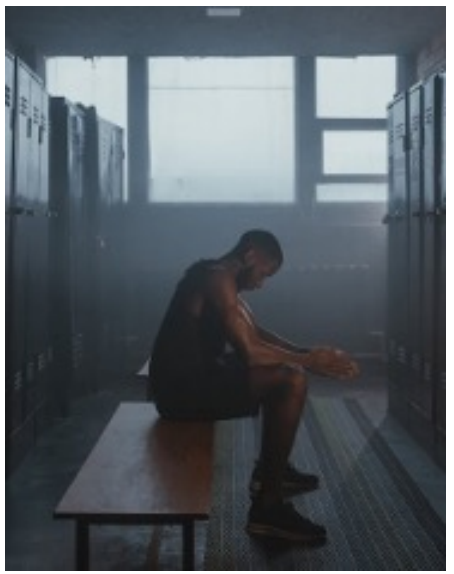
# Disparity Effect and Effect Decomposition

*Further readings*

- **On the importance of heterogeneity in disparity research**
  - → Ward et al. (2019) & Shiba and Inoue (2024)
- **Decomposition/mediation framework**
  - → Jackson and VanderWeele (2018), Jackson (2021), Jackson and VanderWeele (2019)
  - → Comprehensive summary by Qin and Jackson (2025) & Chang et al. (2024)
  - → On using CDE in disparity research by Naimi et al. (2016)
  - → Non-parametric approach by Yu and Elwert (2025)
- **More general disparity estimand**
  - → Excellent review by Opacic et al. (2025)
  - → "Gap-closing estimand" by Lundberg (2024)
  - → Recent development by Jackson et al. (2024)
  - → Wang *et al* (forthcoming)

# Simulating Disparity Effects: An Applied Example

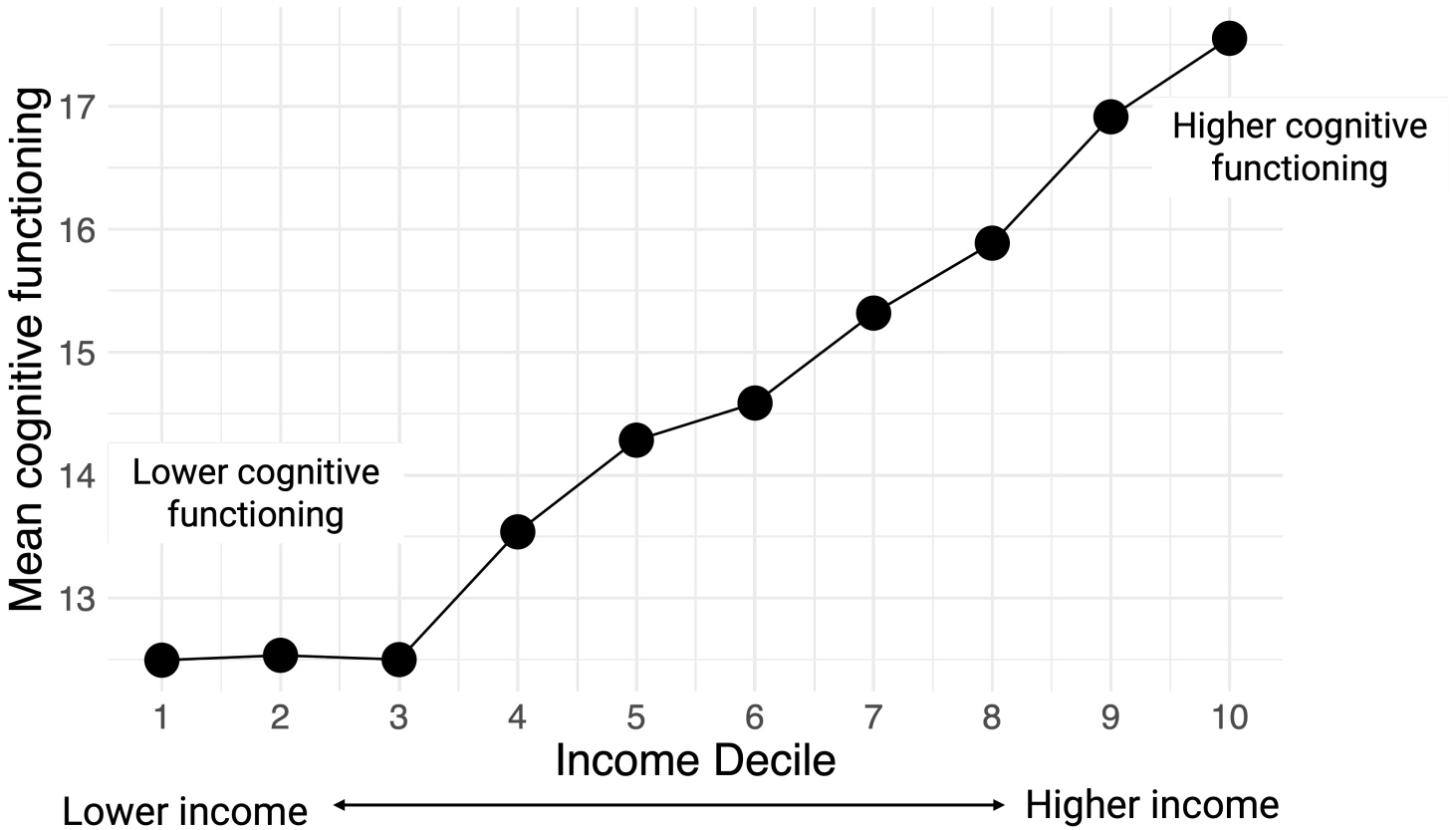
*Social isolation and cognitive functioning of older adults (from Lecture 6)*



- **Data:** Health and Retirement Study (n=11,322)
- **Exposure:** Social isolation (dichotomized composite index)
  - → Marital status and cohabitation
  - → Contact with children, family, and friends
  - → Social participation
- **Outcome:** Cognitive functioning (TICS; 0-27 points)
- **Covariates:** 35 pre-baseline covariates
- **Analysis:**
  - → Non-parametric estimation of CATE ($E[Y^{a=1} - Y^{a=0}|L]$) via Causal Forest
  - → Simulated changes in disparities in cognitive functioning using the standardization approach described in this slide

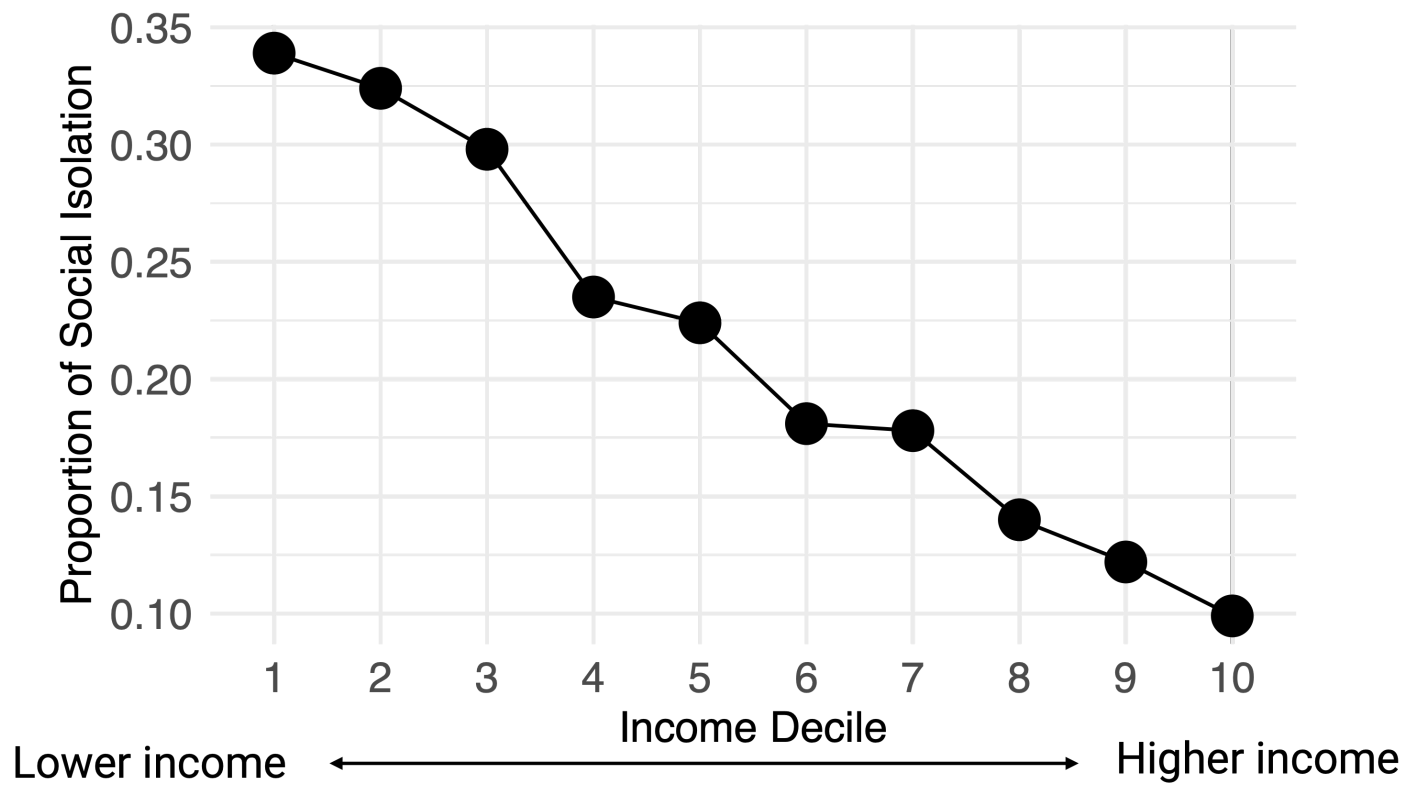
# Observed Outcome Disparities

- Lower income was associated with lower levels of cognitive functioning



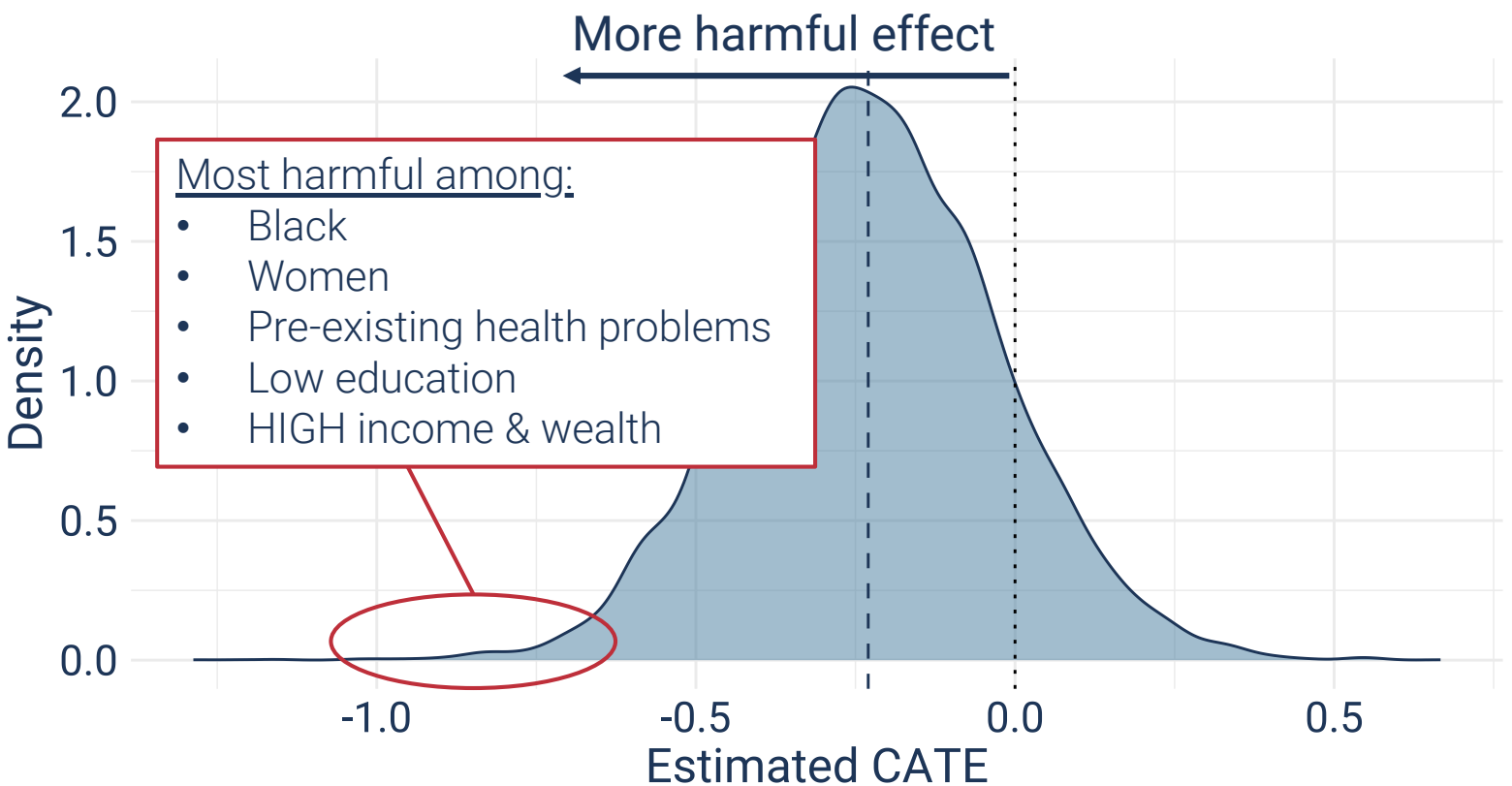
# Ingredient 1: Exposure Disparity

- Lower income was associated with higher prevalences of social isolation
  - → Same trends for wealth, education, and race and ethnicity
    - Socially marginalized groups are more likely to be *exposed* to social isolation



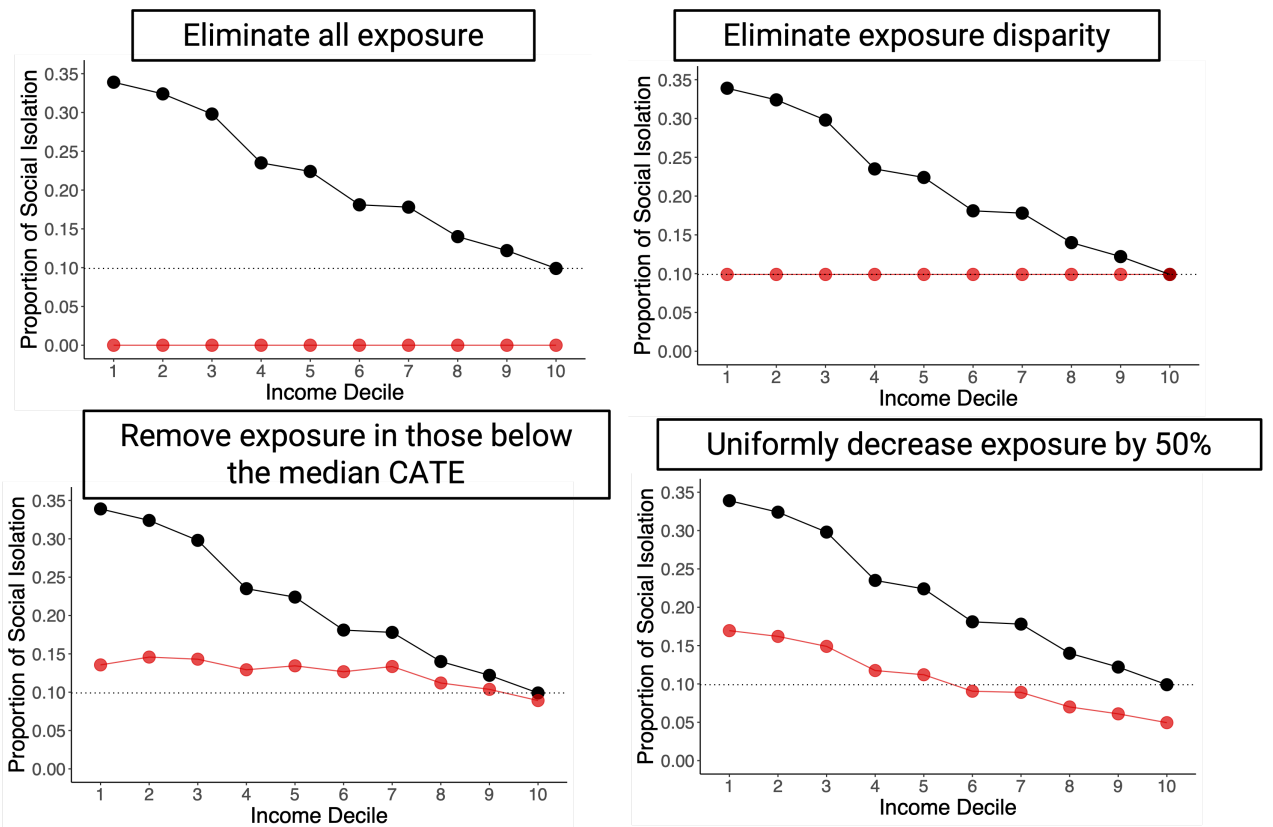
# Ingredient 2: Effect Heterogeneity

- Socially marginalized groups are *harmed* more severely by social isolation
  - → Despite the notable trend by intersections of high income and other forms of social marginalization (small in size)



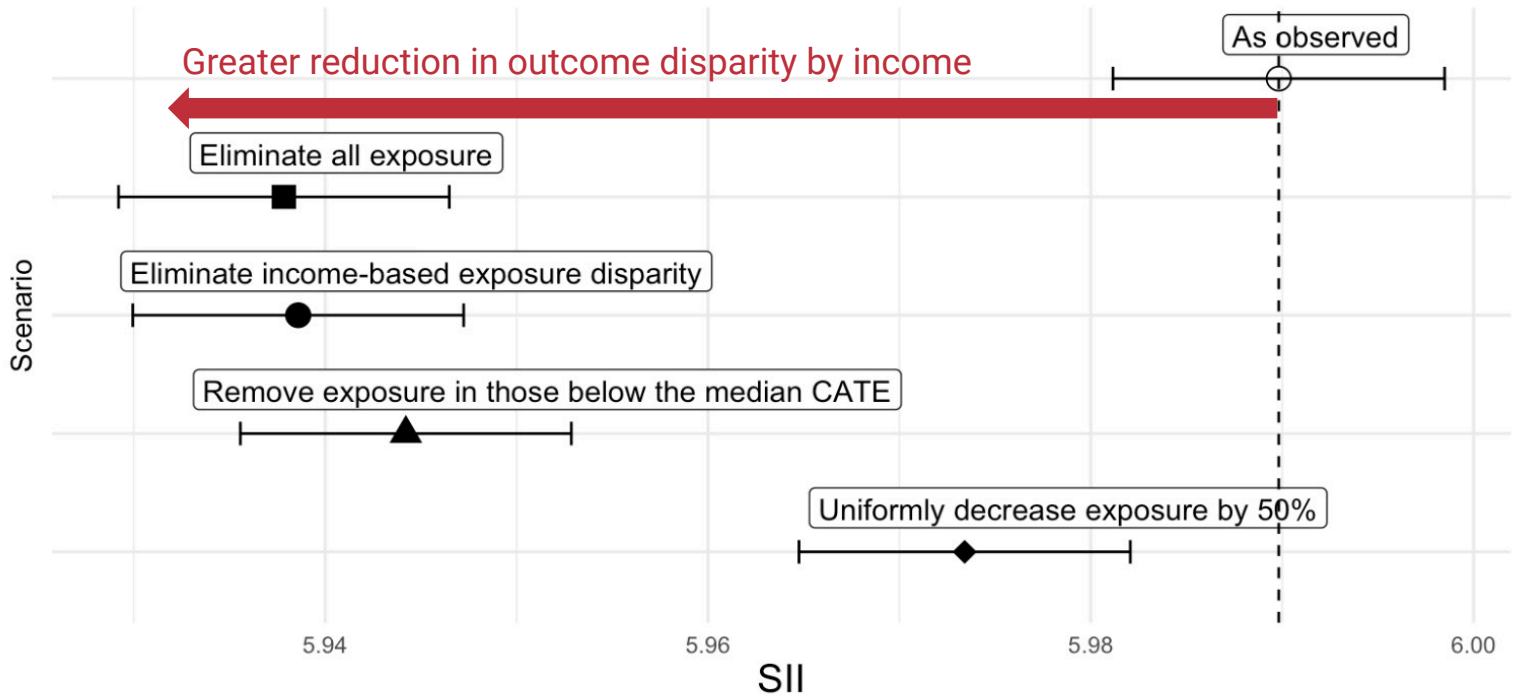
# Hypothetical Interventions

- Interventions that remove social isolation among the exposed
  - → Explicitly addressing exposure disparities
  - → Preserve exposure disparities while reducing the population-wide prevalence



# Simulated Disparity Effects

- Population interventions for social isolation would reduce income-based disparities in cognitive functioning
  - → Same trend for wealth, education, and race and ethnicity
  - → Particularly so when the intervention explicitly addresses exposure disparities



# Summary 2

- **Controlled Direct Effect (CDE)**
  - → Joint intervention for both exposure and mediator
    - Fixing mediator to a specific value
  - → Conditional exchangeability assumptions
    - No A-Y confounding, no M-Y confounding
- **Interventional Direct Effect (IDE)**
  - → Joint intervention for both exposure and mediator
    - Setting a mediator distribution
  - → Conditional exchangeability assumptions
    - Same as CDE + no A-M confounding
- **Disparity Effect**
  - → Extension of stochastic intervention analysis
  - → Can be also viewed as “effect” decomposition
    - But no causal “effect” conceptualized for exposure

# Mediation for Effect Decomposition

- CDE as a joint intervention
  - → "What is the remaining effect of $A$ if I fix $M$ to $m$ via an intervention?"
    - Does not capture the extent to which mediator *explains* the exposure effect that they would experience without the mediator intervention
    - … because people may take various mediator values under the intervention $A \rightarrow a$
      - Counterfactual mediator values $M^a$
      - Mediator level that a *person* would have naturally experienced had the *person* received $a$
- **Natural Direct Effect**
  - → $NDE = E[Y^{a=1,M^1}] - E[Y^{a=0,M^1}]$
    - Can be also defined as $E[Y^{a=1,M^0}] - E[Y^{a=0,M^0}]$
  - → What is the remaining effect of $A$ if mediator is set to the same level for each individual?
    - Hence, direct effect

# Identification for Natural Effects

- Conceptualizing the potential outcome $Y^{a,M^{a^*}}$
  - → Involves the effect of A on M
    - Another set of identification assumptions
      - Conditional exchangeability, consistency, and positivity for the A-M relationship
  - → Two different counterfactuals embedded simultaneously
    - "Cross-world independence"
      - Additional assumption: No exposure-induced M-Y confounding

**NDE/NIE requires stronger assumptions than CDE**

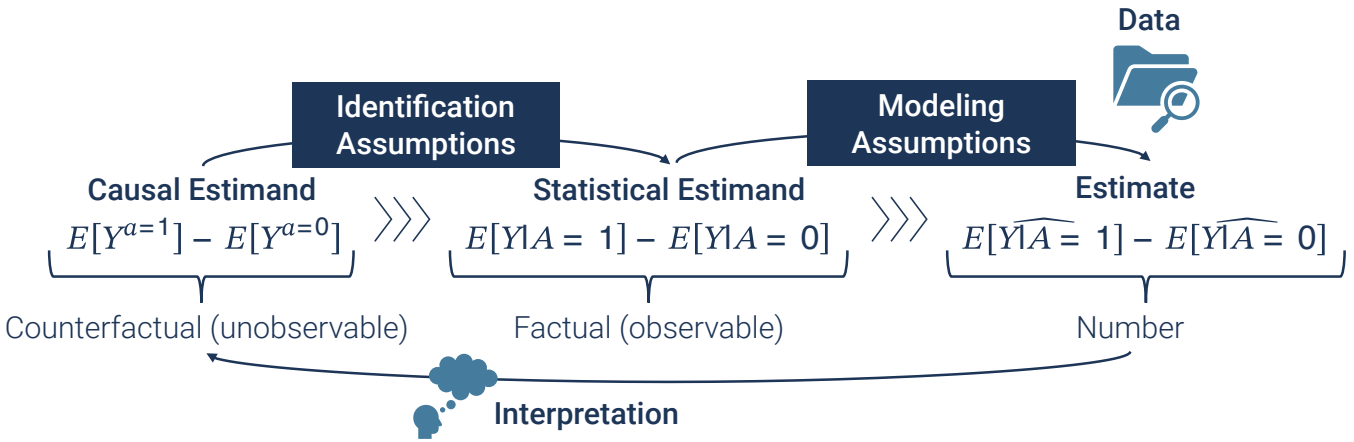
# Mediation for Effect Decomposition

- Total effect $TE = E[Y^{a=1}] - E[Y^{a=0}]$
  - → $TE = E[Y^{a=1,M^1}] - E[Y^{a=0,M^0}]$ by consistency for the effect of $A$ on $M$
  - → $E[Y^{a=1,M^1}] - E[Y^{a=0,M^1}] + E[Y^{a=0,M^1}] - E[Y^{a=0,M^0}]$
  - → $NDE + NIE$
- **"Natural Indirect Effect (NIE)"**
  - → The magnitude of exposure effect mediated through $M$
  - → "Proportion mediated": $NIE/TE$
    - Distinguish this from "proportion eliminated" in this slide
      - Read VanderWeele (2013) on their differences
- Effect can be decomposed into smaller componenents
  - → e.g., separating effects attributable to effect heterogeneity or mediation
  - → Can be useful to test alternative hypotheses about mechanisms
    - e.g., life course epidemiology (Yazawa et al. 2022)

# Summary 3

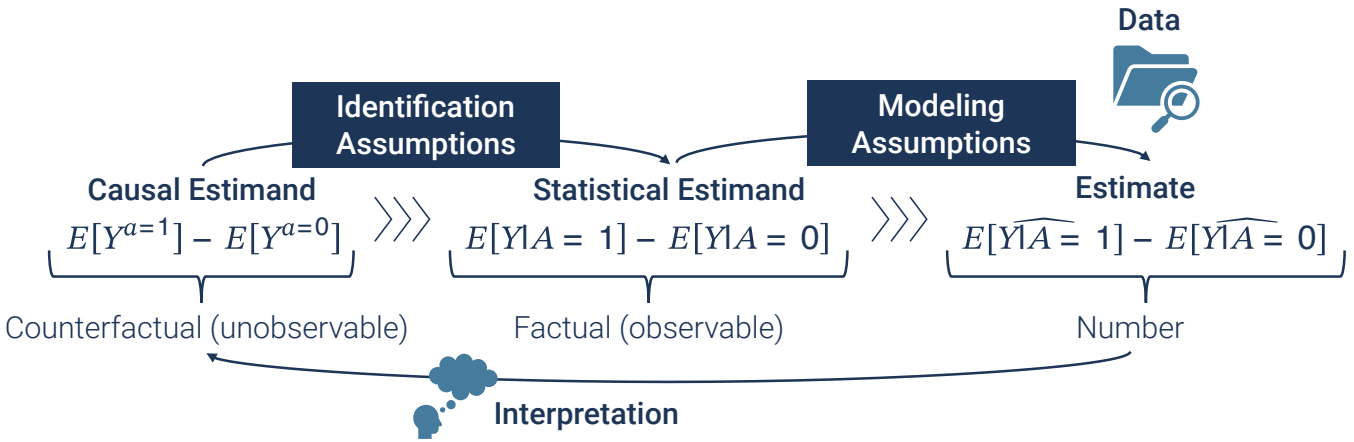
- **Natural Direct Effect (NDE)**
  - → Definition based on cross-world counterfactuals
  - → Useful for effect decomposition
    - Understanding mechanisms
  - → Conditional exchangeability assumptions
    - No A-Y confounding, no A-M confounding, no M-Y confounding affected by A (i.e., no exposure-induced confounding)
- **CDE vs NDE vs IDE, etc**
  - → Know differences in definitions (estimand), identification assumptions, implications
  - → Helpful tutorials: VanderWeele (2016) & Nguyen et al. (2021) & Nguyen et al. (2022)

# How to Critically Assess Methodology in (Social) Epi Papers



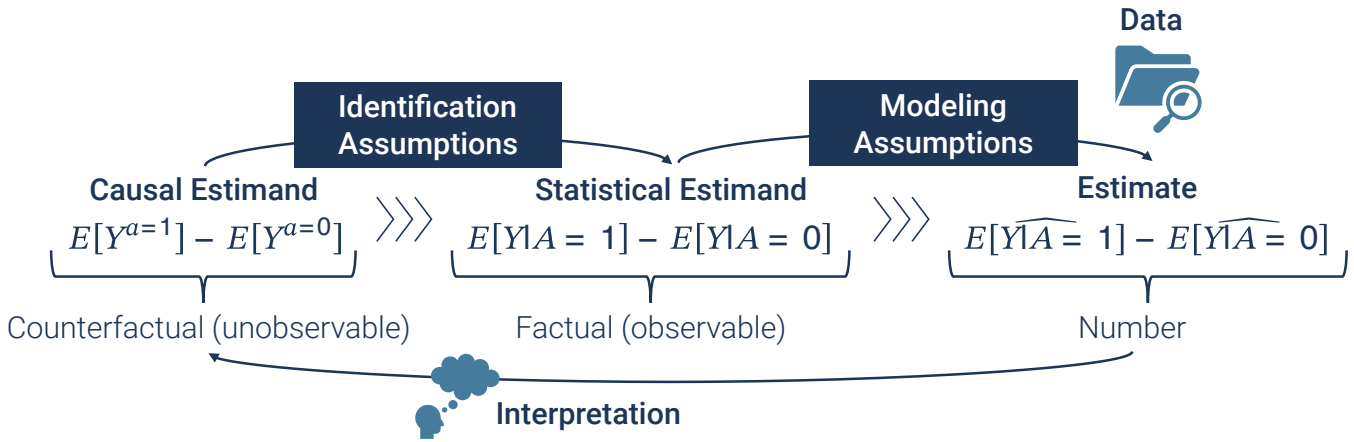

- **#1. Identify causal question under consideration**
  - → Often vague or not useful
    - e.g., not specifying time interval
  - → Is it well-justified?
    - e.g., Using g-methods when a single-point intervention is sufficient
- **#2. Check correspondence between what they examined vs what they claim they did**
  - → Discrepancy may arise from:
    - Statistical approach (e.g., using IV without claiming complier effects)
    - Measurement with a conceptual validity issue

# How to Critically Assess Methodology in (Social) Epi Papers




- **#3. Assess the validity of underlying assumptions**
  - → Causal identifications
    - Conditional exchangeability & consistency
  - → Modeling assumptions (e.g., linearity)
- **#4 Check correspondence between numeric estimates and their interpretation**
  - → e.g., interpreting effect heterogeneity as causal interaction
    - Did they discuss alternative explanations? (e.g., multiple versions of treatment)
  - → e.g., no association with baseline exposure as evidence of no effect at all
    - absence of evidence is not evidence of absence
    - but also potential non-adherence (i.e., time-varying treatment)

# When You Learn Methods




- **It is all about trade-off**
  - → No single "winning" method
  - → Fancy methods ≠ better methods
  - → Consider estimand and assumptions
    - More relevant estimand & stronger assumptions vs vague estimand & weaker assumptions
- **Distinguish identification and estimation**
  - → Which of these two is the method improving?
  - → e.g., ~~"Propensity score matching can estimate causal effects"~~
  - → e.g., ~~"Machine learning methods must not be used in causal inference"~~

# When You Learn Methods

- **Focus on mathematically defined causal estimand**
  - → Try not to be obsessed with terminology
    - e.g., effect modification, effect heterogeneity, causal estimand
  - → Often overlapping concepts and methods but different terminology
    - e.g., Controlled direct effect as a time-varying treatment effect
    - e.g., Causal interaction as a joint intervention
      - Can use the time-varying treatment analysis when conceptualizing a joint intervention for temporally separated targets
    - e.g., disparity effect vs “effect” decomposition/mediation

**Always keep in mind**

- Many different approaches to the same problem
- There is no single “correct” view/approach
  - → Be flexible and creative

# Announcements

- Final Assignment (due October 24th at 11:59 PM)
- Course survey
  - → Formal and informal surveys
- Photo & Marketing
- Research projects

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