

# STAT6061/STAT5008 – Causal Inference

## Part 3-1\*. Causal mediation analysis

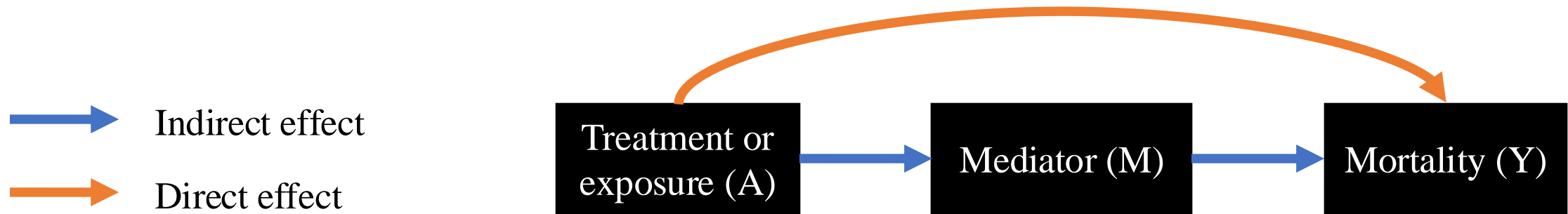
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# Mediation analysis

Effect decomposition of the total effect in the presence of a mediator



## **Prescriptive interpretation (Controlled direct and indirect effects)**

- It is the effect of A after prescribing or intervening on the mediator M.
- Policy-making

## **Descriptive interpretation (Natural direct and indirect effects)**

- It is the effect of A if we let the mediator be whatever it naturally would have been under a particular scenario.
- Mechanism investigation

# Direct and indirect effects

Effect decomposition of the total effect in the presence of a mediator

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→ Indirect effect

→ Direct effect



## **Prescriptive interpretation**

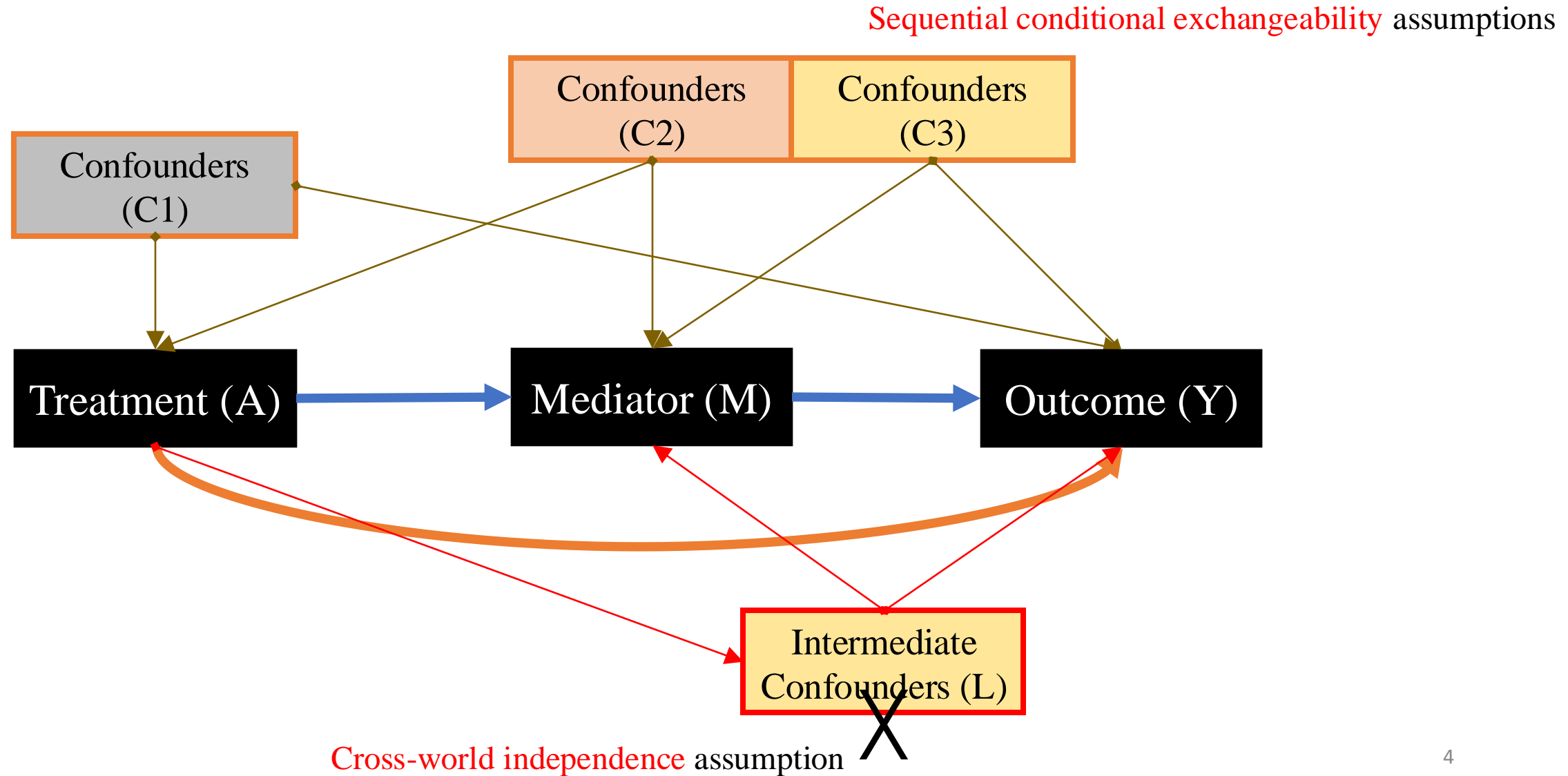
We may be interested in understanding what happens if a new public health policy is promoted and implemented.

## **Descriptive interpretation:**

It aims to investigate the natural mechanism that HCV affects mortality in patients with liver disease.

# Identification assumptions in mediation analysis

No unmeasured confounding



# Cross-world independence assumption

Why are we not allowed to have an intermediated confounder?

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Direct effect:  $(A \rightarrow Y) + (A \rightarrow L \rightarrow Y)$

Indirect effect:  $(A \rightarrow M \rightarrow Y) + (A \rightarrow L \rightarrow M \rightarrow Y)$

## To Control or Not to Control?

### ➤ To control for the intermediated confounder

We would be blocking one of the direct effect pathways not through M that we were interested in.

### ➤ Not to control for the intermediated confounder

Direct and indirect effect estimates will be biased since L is a confounder of the M – Y relationship.

# Cross-world independence assumption

A short conclusion for this assumption

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Direct effect:  $(A \rightarrow Y) + (A \rightarrow L \rightarrow Y)$

Indirect effect:  $(A \rightarrow M \rightarrow Y) + (A \rightarrow L \rightarrow M \rightarrow Y)$

If an intermediated confounder is present in the mechanism, then...

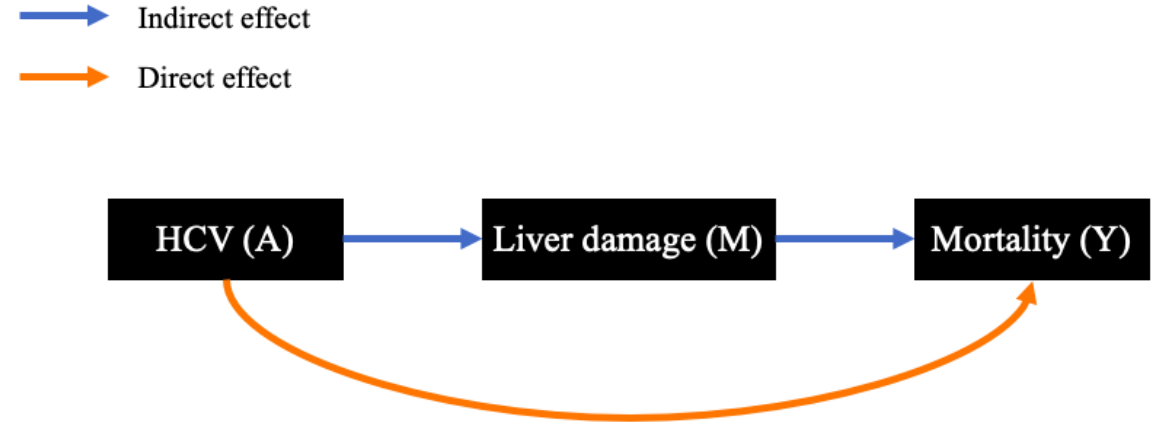
1. The effects of  $(A \rightarrow L \rightarrow Y)$  and  $(A \rightarrow L \rightarrow M \rightarrow Y)$  cannot be distinguished empirically.
2. Natural direct and indirect effects are unidentifiable.

# Identification and Estimation

## Direct and indirect effects

For an individual, the counterfactuals are defined as

- $Y(a,m)$ : counterfactual outcome if the exposure and mediator had been  $a$  and  $m$  respectively.
- $M(a')$ : counterfactual mediator if the exposure =  $a'$ .



### ➤ The effects of mediation analysis

Natural indirect effect (NIE):  $E(Y(1,M(1))) - E(Y(1,M(0)))$

Natural direct effect (NDE):  $E(Y(1,M(0))) - E(Y(0,M(0)))$

### ➤ Given identification assumptions of mediation analysis, $E(Y(a,M(a')))$ is identified as

$$\int_c \int_m E(Y|a, m, c_0) dF_{M|c}(m|a', c) dF_c(c).$$

# Estimators of natural direct and indirect effects

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➤ Given identification assumptions of mediation analysis, these are identified as

*Natural direct effect*

$$\int_c \left[ \int_m E(Y | a = 1, m, c) dF_{M|c}(m | a = 0, c) - \int_m E(Y | a = 0, m, c) dF_{M|c}(m | a = 0, c) \right] dF_c(c)$$

*Natural indirect effect*

$$\int_c \left[ \int_m E(Y | a = 1, m, c) dF_{M|c}(m | a = 1, c) - \int_m E(Y | a = 1, m, c) dF_{M|c}(m | a = 0, c) \right] dF_c(c)$$

➤ Estimation

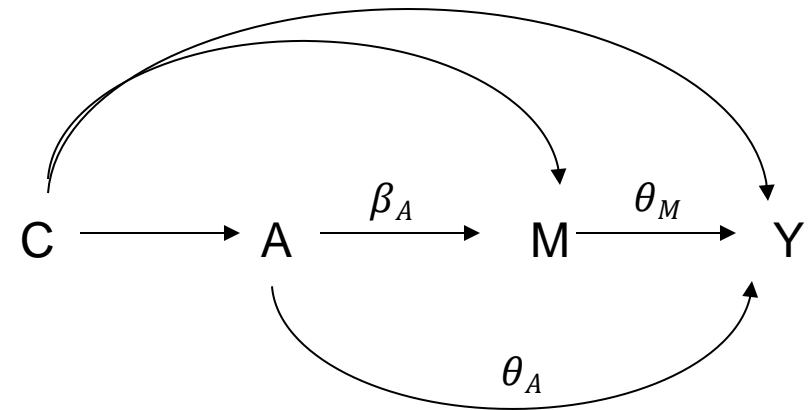
- $E(Y | a, m, c)$
- $F_{M|c}(m | a, c)$
- $F_c(c)$



# Product Method

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- $E[Y|A, C] = \tau_0 + \tau_A A + \tau_C C$
- $E[Y|A, M, C] = \theta_0 + \theta_A A + \theta_M M + \theta_C C$
- $E[M|A, C] = \beta_0 + \beta_A A + \beta_C C$
- Total effect =  $\tau_A$
- Natural Indirect Effect =  $\beta_A \theta_M$



# A summary for causal mediation analysis

- For causal inference, we should

**Research question → Causal structure → Assumptions → Identification → Statistical inference**

- A series of exchangeability assumptions is crucial to avoid confounding.

**1. No unmeasured A-Y confounding assumption (C1)**

⇒ Verifiable, RCT

**2. No unmeasured A-M confounding assumption (C2)**

⇒ Verifiable, RCT

**3. No unmeasured M-Y confounding assumption (C3)**

⇒ It is theoretically verifiable but practically challenging.

**4. No intermediated M-Y confounding assumption (L)**

⇒ It cannot be tested and verified.

