# Conceptual overview: Techniques for establishing causal pathways in programs and policies

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OPRE/ACF Meeting on Unpacking the "Black Box" of Programs and Policies

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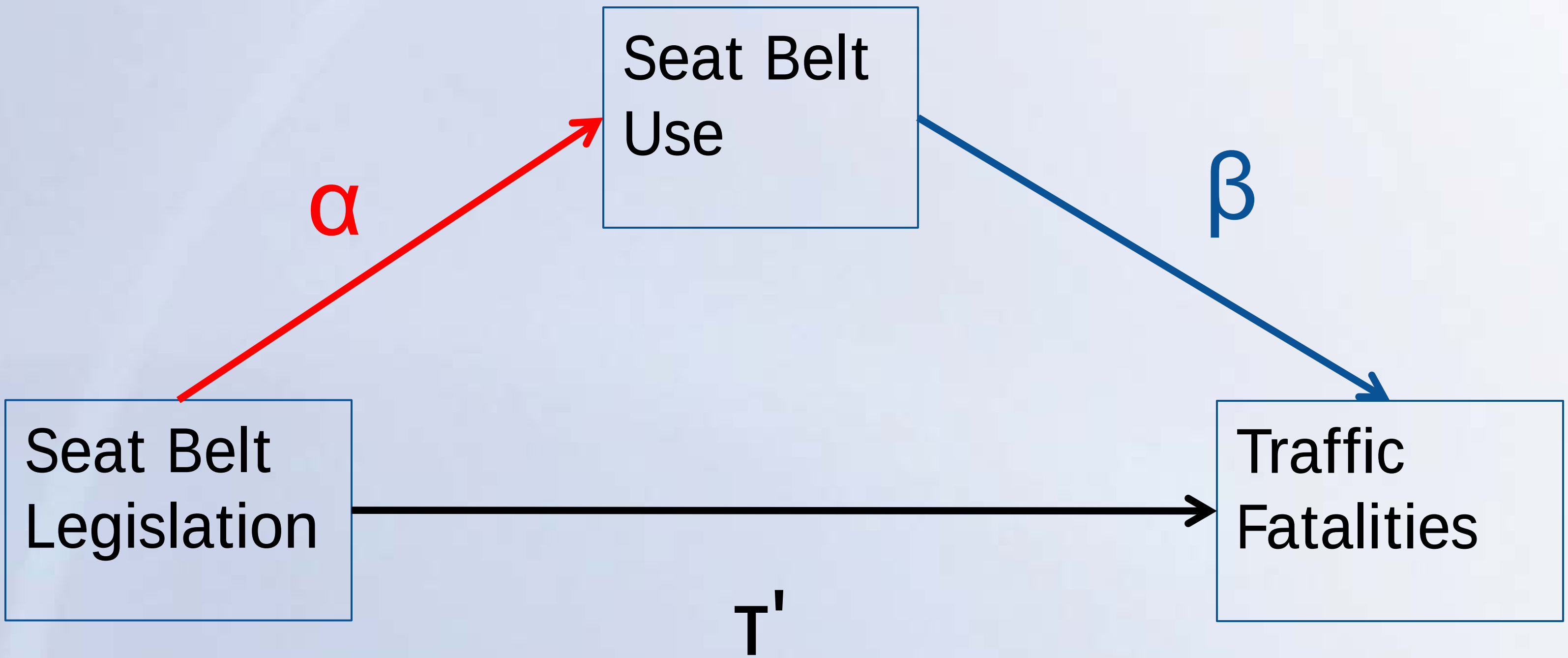
# "Black Box" of Programs and Policies: Fundamental Questions

- What are the risk conditions that increase the probability of observing the outcome of interest? (Conceptual Theory)
  - Can we target the risk condition(s) directly or must we identify other targets linked to the risk condition?
- How can we build programming and/or policy to change the target(s) (which should then change the outcome)? (Action Theory)

(Chen, 1990; MacKinnon, Taborga & Morgan-Lopez, 2002)

# Targeting the Risk Condition Directly: Seat Belts

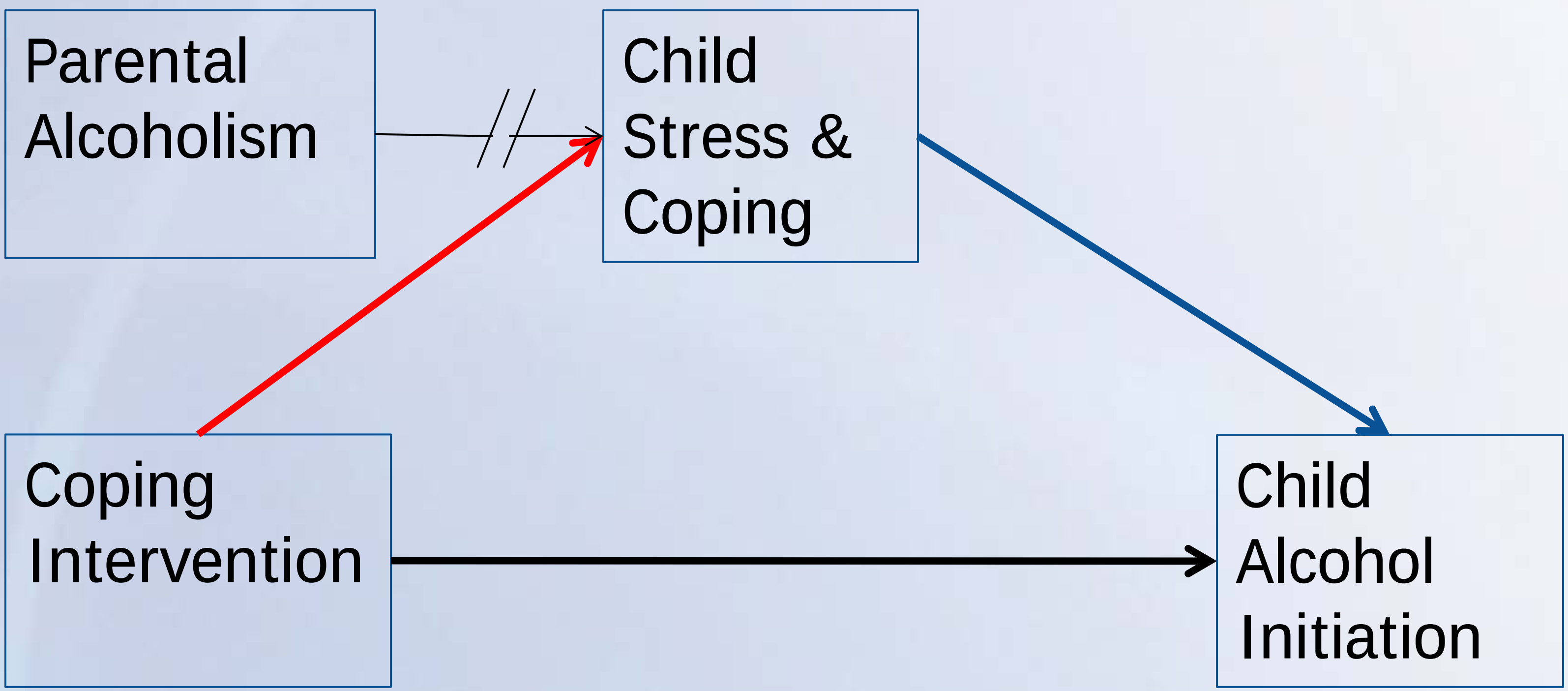



Indirect Effect: $\alpha\beta$

Direct Effect: $\tau'$

Total Effect: $\alpha\beta + \tau'$

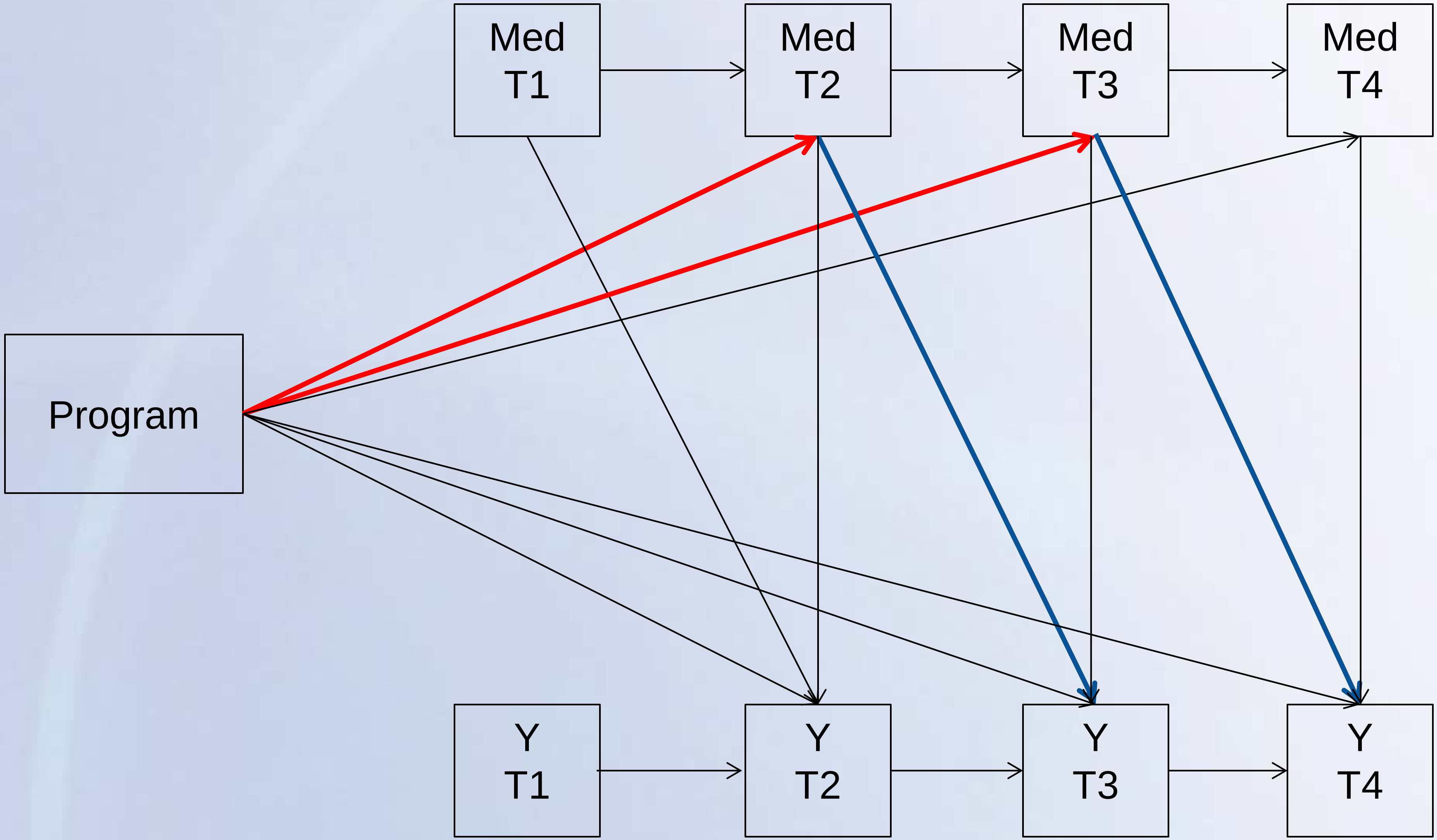
# Selecting Targets with Non-Modifiable Risk Factors: Child Stress and Coping




(based on Chassin et al., 1996)

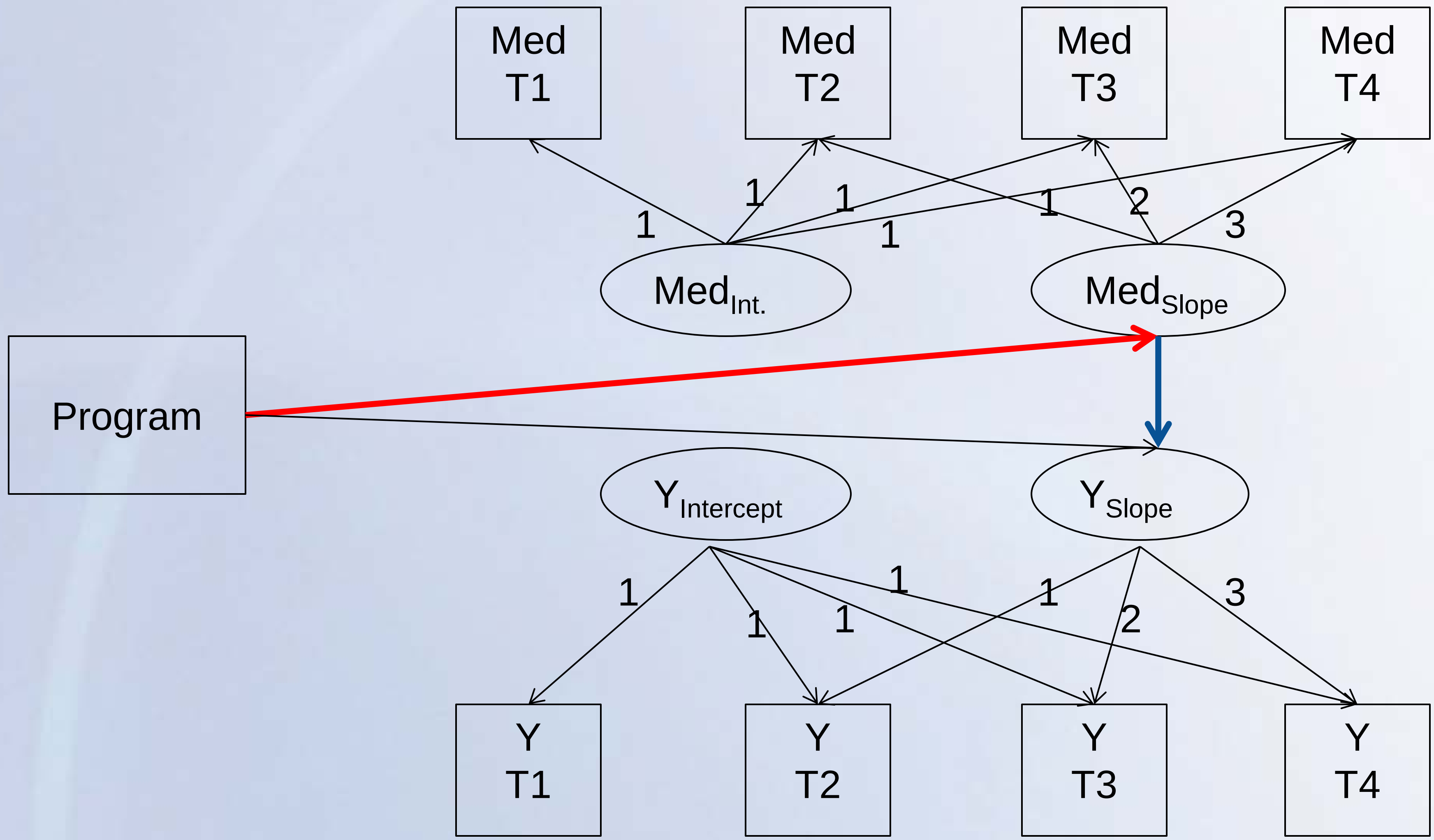
# Issues in Mediation I: Types of Evaluation Models

# Cross-Lagged Panel Mediation



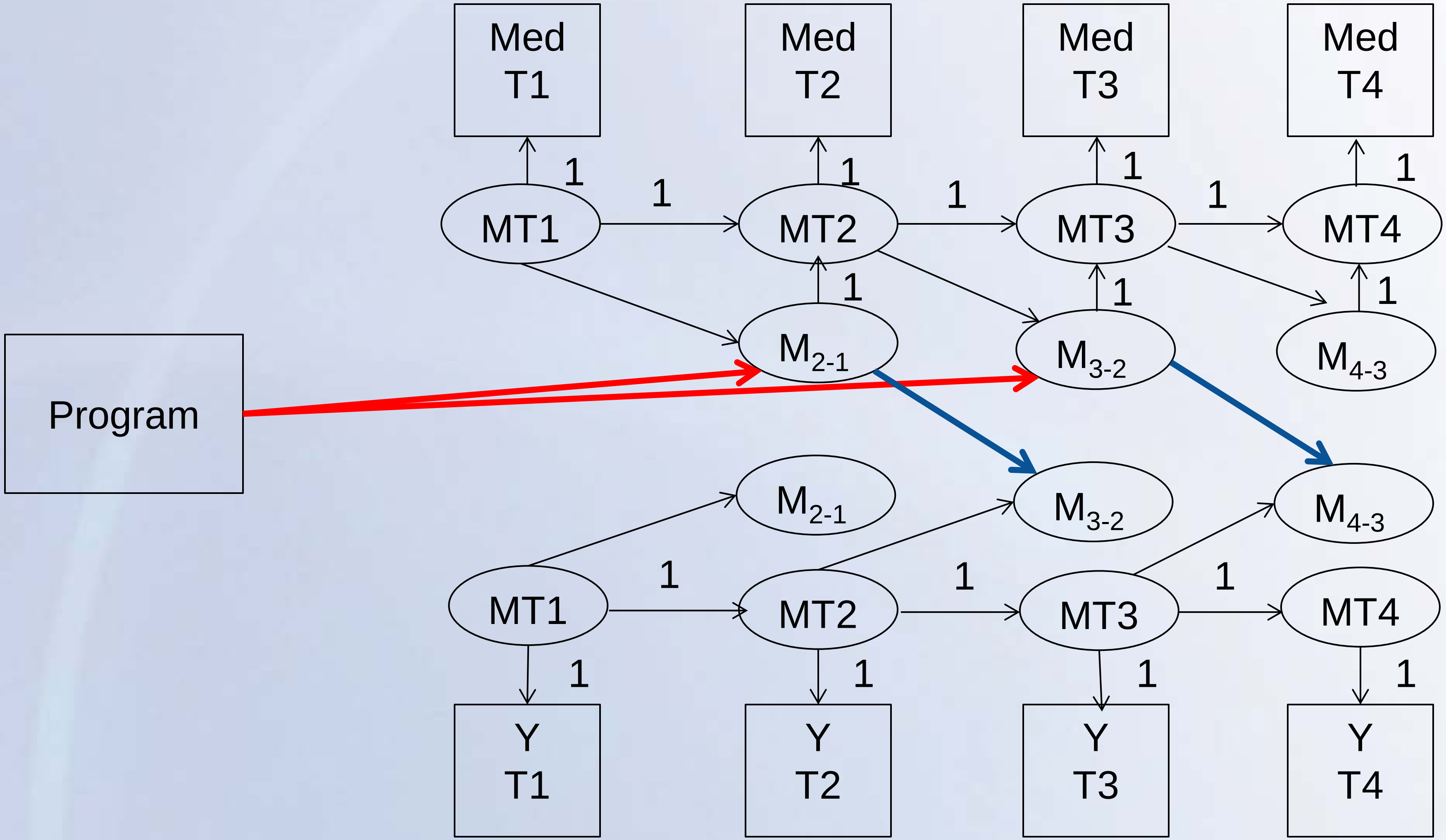

(Cole & Maxwell, 2003; Patock-Peckham & Morgan-Lopez, 2006, 2007, 2010a)

# Latent Growth Modeling Mediation




(Cheong, MacKinnon & Khoo, 2003; Morgan-Lopez, Saavedra, Hien et al., 2014)

# Latent Difference Score Mediation




(MacKinnon, 2008)

# Evaluation Models for Mediation

- Cross-lagged Panel Models
  - Mean differences between program conditions at time t (adjusted for t-1)
  - Inferences regarding adjusted differences at time t ≠ changes over time, especially in non-experimental data (Lord, 1967)
    - But may be less problematic than it used to be (see Keele and Reardon, this session)
- Latent Growth Models
  - Linking changes over time in M to program conditions; changes in Y linked to changes in M
  - Cannot isolate periods of when change is most critical
- Latent Difference Score Models
  - Model greater specificity in the timing of changes in M and Y

# Issues in Mediation II: Sampling Distribution and CI Estimation

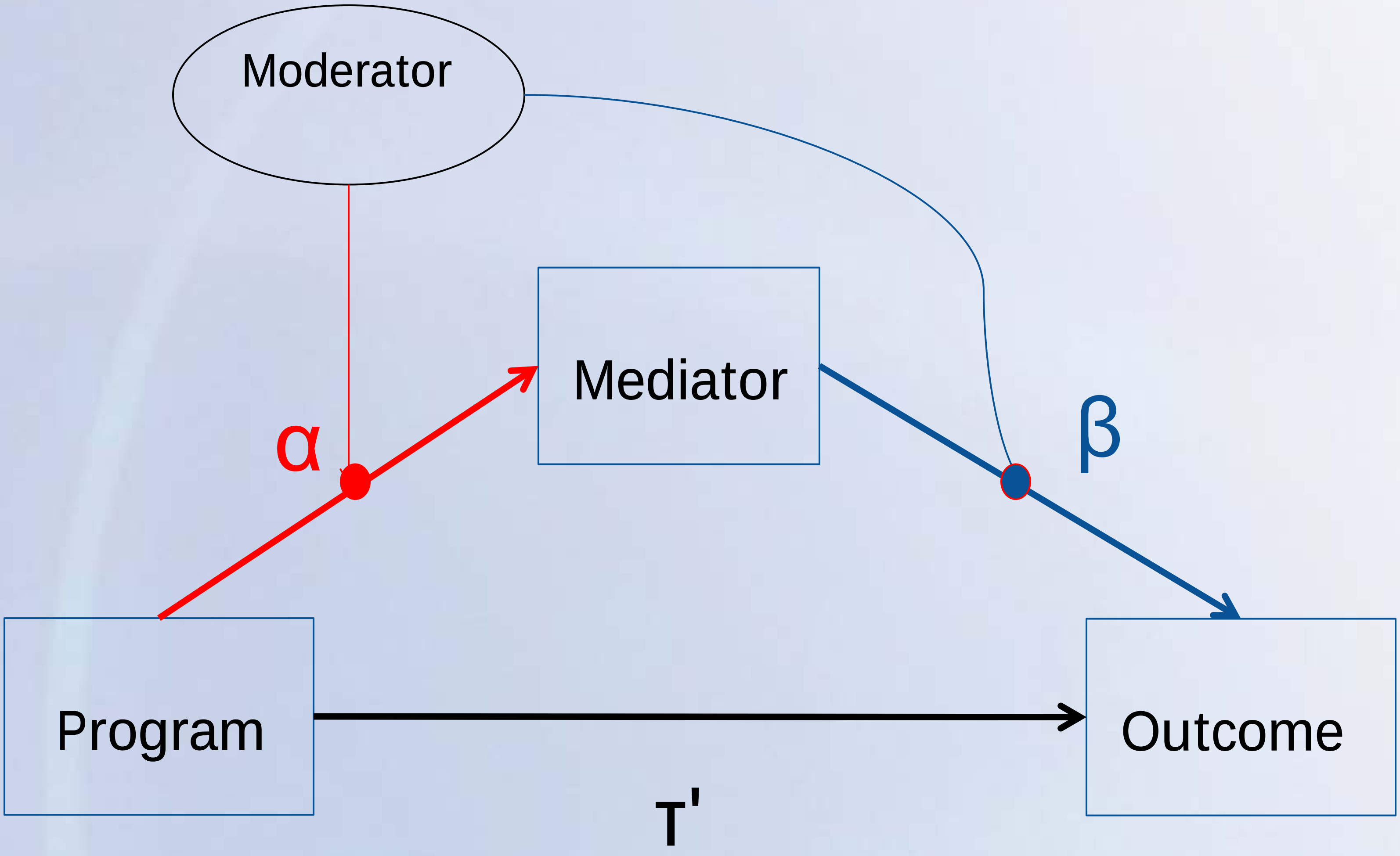
- Causal Steps (Baron & Kenny, 1986)

- Testing the significance of ab
  - Assuming the sampling distribution is normal (e.g., Sobel, 1982, 1986)
  - a is normally distributed
  - b is normally distributed
  - a*b is most often not normally distributed

# Issues in Mediation II: Sampling Distribution and CI Estimation

- Assuming (correctly) that the SD of ab is non-normal by:
  - Estimating the confidence interval based on the moments of the distribution of the product (e.g., MacKinnon et al., 2002)
  - Simulating the distribution of ab directly (i.e., parametric bootstrap; MacKinnon et al., 2004; Selig & Preacher, 2008)
  - Simulating the distribution of ab indirectly through resampling of the data you have (i.e., non-parametric bootstrap; MacKinnon et al., 2007)
- **Plenty of user-friendly software to estimate these effects as stand-alones (e.g., SAS, SPSS, R), within existing SEM packages (e.g., Mplus) and in Java applets (e.g., quantpsy.org)**

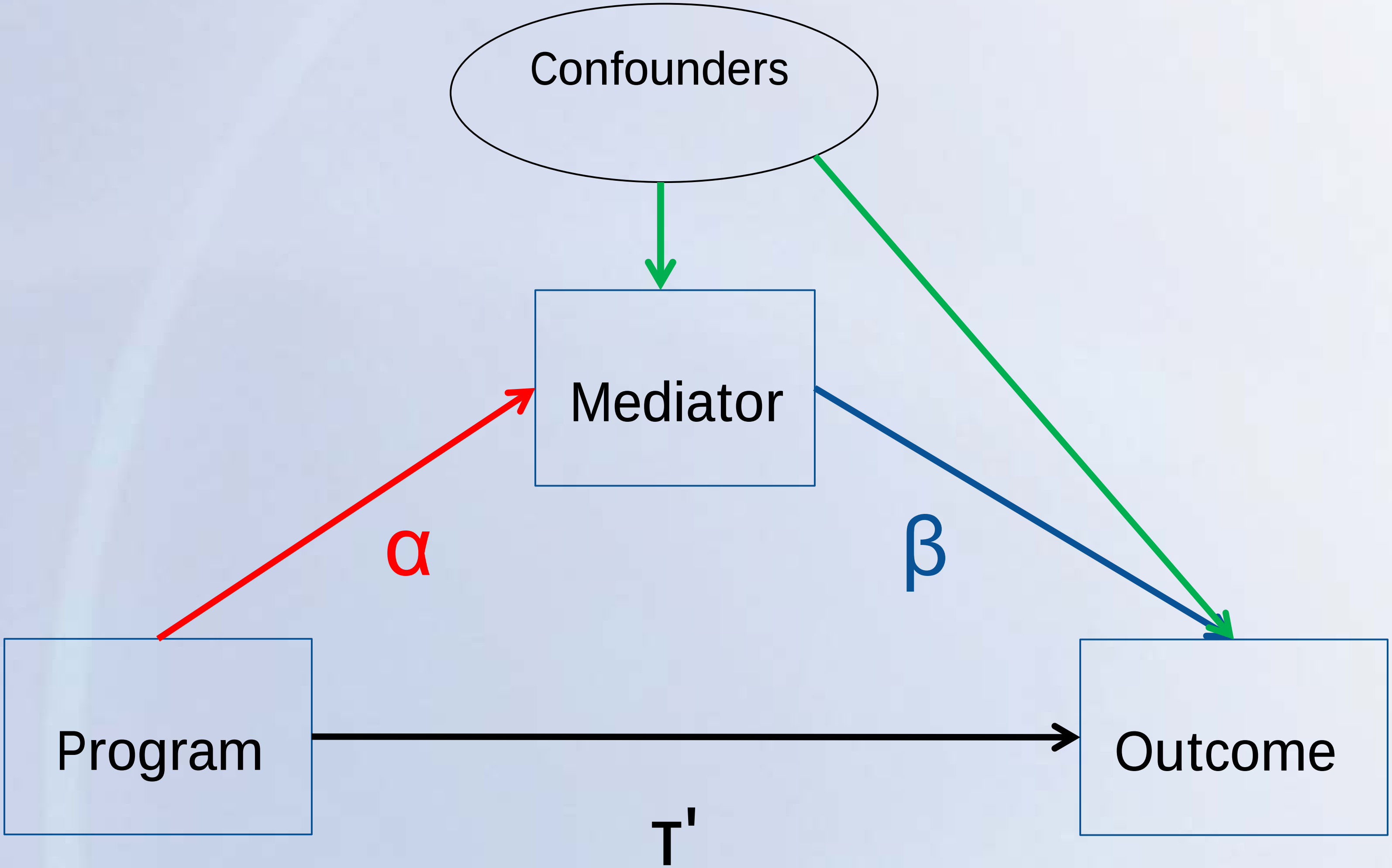
# Issues in Mediation III: Conditional Mediation



# Issues in Mediation III: Conditional Mediation

- Do the action and conceptual theories apply equally across populations?
  - Types of moderators:
    - Demographics
    - Pre-intervention risk
    - Baseline levels of M and/or Y
  - Distinguishing between mediated moderation and moderated mediation (e.g., Fairchild, this session)
  - Estimating mediation effects at different levels of the moderator (i.e., simple mediation effects; Morgan-Lopez et al., 2003, 2006)

# Issues in Mediation IV: Causal Inference in Mediation



# Causal Inference in Mediation

- Causal Inference in Mediation Analysis (Coffman & Zhong, 2012; MacKinnon, Taborga & Morgan-Lopez, 2002; VanderWeele, 2009)

- In "conventional" RCTs, confounder unrelated to program condition but can **still be related to both** M and Y
  - Unbiased estimates of **P -> M**, biased estimates of **M -> Y** because C is a **"common cause"** of M and Y
  - In quasi-experimental contexts, both **P -> M** *and* **M -> Y** may be biased as a function of C
    - Other more insidious forms of bias may ensue if C was a post-treatment confounder of the **M->Y** effect

# Marginal Structural Models for Mediation

- Causal Effect on the Mediator
  - $E[M(1) – M(0)] = (\beta_0 + \boldsymbol{\beta_1}1) - (\beta_0 + \boldsymbol{\beta_1}0) = \boldsymbol{\beta_1}$
- Causal Effect on the Outcome *when T = 1*
  - $E[Y(1, m) – Y(1,m')] = (\boldsymbol{\beta_2} + \boldsymbol{\beta_4}) (m – m')$
- Causal Effect on the Outcome *when T = 0*
  - $E[Y(0, m) – Y(0,m')] = (\boldsymbol{\beta_2}) (m – m')$
- "Natural" Mediation Effect:
  - Estimation of **M -> Y** effect under the **level of T that individuals experience**

# Estimation of Causal Effects

- Propensity Scoring for Mediation
  - Estimate the joint probability of experiencing P = p and M = m
  - PS Weights = $\Phi(M|T)$ / $\Phi(M|P,C)$ (Coffman & Zhong, 2012; Keele, this session(?); Robins et al., 2000)
- Instrumental Variables for Mediation (Reardon, this session)

# In Summary

- Mediation Analysis in Program and Policy Evaluations
- Multiple Options for Modeling Depending on
  - Interest in time point-specific effects versus changes over time
- Action and Conceptual Theories may not be one-size-fits-all
- Causal inferences may be tenuous (even in RCTs) unless one uses newer causal effect frameworks