

Causal mediation analysis with multiple causally-ordered mediators

Rhian Daniel, Bianca De Stavola and Simon Cousens
with thanks to Stijn Vansteelandt and Dave Leon

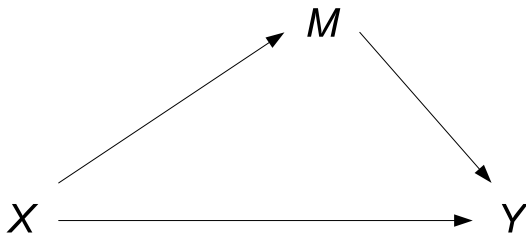
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London School of Hygiene and Tropical Medicine

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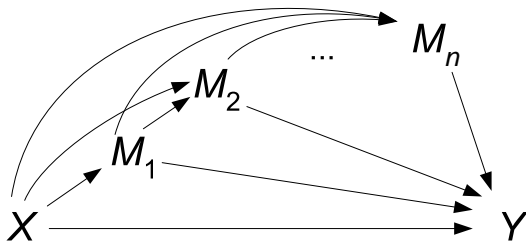
Single mediator



— Almost all the causal inference literature on mediation is based on a **single mediator**.



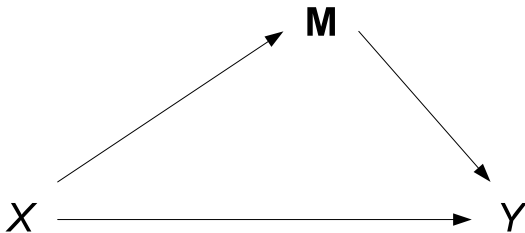
Multiple mediators



— However, as we have seen over the last two days, many realistic applications involve **multiple mediators**.



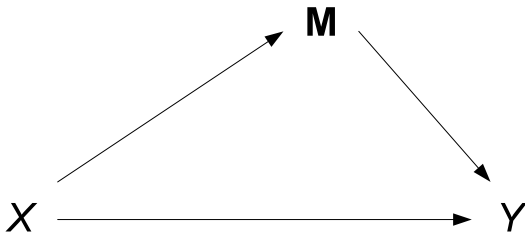
Many mediators considered *en bloc*



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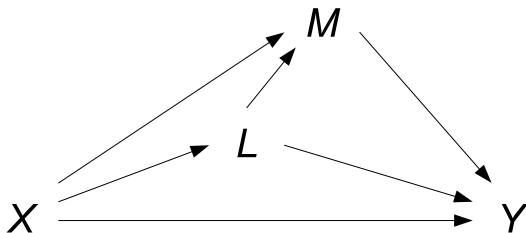
Many mediators considered *en bloc*



- Multiple mediators are trivially accommodated by the existing formal literature if viewed *en bloc* (with **M** a vector).
- But then the direct effect is around **all** of them, and the (single) indirect effect is through one, more or all of them, and is **not further disentangled**.



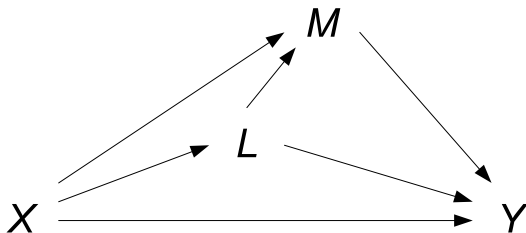
Two mediators but only one 'of interest'



— The causal inference literature does focus on ‘two mediators’, L and M , in settings with **intermediate confounding** (cf Vanessa’s talk yesterday).



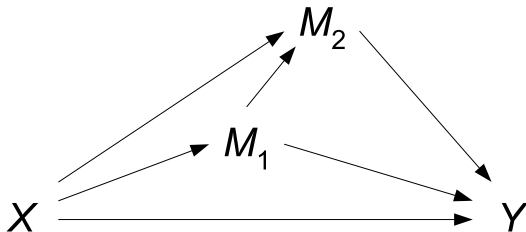
Two mediators but only one 'of interest'



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- But M is the mediator of interest, with decomposition again into two effects—through and not through M .



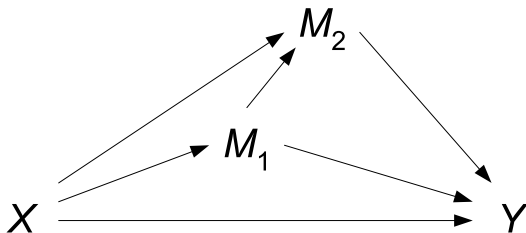
Two mediators, both of interest (1)



— What if both mediators are ‘of interest’?



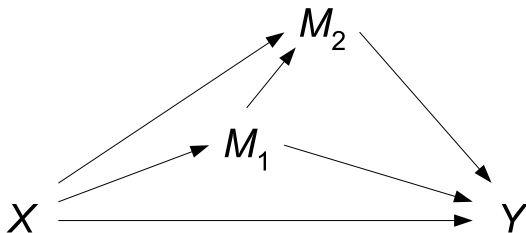
Two mediators, both of interest (1)



- What if both mediators are ‘of interest’?
- We could then be interested in a **finer decomposition**, with path-specific effects through M_1 alone, M_2 alone, both and neither.



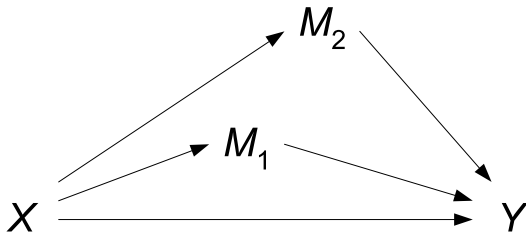
Two mediators, both of interest (2)



— This setting has been studied, but either (a) **without a focus on decomposing** the total effect [Avin et al (2005), Albert and Nelson (2011)]...



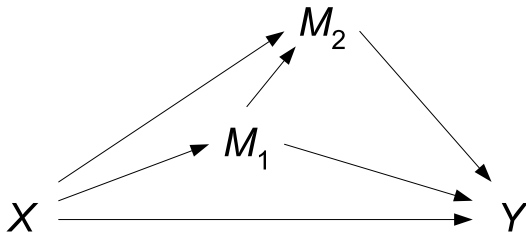
Two mediators, not causally ordered



— ... or (b) in the setting with **no effect of M_1 on M_2** [MacKinnon (2000), Preacher and Hayes (2008), Imai and Yamamoto (in press)] (many examples yesterday).



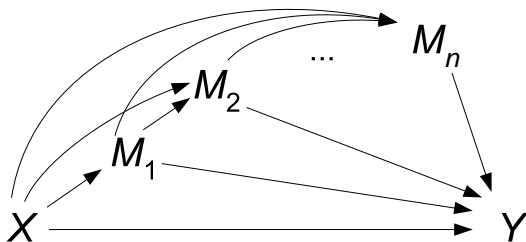
Our setting



— This talk is about a **path-specific decomposition** of the total causal effect in the setting where M_1 affects M_2 (**causally-ordered mediators**).



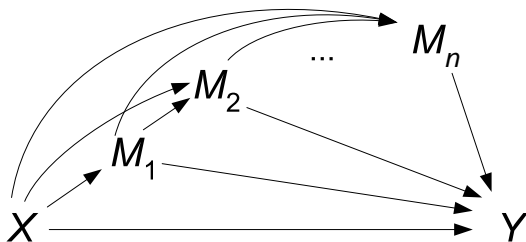
More generally



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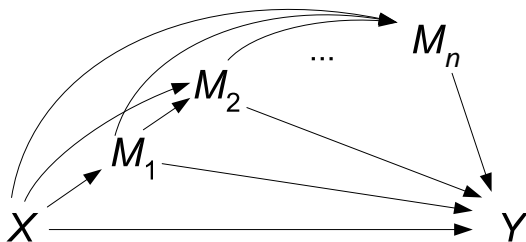
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- **Traditional path analysis** generalises easily to this setting, but under strong assumptions, including linearity everywhere.



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- More generally there could be n **causally-ordered mediators**.
- **Traditional path analysis** generalises easily to this setting, but under strong assumptions, including linearity everywhere.
- Can these be relaxed somewhat by generalising ideas from causal inference?



- 1 Background
- 2 Quick revision: effect decomposition with one mediator
- 3 Path-specific effect estimands with two mediators
- 4 Identification
- 5 Example: Izhevsk study
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Effect decomposition, single mediator

— With one mediator, there are two possible decompositions:

$$\begin{aligned}
 \text{TCE} &= E\{Y(1, M(1)) - Y(0, M(0))\} \\
 &= E\{Y(1, M(1)) - Y(1, M(0)) + Y(1, M(0)) - Y(0, M(0))\} \\
 &= \qquad \qquad \text{TNIE} \qquad \qquad + \qquad \qquad \text{PNDE} \\
 &= E\{Y(1, M(1)) - Y(0, M(1)) + Y(0, M(1)) - Y(0, M(0))\} \\
 &= \qquad \qquad \text{TNDE} \qquad \qquad + \qquad \qquad \text{PNIE}
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NB: TCE = total causal effect, PNDE = pure natural direct effect, TNDE = total natural direct effect, PNIE = pure natural indirect effect, TNIE = total natural indirect effect



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— VanderWeele [Epidemiology, 2013] shows that:

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— So the two decompositions amount to apportioning the mediated interaction either to the direct or indirect effect.



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Counterfactuals



— With one mediator, we need:

$$M(x), Y(x, m), Y(x, M(x'))$$



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— There are 8 choices for how to fix x', x'', x''' .



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- We can choose $(x', x'', x''') = (0, 0, 0)$. We call this **NDE-000**.



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— Similarly, can choose $(x', x'', x''') = (0, 0, 1)$. We call this **NDE-001**.



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— Similarly, can choose $(x', x'', x''') = (\mathbf{1}, \mathbf{1}, \mathbf{1})$. We call this **NDE-111**.



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- Similarly, can choose $(x, x'', x''') = (0, 0, 1)$. We call this **NIE₁-001**.



Indirect effect through M_1 only

— A **natural indirect effect through M_1 only** is of the form:

$$E\{Y(0, M_1(1), M_2(1, M_1(0))) - Y(0, M_1(0), M_2(1, M_1(0)))\}$$

- The second argument changes and all other arguments stay the same, making it an indirect effect through M_1 only.
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- Similarly, can choose $(x, x'', x''') = (1, 1, 0)$. We call this **NIE_1-110** .



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- We can choose $(x, x'', x''') = (0, 0, 0)$. We call this **NIE₁-000**.
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Indirect effect through M_2 only

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- Similarly, can choose $(x, x', x'') = (0, 0, 1)$. We call this NIE_{12-001} .



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- We can choose $(x, x', x'') = (0, 0, 0)$. We call this NIE_{12-000} .
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- More generally, with n mediators, there are **$2^{(2^n-1)} \cdot 2^n$** possible sums, **$(2^n)!$** of which are equal to the TCE.



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$$\frac{n \mid (2^n)!}{1 \mid 2}$$



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1	2
2	24



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3	40,320



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2	24
3	40,320
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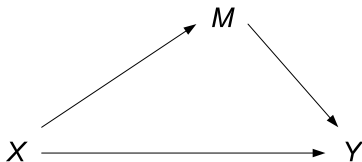
n	$(2^n)!$
1	2
2	24
3	40,320
4	2.092×10^{13}
5	2.631×10^{35}



- 1 Background
- 2 Quick revision: effect decomposition with one mediator
- 3 Path-specific effect estimands with two mediators
- 4 Identification**
- 5 Example: Izhevsk study
- 6 Summary
- 7 References



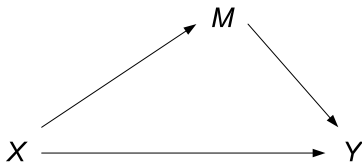
Nonparametric identification: single mediator



— Throughout, we omit **background confounders** C from our diagrams, but they are always implicitly there.



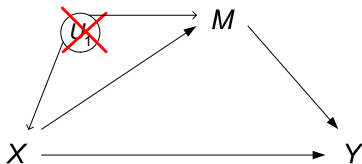
Nonparametric identification: single mediator



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- Recall that for nonparametric identification of PNDE, TNDE, PNIE and TNIE in the one-mediator setting, we require



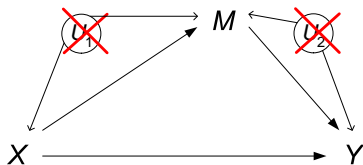
Nonparametric identification: single mediator



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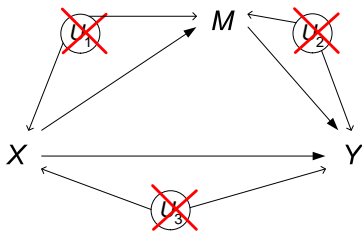
Nonparametric identification: single mediator



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- Recall that for nonparametric identification of PNDE, TNDE, PNIE and TNIE in the one-mediator setting, we require **no unmeasured confounding** of X and M , M and Y ,



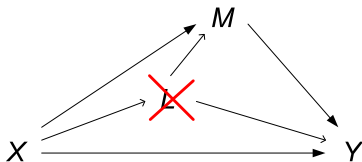
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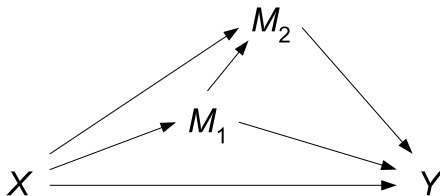
Nonparametric identification: single mediator



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- Recall that for nonparametric identification of PNDE, TNDE, PNIE and TNIE in the one-mediator setting, we require **no unmeasured confounding** of X and M , M and Y , and X and Y .
- And **no intermediate confounders**, L .



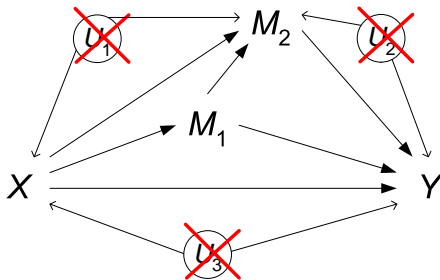
Extension to two mediators



— Consider the **natural extensions** of these assumptions.



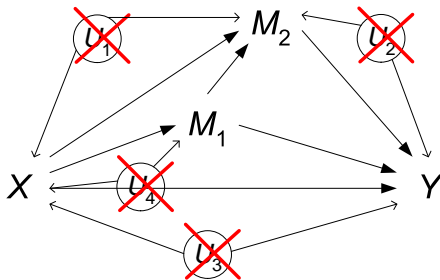
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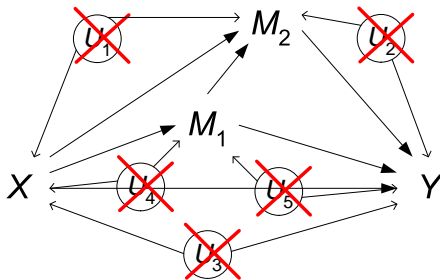
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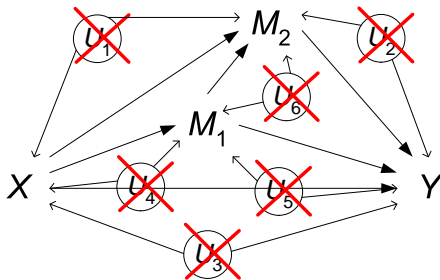
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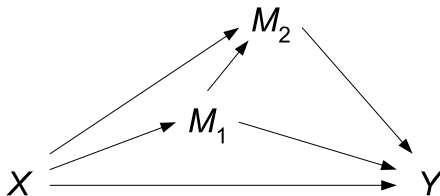
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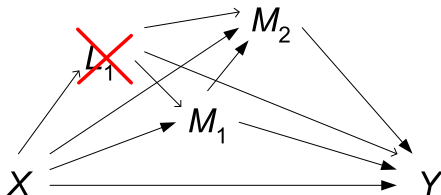
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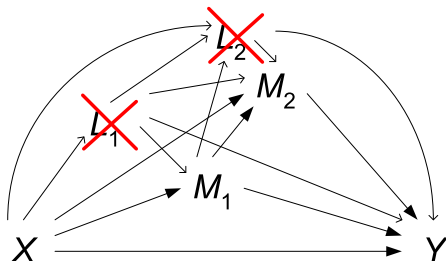
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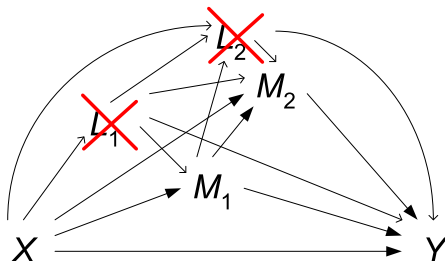
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- Consider the **natural extensions** of these assumptions.
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- Are these sufficient for identification?

Identification?



— Consider the 32 path-specific effects we wish to identify:

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- Using these assumptions, we can re-write (1) as:

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Unidentified density

— Everything on the previous slide is a function of the distribution of the observed data, **except for**:

$$f_{M_1(x''')|C, M_1(x')} (m'_1 | c, m_1) \quad (2)$$

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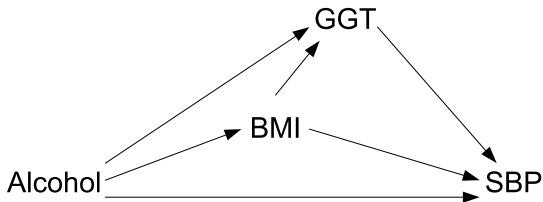
— For all other effects, and when there is an arrow from M_1 to M_2 , we vary (2) in a **sensitivity analysis**.



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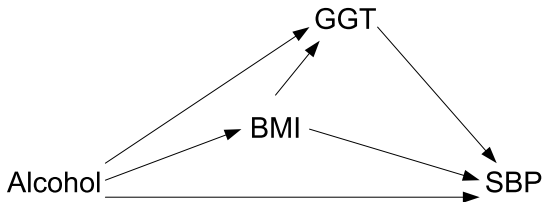


The Izhevsk study data





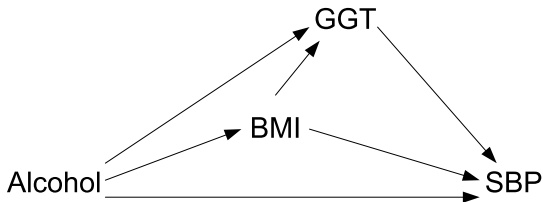
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— **Question:** how much of the causal effect of alcohol consumption on SBP is via GGT (a liver enzyme), via BMI, via both, via neither?



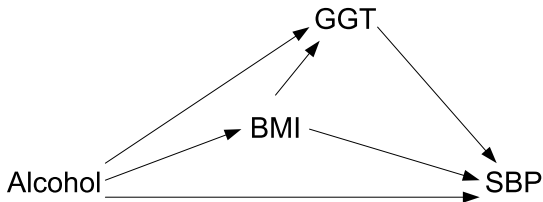
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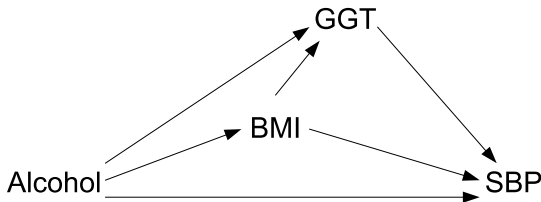
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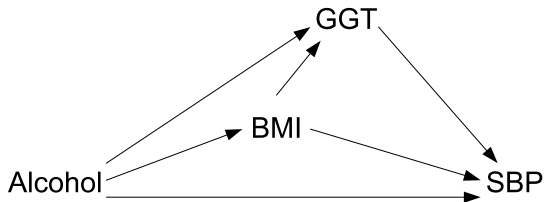


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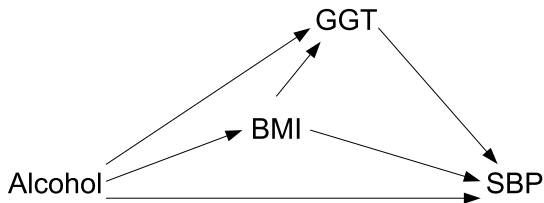
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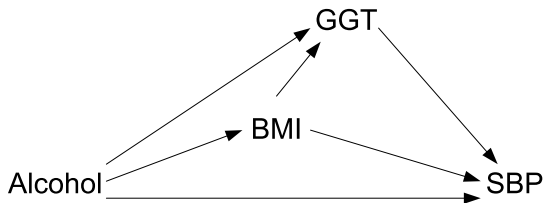
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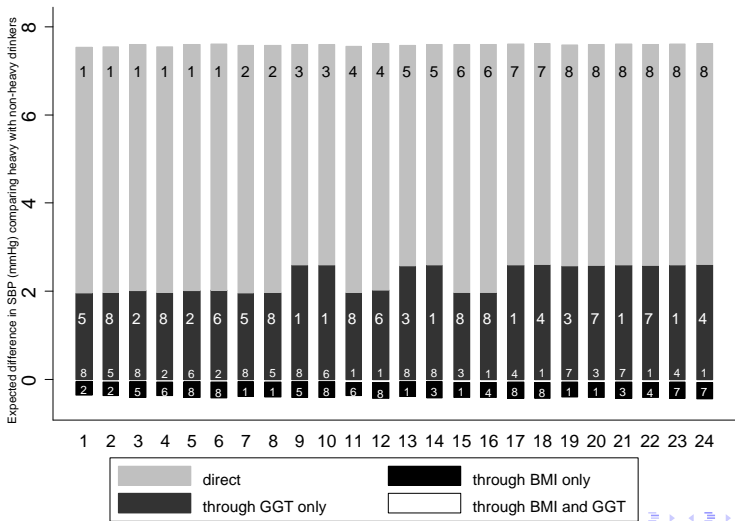
- **Fully-parametric** estimation (linear models with all interactions), approximated by Monte Carlo simulation.
- With a **sensitivity parameter** (κ) representing the proportion of the residual variance in $M_1(x)$ shared across worlds.



Results

Caveat: CIs are wide!

$$\kappa = 1$$

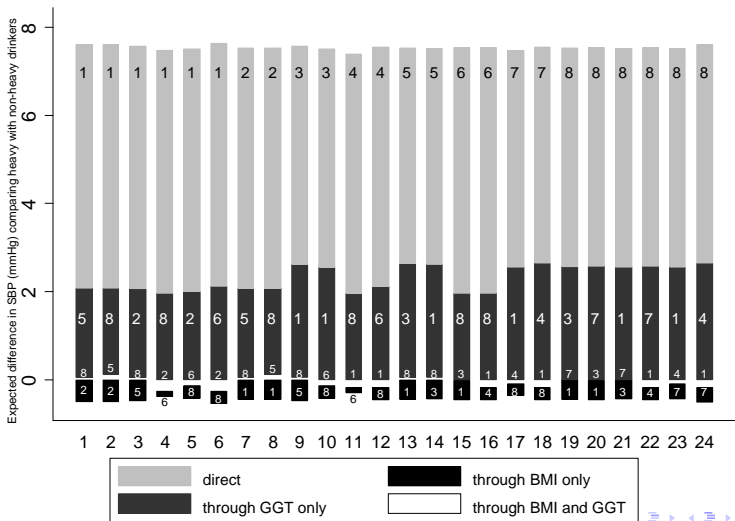




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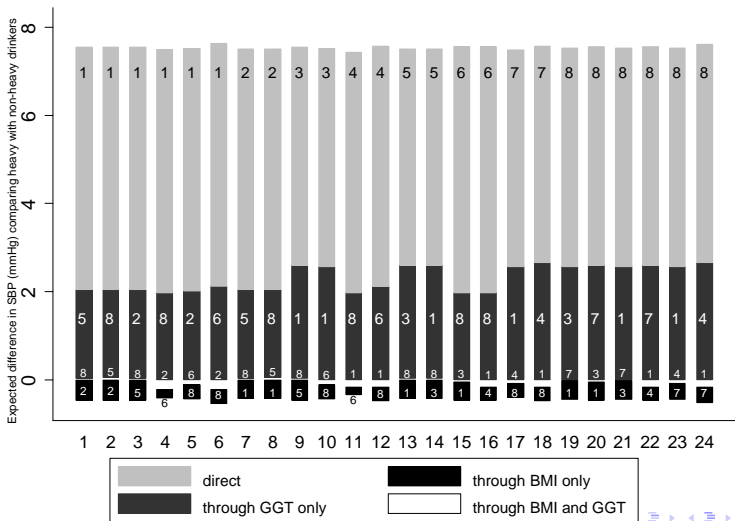




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- Would **semiparametric estimation methods** of these estimands be viable?
- How far beyond **traditional path analysis** can we really go?



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