“Have DAGs fulfilled their promise?”: the case for NO

Margarita Moreno-Betancur
University of Melbourne & Murdoch Children’s Research Institute

Outline

- What is the promise of DAGs?
- A broken promise
- A betrayal
- Where to from here

What is "the promise" of DAGs?

To improve the design and interpretation of causal inference studies. Specifically:

Given a causal DAG, it is possible to:

- Anticipate some potential biases
- Design analysis to minimise these as much as possible
- Understand remaining biases to inform interpretation

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DAGs within a formal causal inference framework

Formal causal inference framework

Step 1	Define the causal effect to be estimated	**Estimand assumptions**
Step 2	Identify estimand as a function of observable data	**Causal identifiability assumptions**
Step 3	Estimate function using finite study sample	**Parametric modelling assumptions**

DAGs within a formal causal inference framework

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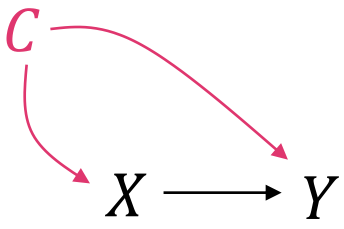
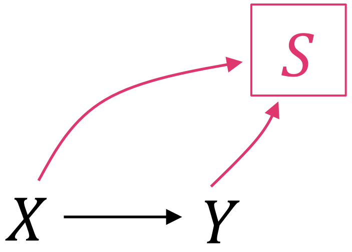
Causal DAGs:
a tool to depict some of these assumptions & assess bias risks

DAGs within a formal causal inference framework

Critically: DAGs clarified the structure of key types of biases



Confounding bias



Selection bias

DAGs within a formal causal inference framework

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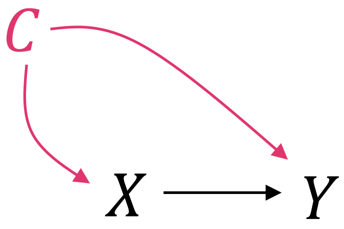

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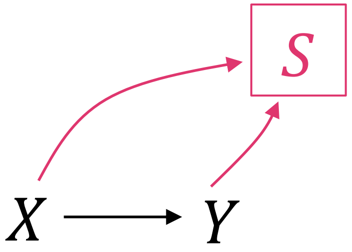

Selection bias

There are some caveats (but no one is perfect?)

- No unique way of representing measurement bias
- No agreed way of representing causal interactions, effect modification, “type 2” selection bias
- No portrayal of strength/direction/form of causal relationships
- No direct link between estimand (expressed in terms of counterfactuals) and DAGs

What is “the promise” of DAGs?

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This is a beautiful promise…

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This is a beautiful promise… however, it is far from being fulfilled!

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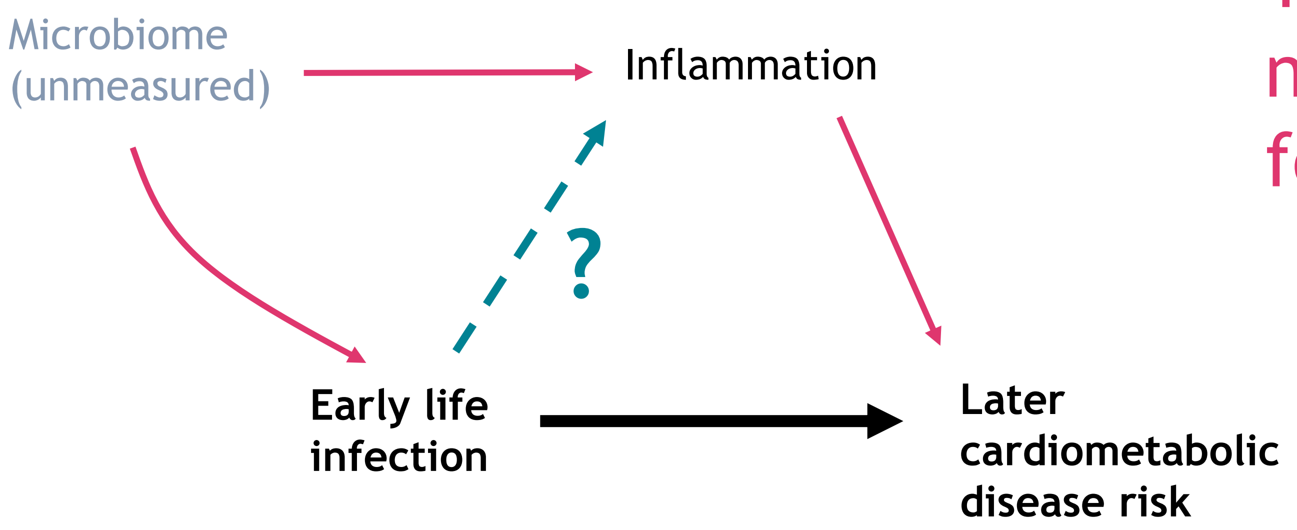
Hinges on positing a defensible causal DAG: this is either impossible or very difficult to achieve in many epidemiological settings

Challenges in positing a defensible causal DAG

1. **Lack of sufficient substantive knowledge**

   <u>Example:</u> Studies examining complex questions about early life origins of NCDs

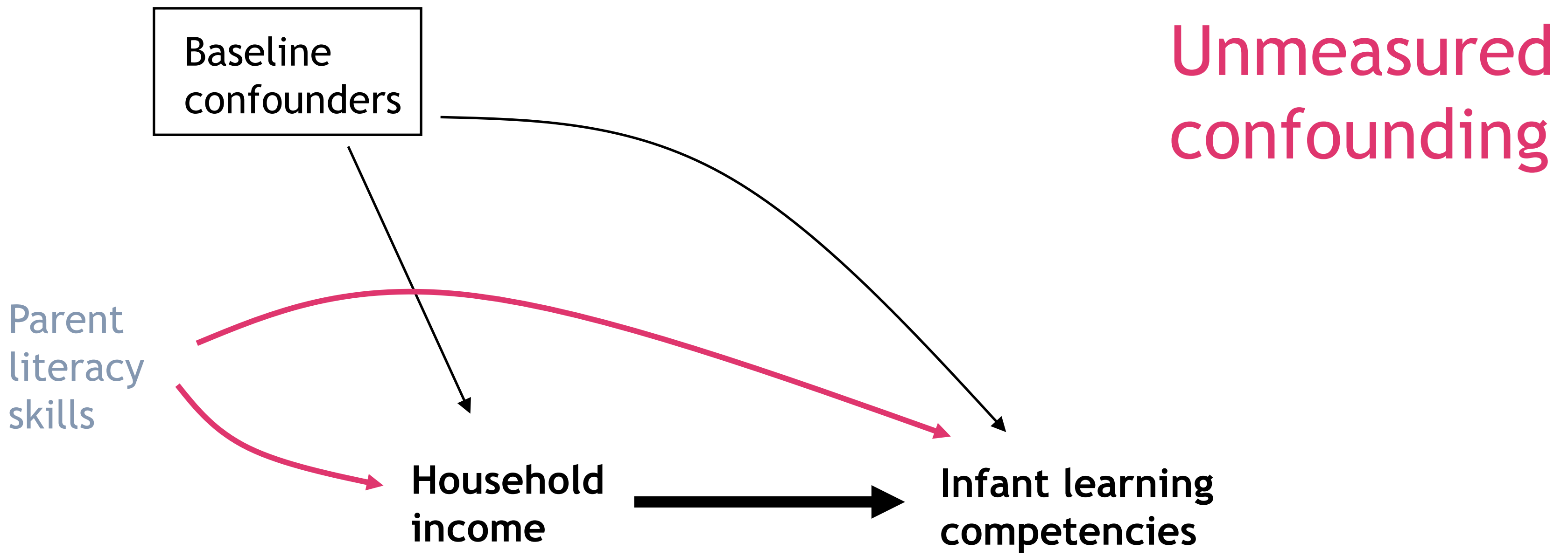


To adjust or
not to adjust
for inflammation?

Challenges in positing a defensible causal DAG

2. **Tendency to focus on measured variables**

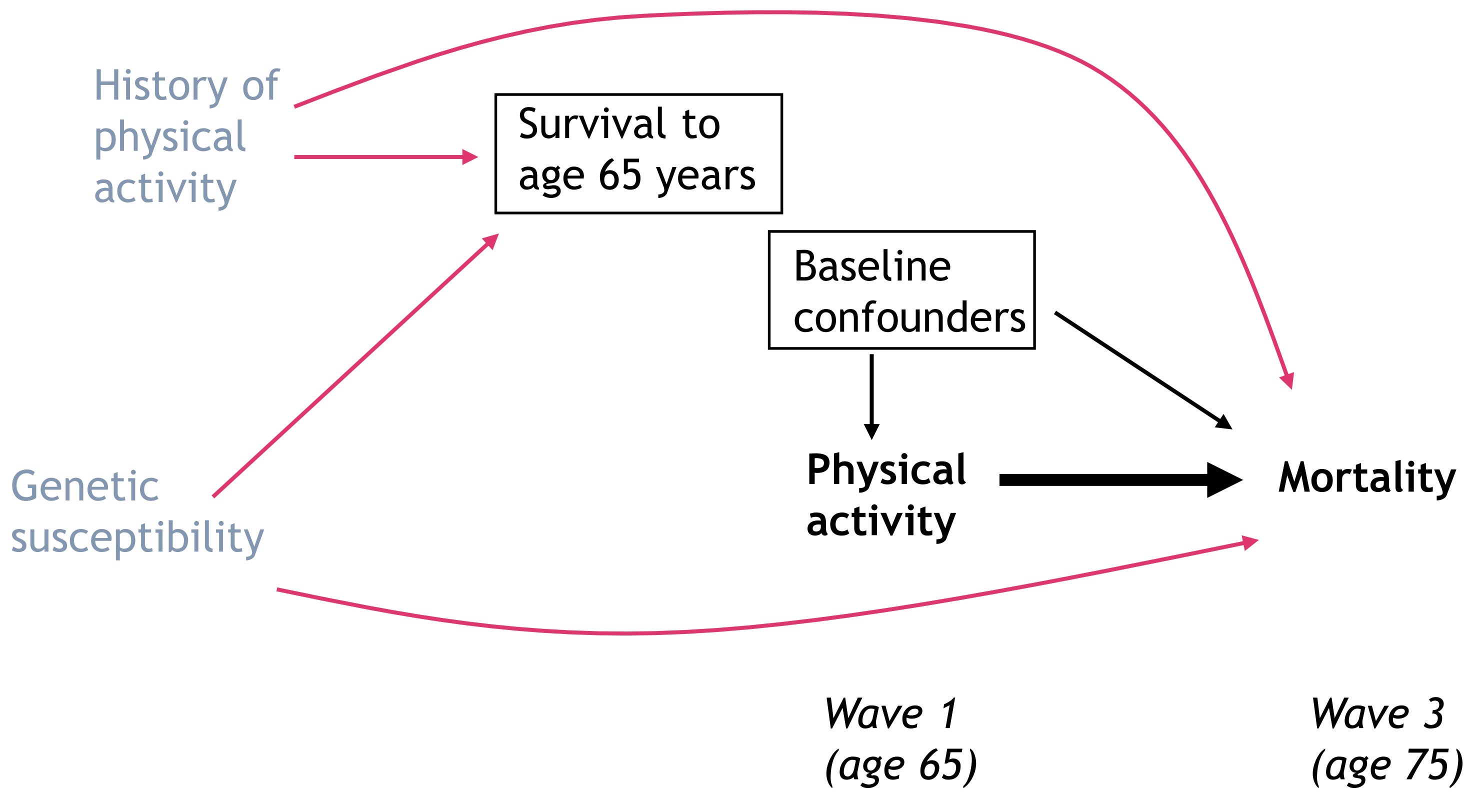
   <u>Example:</u> Studies using non-research (e.g. administrative) data



Challenges in positing a defensible causal DAG

3. Difficulty in considering complex time-dependent processes, often unmeasured

Example: Studies recruiting participants in older age groups

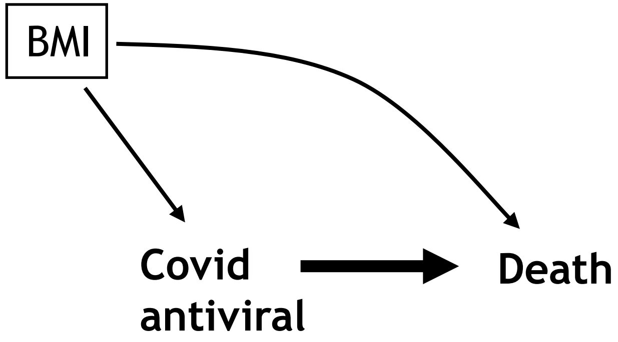


Selection bias

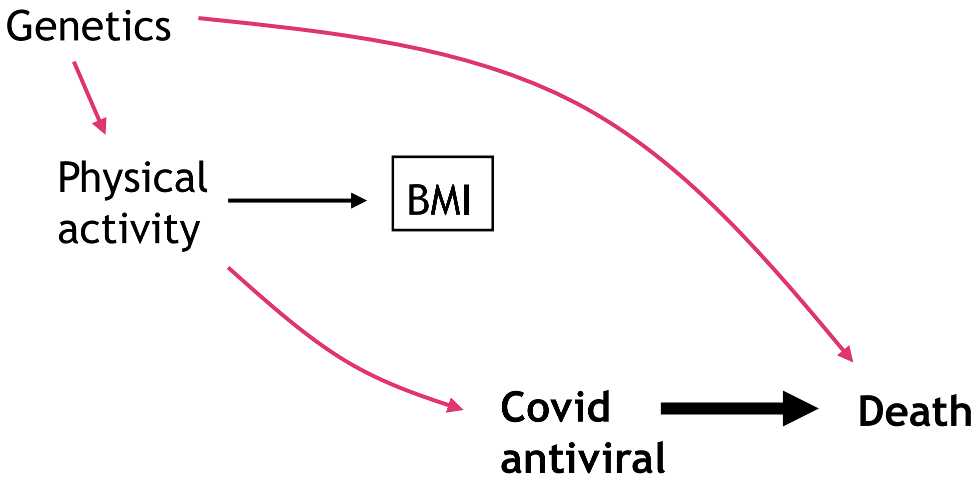
Challenges in positing a defensible causal DAG

4. **Unavoidable "non-causal" arrows, that do not correspond to well-defined interventions**

   <u>Example:</u> Studies involving complex constructs (example adapted from Hernan & Robins 2020, Chapter 9)



BMI-adjustment
sufficient

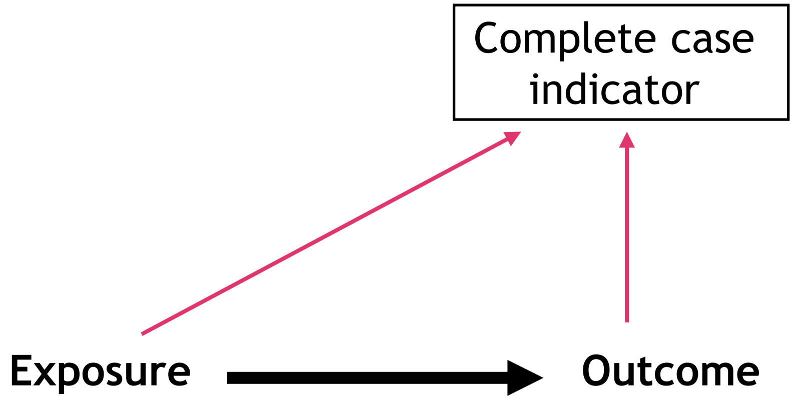


BMI-adjustment
<u>in</u>sufficient

Challenges in positing a defensible causal DAG

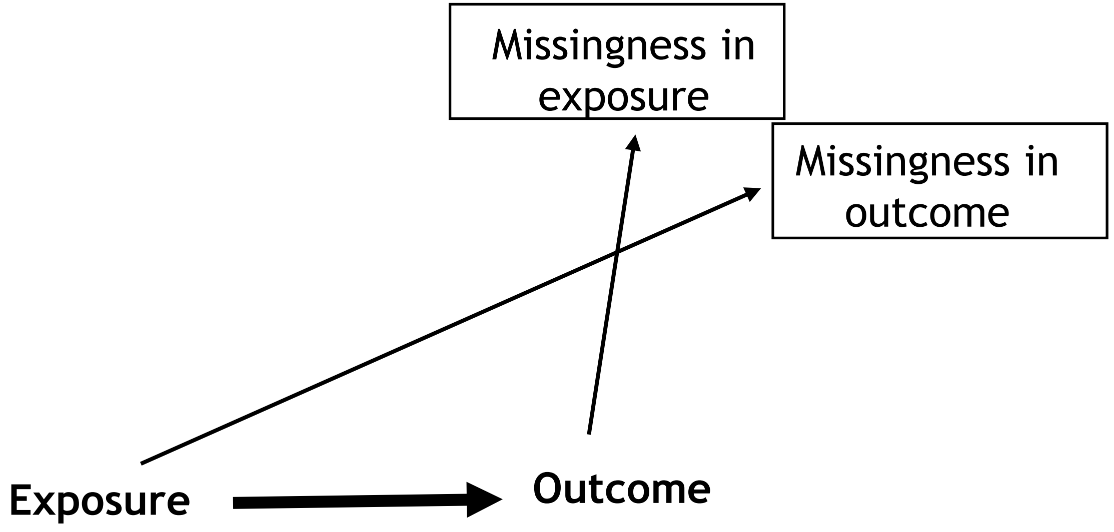
5. Oversimplification of complex study features

<u>Example:</u> Studies with multivariable missing data



Causal effect non-identifiable

(Daniel et al. *SMMR* 2012)



Causal effect identifiable

(Zhang et al. *Biometrical Journal* 2023)

A broken promise

Given the infeasibility of positing a defensible causal DAG, we cannot reap the promised benefits of DAGs in a wide range of epidemiological settings, and can actually be led astray

~~**Given a causal DAG, it is possible to:**~~

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Importantly, there is lack of awareness of the challenges described

A betrayal?

This lack of awareness, combined with <u>misguided use and perception of DAGs</u> in practice, has likely caused more harm than good:

- A “technique” that makes studies “causal”
- Overconfidence in a single DAG, ignoring uncertainty and other challenges that can lead astray
- Overcomplicated DAGs used to justify a reduced confounding adjustment set

Focus on DAGs as a “technique” misses the point about their promise, which is to reveal and help us understand and thus minimise causal biases to an extent rather than to abolish or hide them

So… should we forget about DAGs?

Diverse philosophies to using DAGs

Philosophy 1: Draw very detailed DAG on which to base every analysis decision

- As if it were a “magic bullet”
- Underlies how most people use tools such as DAGitty

This approach is at the origin of the “betrayal”: the challenges in positing a defensible DAG means we will be easily led astray, resulting in inappropriate analyses and interpretation

Diverse philosophies to using DAGs

Philosophy 2: Use DAGs to help communicate and think about bias in planning analyses

- Draw DAGs with some simplified features, e.g. grouping some variables
    - Don’t need to know all relationships amongst confounders to know the need to adjust for them
- Focus energies on detailing key paths of concern to assess bias arising in those structures
    - Focus energies on specific aspects (e.g. whether to exclude some participants) and assess biasing paths, ignoring the rest of DAG
- Sensitivity analyses that acknowledge uncertainties

This more nuanced approach doesn’t solve all the challenges, but can make it easier to navigate them and thereby partially fulfill the promise of DAGs, especially combined with other approaches

Example: Approaches to confounder selection

[VanderWeele, *European Journal of Epidemiology*, 2019]

	Approach	Issues	Type
1	Draw complete DAG & use graph rules (i.e. Philosophy 1)	Cf. issues with Philosophy 1	Philosophy 1
2	Adjust for all pre-exposure covariates	Too liberal	No DAGs
3	Common cause criterion (adjust for common causes of X & Y)	Too conservative	Philosophy 2
4	Disjunctive cause criterion (adjust for causes of X &/or Y)	Includes IVs , excludes proxies	Philosophy 2
5	Modified disjunctive cause criterion (disjunctive cause criterion + exclude IVs + include proxies of unmeasured common causes)		Philosophy 2
6	Approach 5 + causal machine learning (to tackle high-dim confounding)		Philosophy 2 + complementary approach

Other settings and complementary approaches

- Development of general criteria for handling complex multivariable missing data problems based on the study of missingness DAGs is a growing area of research

- Quantitative bias analyses enable examination of the impact of the unknowns, so we don't feel the need to hide them (for example behind a non-causal arrow)

- Target trial approach facilitates articulation of complex time-dependent processes that might lead to selection or measurement bias

Summary

- The promise of DAGs hasn't been fulfilled because it is largely unrealistic: it is infeasible to posit a defensible DAG in a wide range of settings

- What is worse, DAGs probably have caused harm due to lack of awareness of these challenges and their misguided use and perception

DAGs still hold promise, but fulfilling it will require a change in philosophy for how they are used and combining with other approaches