# Causal questions and principled answers: exposures, populations and effect estimation


**STRATOS Topic Group 7**

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This is where STRATOS TG7 aims to contribute

# Outline

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- In general, contributions from within this framework are concerned with causal questions formulated as contrasts of outcomes that would occur under hypothetical interventions on the exposure of interest:

  *Would the outcome of an individual differ if that individual had been with versus without that exposure?*

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  > *Would the outcome of an individual differ if that individual had been with versus without that exposure?*

Formally, for a binary exposure: Is $Y(1) \neq Y(0)$?

Here $Y(a)$ denotes the outcome that would have occurred had exposure $A$ been set to take value $a$ †

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† Assuming no interference; see slide 18

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  - Intervention: breastfeeding (BF) encouragement program
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  - Cluster RCT of $\sim$ 20,000 expecting mothers in Belarus carried out in 1996-97
  - Intervention: breastfeeding (BF) encouragement program
  - Primary outcomes: BF uptake and infection rates in infancy
- Imagine we wish to ask a new question regarding, not the effect of the intervention, but of BF (downstream from the randomization):

  *To what extent BF influences an infant's weight at 3m?*

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- In general, addressing this question would require a specifications of population, exposure and outcome
- What is distinctive of the PO perspective when considering these choices is that they should be selected in such a way that the PO under each level of the exposure is well-defined for each individual in the population
- If this were not the case, then contrasts of POs, used to define causal effects, would be ambiguous

# The example



- Let's select the following for our example:

1. population: all singleton births in Belarus in 1996-7 for whom BF is not counter-indicated
2. outcome: baby's weight at exactly 3m taken before the first feed using a standardized scale
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  - We could expand the definition of exposure to be "Exclusively BF for 1m": $Y(1)$ would still not be unique
  - We could choose a finer and finer definition . . . But even the finest may not be sufficiently unique, or may be present in an insufficiently large portion of the data

# Consistency [1]

- These considerations lead to invoking the 'technical assumption'‡ of consistency, defined as (in its simplest form):

$$Y(a) = Y, \text{ for everyone with } A = a$$

This says that, when $A$ is set to a certain level for all individuals, it would not change the outcome of those who actually have that exposure level, from the outcome that was actually observed (*"setting the exposure is non-invasive"*)

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- Consistency implies that the POs are well-defined
- It also links the selected exposure levels to the data via the equality in $Y(a) = Y$

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- In practice we often have multiple versions of the exposure—as in the BF example—each version potentially linked to a different PO
- A pragmatic approach:
  - aims for a sufficiently well-defined POs which are relevant for the data
  - interprets the POs as averages of the various POs that correspond to the multiple versions of the exposure

# Possible causal estimands

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▷▷▷ A different definition of exposure would lead to a different average

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- Question (b):

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▷▷ This estimand captures the best case scenario of what an encouragement intervention would achieve

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- ▷ Defined independently of any model
- ▷ Expressed in terms of POs, only some of which are identified via consistency ($Y(a) = Y,$ for everyone with $A = a$)
- ▷ How to proceed?

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  - Inverse probability of treatment: via propensity score
  - Combination of the two above: double robust methods [Bang and Robins,2005]

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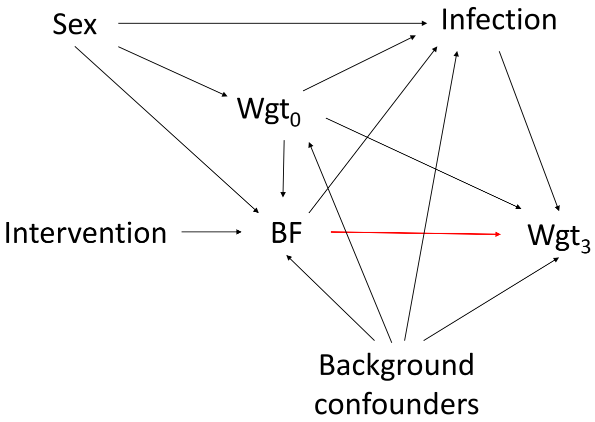
  - (B) Those that assume there is valid instrument
- All invoke parametric assumptions for some/all of their models, while positivity is invoked when the propensity score is used

# Simulated example inspired by PROBIT

## Overall 56% BF; 58% among those in the intervention arm; N∼20,000



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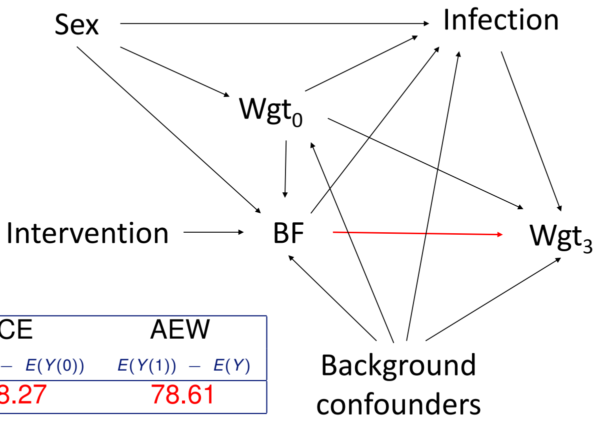


| ACE | AEW |
|---|---|
| $E(Y(1)) - E(Y(0))$ | $E(Y(1)) - E(Y)$ |
| 148.27 | 78.61 |

# Estimated ACE by estimation method

| | True value | 148.27 | |
|---|---|---|---|
| Class | Method | Estimate | (SE) |
| | Crude regression | 253.42 | (5.45) |
| A | Regression adjustment | 151.03 | (1.85) |
| | Regression with PS* | 156.14 | (2.04) |
| | PS stratification* (6 strata) | 157.49 | (6.48) |
| | PS matching | 154.46 | (3.96) |
| | PS IPW | 147.16 | (2.44) |
| B | IV (simple) | 136.00 | (29.38) |
| | IV (with confounders) | 152.44 | (10.79) |

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Mostly it is accused of *paralysing* research by:

- restricting causal investigations to exposures that are humanly feasible
- not being able to deal with complex exposures

Our view is that the PO framework:

- provides sufficient conditions for the quantitative assessment of certain causal effects
- has achieved important methodological advances where standard methods fail

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- It allows the quantitative definition of causal effects, the assessment of whether and under which assumptions they can be identified from the distribution of the available data, and the choice of estimation methods.
- However application of this framework is demanding, conceptually and technically
- Improving our understanding of this approach should be beneficial across many applied fields of research: STRATOS has a role to play!

# References


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# Additional slide

# No interference

- Another technical assumption implicitly invoked in this talk is that of no interference. It says:

  > *one individual's outcome does not depend on the exposure status of others*

  This allows us to write $Y(0)$ and $Y(1)$ to indicate the potential outcomes under the two levels of exposure.

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- This would occur *e.g.* if babies set not to be BF-ed suffer from infections that themselves affect the infection status, and hence the POs, of other babies
- We should use an extended notation using external information/assumptions regarding who is interfering with whom

# Positivity

- $Pr(A = a|L = l > 0$ for all $l$ and with $Pr(L = l) \neq 0$ in the population of interest
- Positivity holds when there are people at all levels of treatment in every level of the confounder.