Identifiable causal estimands in nutritional epidemiology

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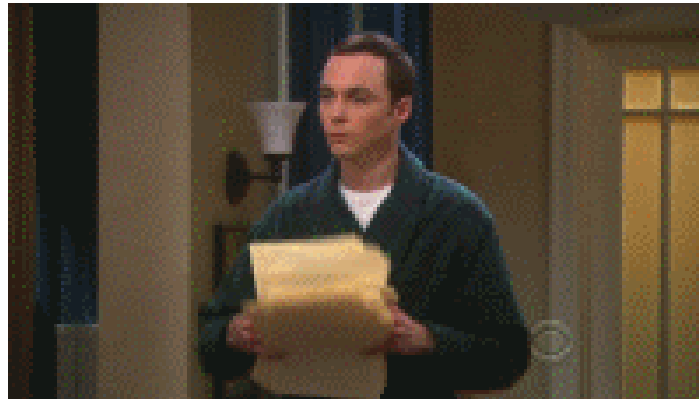Population Health Laboratory (#PopHealthLab), University of Fribourg, Fribourg

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Parameter that we want to estimate in a population of interest

Hernán MA, Robins JM (2020). Causal Inference: What If. Boca Raton: Chapman & Hall/CRC. Ch. 3

e. g., $\Pr[Y = 1 | A = a]$

Identifiable causal estimands in nutritional epidemiology

Consistency → values of treatment under comparison correspond to well-defined interventions and correspond to the versions of treatment in the data

Exchangeability → conditional probability of receiving every value of treatment depends only on measured covariates

Positivity → probability of being assigned the treatment conditional on covariates > 0

*In RCTs, they hold by design

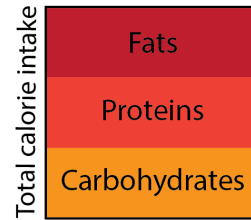Hernán MA, Robins JM (2020). Causal Inference: What If. Boca Raton: Chapman & Hall/CRC. Ch. 3

Identifiable causal estimands in nutritional epidemiology

- Conflicting results in studies focusing on the same exposure/outcome

- No explicit definition of the causal estimands and the id ass

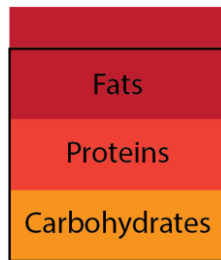# Exposures susceptible to intervene on in nutritional epidemiology

- Diets (e.g., Mediterranean diet)

- Foods (e.g., dairy, apples, whole grains)
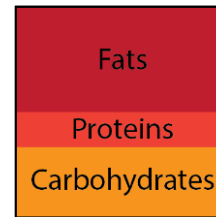
- Nutrients (e.g., caffeine, ω-3, vitamin E)

Foods

Consistency

Total calorie intake

Fats

Proteins

Carbohydrates

Estimands

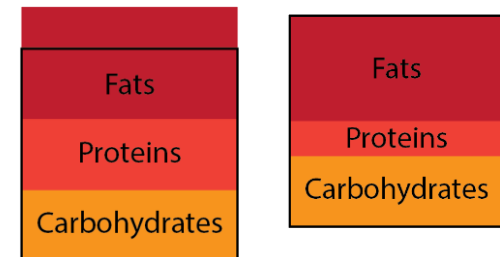| Total causal effect	Relative causal effect	WACE
Fats / Proteins / Carbohydrates	Fats / Proteins / Carbohydrates	Fats / Proteins / Carbohydrates (two stacks)
- Partially consistent → not realistic intervention - Joint effect of food group & calorie consumption - Clear public health message	- Joint effects if not explicit replacements hindering concistency - Direct effect, not though total calorie consumption - Good interpretability if explicit about the substitution	- Difficult to interpret, related to the effect of the intervention - Fully consistent with the intervention

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Arnold et al. https://doi.org/10.1093/ije/dyaa021, Breskin et al. 10.1093/ije/dyaa084 Tomova et al 2022

A word on exchangeability and positivity

Without consistency, it is difficult to assess exchangeability and positivity.

- Exchangeability:
    - E.g., Relative causal effects must include confounders between the other components and Y, not for total causal effects
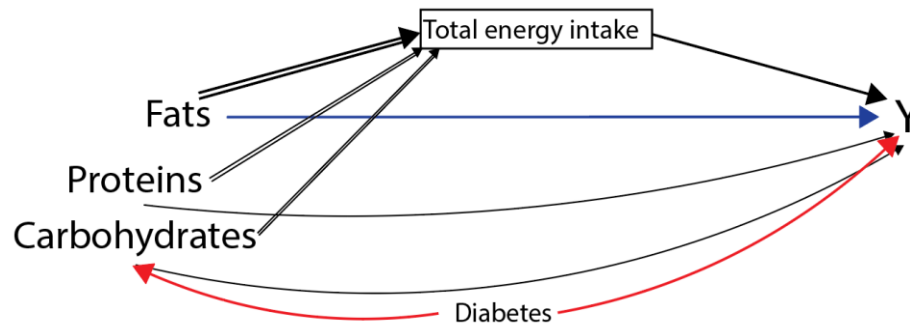
- Positivity: lots of covariates (all food groups)

A case study: dairy & cognition

- Literature review on the association between dairy and cognition.

- **All** but one (Ylirauri et al. 2020) were interpreted causally.

- **None** were explicit about targeted estimand.

- All (12) studies interpreted as total effects (addition).

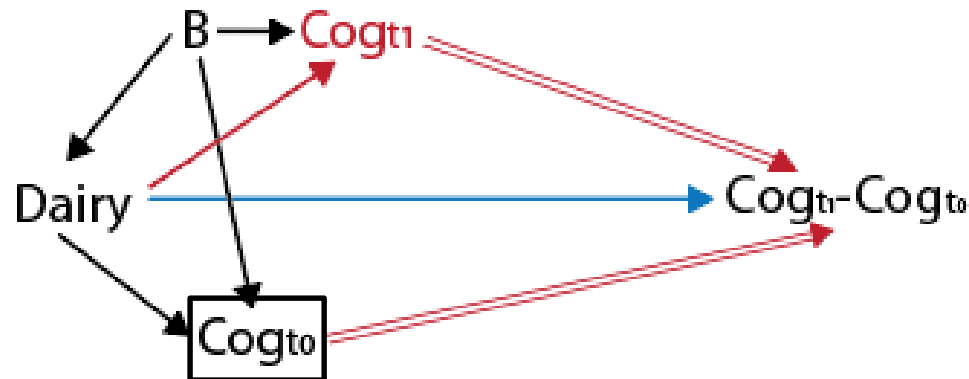# A case study: dairy & cognition
Identification problems

- Consistency
  - Interpret total causal effects but compute relative causal effects
    - Not explicit replacements

vs.

A case study: dairy & cognition
Identification problems

- Consistency
  - Interpret total causal effects but compute relative causal effects
    - Not explicit replacements
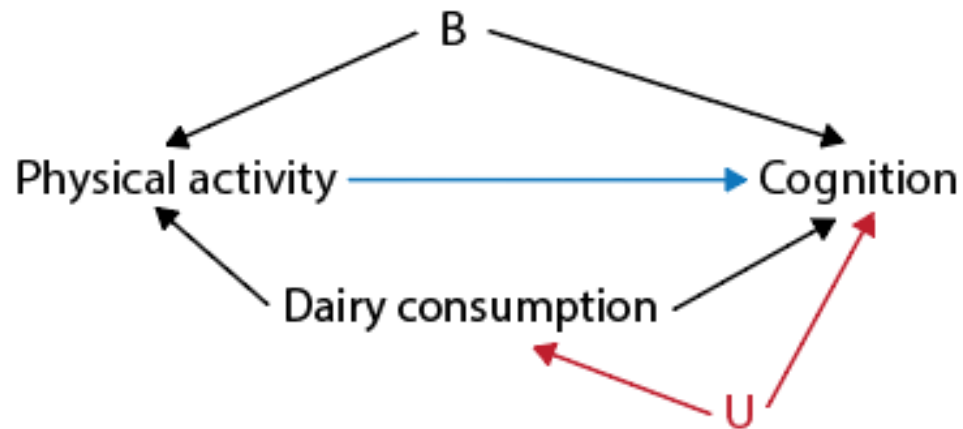
  - Outcome: Change score analysis

B denotes baseline characteristics confounding the relationship
Double arrows represent deterministic relationships

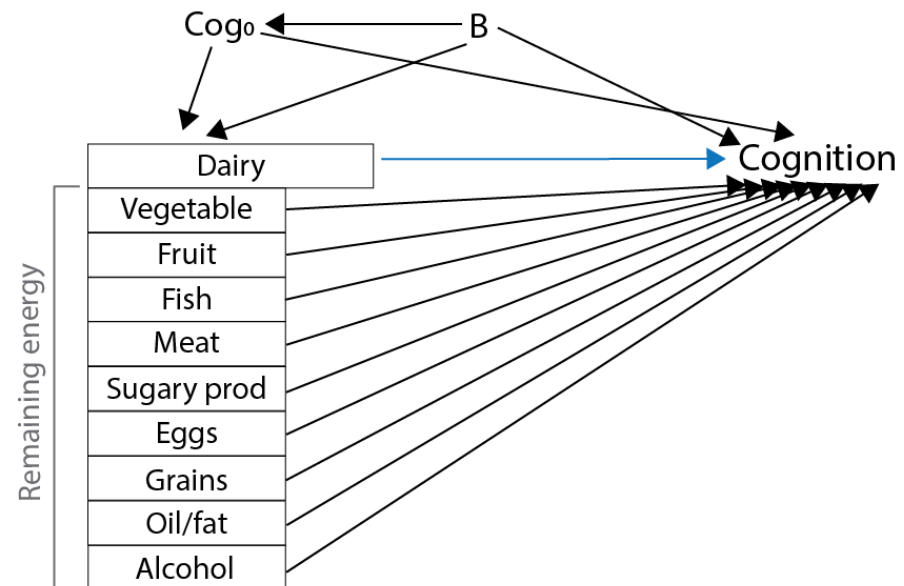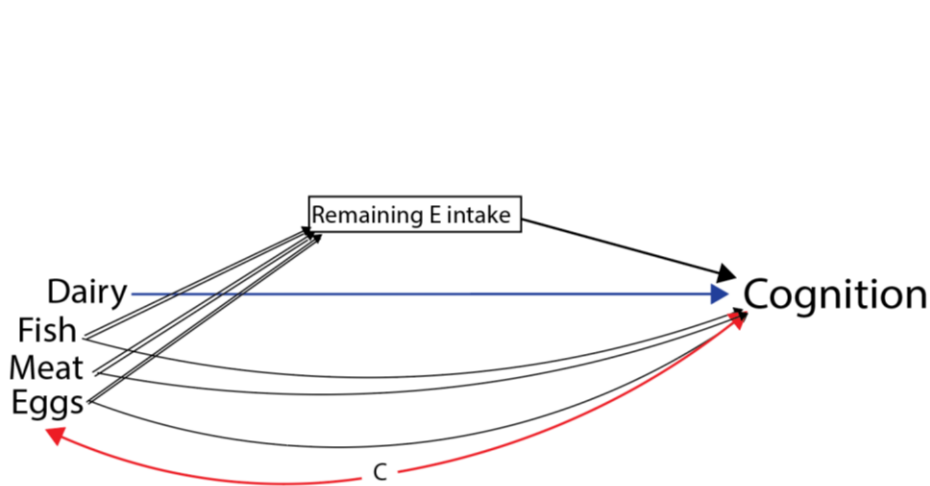# A case study: dairy & cognition
Identification problems

- Consistency

- Exchangeability

A case study: dairy & cognition
## Overcoming some identification problems

- Consistency: Relative causal effects with explicit replacements & total causal effects without the effect of total calories by remaining energy adjustment

A case study: dairy & cognition
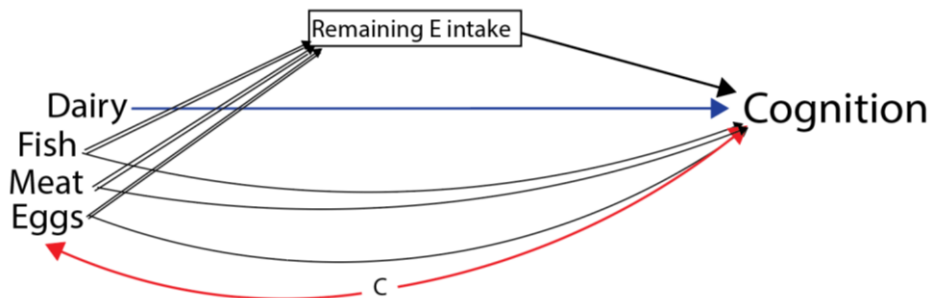# Overcoming some identification problems

- Consistency: Relative causal effects with explicit replacements & total causal effects without the effect of total calories by remaining energy adjustment
- Exchangeability: Confounders depending on the estimand targeted
- ! Positivity: low sample size
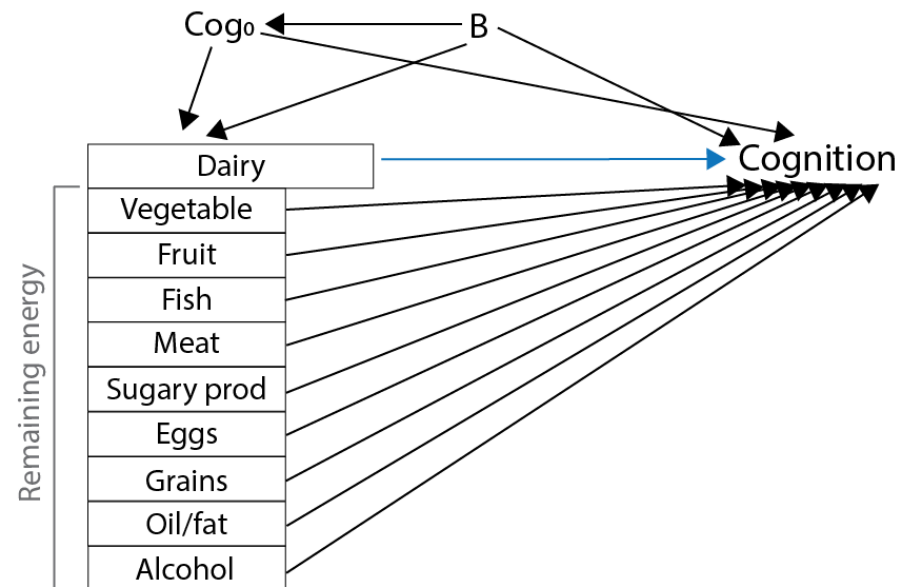
Simplified DAG where B represents the following baseline characteristics: age, sex, education, CV events, depression, diabetes, occupational level, smoking status, physical activity, hypertension and BMI. Cog_0: baseline cognition

Thank you for your interest

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