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# A COMPARISON OF ANALYTICAL APPROACHES TO OBTAIN MENDELIAN RANDOMIZATION ESTIMATES WITH LONGITUDINAL EXPOSURES

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# MOTIVATIONS.

## MENDELIAN RANDOMIZATION



- Genetic variants are proposed as an instrumental variable (IV)
- Increasingly popular approach to causal inference

## CURRENT LIMITATIONS



- Exposures of interest are often time-varying, e.g. alcohol, cholesterol levels
- Conventional IV methods designed to only handle time-fixed exposures
- MR estimates based on a single measurement of the exposure

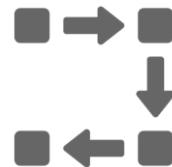
# OBJECTIVES.



Describe the **instrumental conditions** in the context of a **time-varying exposure**

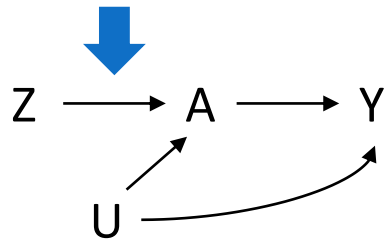


Review the possible **causal interpretations of MR estimates** and the additional assumptions required to do

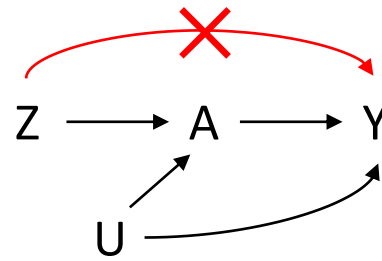


Propose methods to incorporate time-varying exposures in MR analyses of continuous outcomes based on **g-estimation of structural mean models**

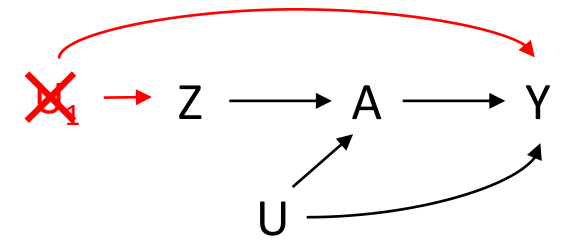
# IV CONDITIONS.



(1) Genetic variant is associated with the exposure.



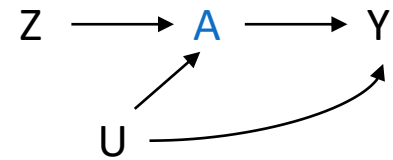
(2) The genetic variant does not affect the outcome except through its potential effect on the exposure.



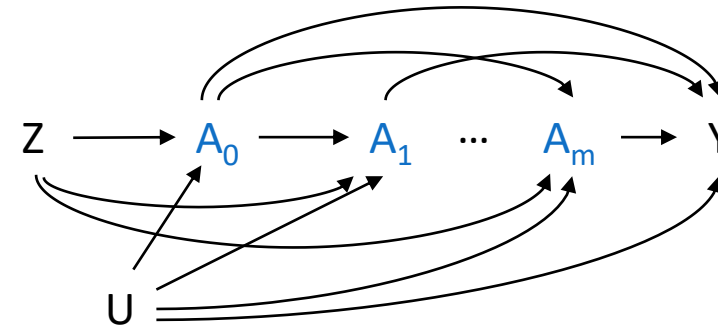
(3) The genetic variant and the outcome do not share common causes.

- Z = Genetic variant
- A = Exposure
- Y = Outcome
- U = (Unmeasured) confounders

# IV CONDITIONS WITH A TIME-VARYING EXPOSURE.



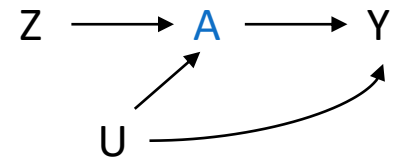
TIME-FIXED EXPOSURE



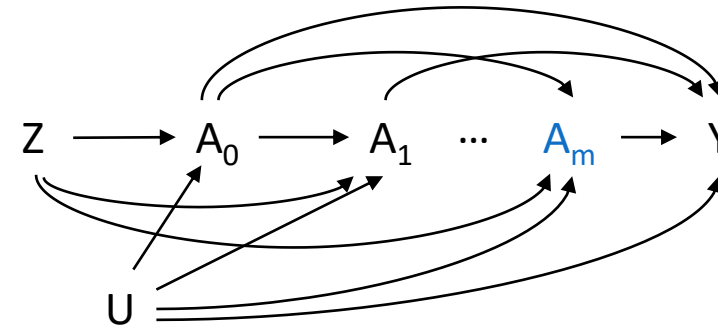
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# IV CONDITIONS WITH A TIME-VARYING EXPOSURE.



TIME-FIXED EXPOSURE



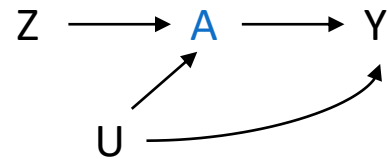
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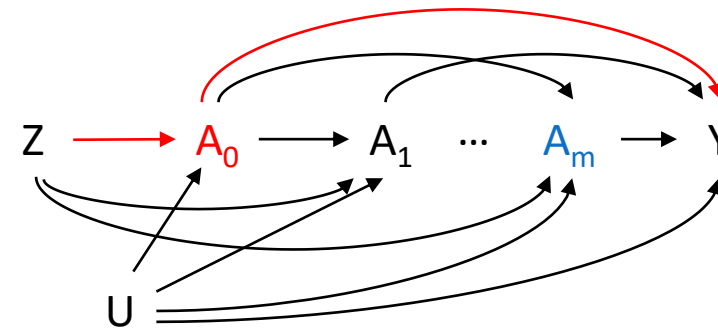


Second IV condition: the genetic variant does not affect the outcome except through its possible effect on the exposure

# IV CONDITIONS WITH A TIME-VARYING EXPOSURE.



TIME-FIXED EXPOSURE



TIME-VARYING EXPOSURE

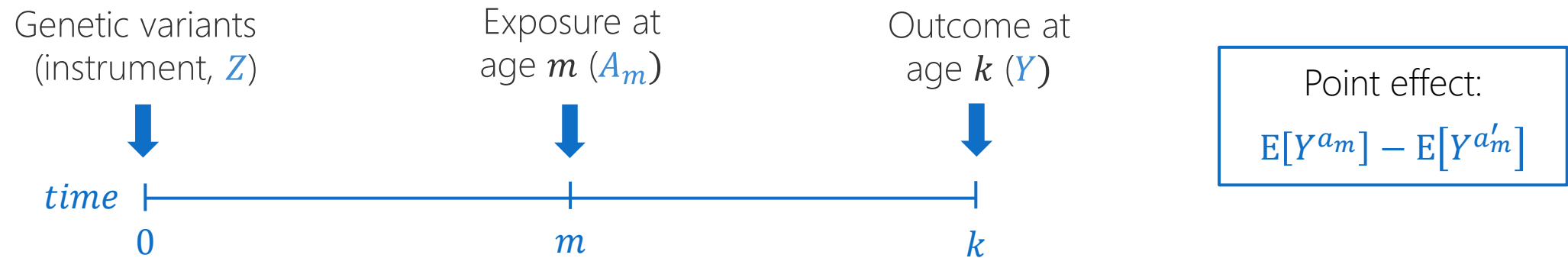
- Z = Genetic variant
- A = Exposure
- Y = Outcome
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Recall: the second IV condition states that the instrument does not affect the outcome except through its possible effect on the exposure

# FIRST TYPE OF CAUSAL EFFECT: THE POINT EFFECT.

Suppose for each individual, we have measurements on:

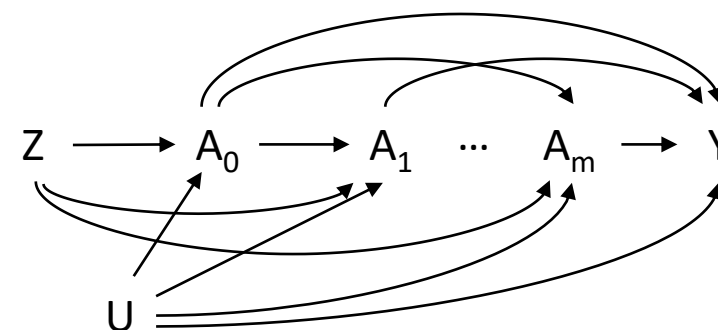


Outcome that an individual would have had had they received exposure level  $a$  at age  $m$  ( $Y^{a_m}$ )  
exposure level  $a'$  at age  $m$  ( $Y^{a'_m}$ )



# FIRST TYPE OF CAUSAL EFFECT: THE POINT EFFECT.

Requires genetic variant  $Z$  to be a valid instrument for  $A_m$   
(and only  $A_m$ )

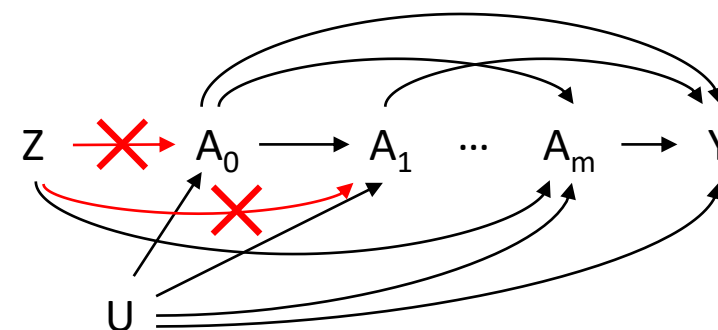


Point effect:  $E[Y^{a_m}] - E[Y^{a'_m}]$

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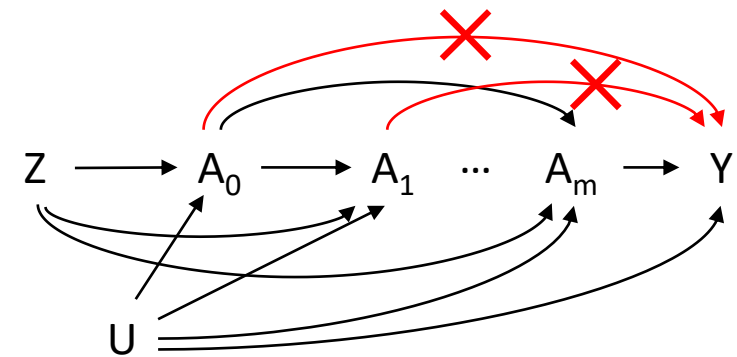


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Requires genetic variant  $Z$  to be a valid instrument for  $A_m$  (and only  $A_m$ )

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- No arrows from other exposure time points to the outcome

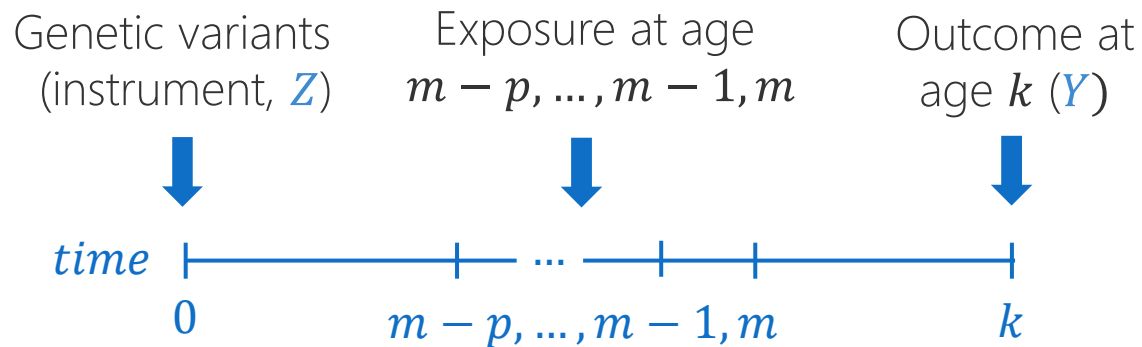


The assumptions to estimate the point effect in MR studies generally do not hold.

Point effect:  $E[Y^{a_m}] - E[Y^{a'_m}]$

# SECOND TYPE OF CAUSAL EFFECT: THE PERIOD EFFECT.

Suppose we are now interested in the effect of an exposure during a specific period, e.g.  $[m - p, \dots, m - 1, m]$



Interested counterfactual outcomes under:

1. Some exposure trajectory  $(a_{m-p}, \dots, a_{m-1}, a_m)$
2. Same exposure trajectory as (1), but shifted upwards by 1 unit

Period effect:

$$E[Y^{a_{m-p}+1, \dots, a_{m-1}+1, a_m+1}] - E[Y^{a_{m-p}, \dots, a_{m-1}, a_m}]$$

## SECOND TYPE OF CAUSAL EFFECT: THE PERIOD EFFECT.

If we measure the period effect with a single measurement time point:

1. The genetic variant  $Z$  is a valid instrument for the exposure during the period  $[m - p, \dots, m - 1, m]$
2. The association between the genetic variant and the exposure stays constant over time

This is a weaker form of the assumption required for the point effect

With multiple measurements of an exposure, we can relax this assumption by allowing the association to change over time.

For the period effect:

$$E\left[Y^{a_{m-p}=a, \dots, a_{m-1}=a, a_m=a} - Y^{\bar{0}} \mid A_{m-p}, \dots, A_{m-1}, A_m, Z\right] = \gamma(a; \psi)$$

## STRUCTURAL MEAN MODELS.

Model for the expected  
difference between two  
counterfactual outcomes

For the period effect:

$$E[Y^{a_{m-p}=a, \dots, a_{m-1}=a, a_m=a} - Y^{\bar{0}} | A_{m-p}, \dots, A_{m-1}, A_m, Z] = \gamma(a; \psi)$$

## STRUCTURAL MEAN MODELS.

Model for the expected  
difference between two  
counterfactual outcomes

Function of the exposure,  
indexed by the unknown  
parameter  $\psi$

E.g., with one measurement of the exposure,  $\gamma(a; \psi) = \psi a$

with  $p + 1$  measurements of the exposure:  $\gamma(a; \psi) = \sum_{j=m-p}^p \psi_j a$

**Homogeneity:**  $Z$  does not modify the relationship between the  
exposure and the outcome

## G-ESTIMATION.

Define an estimating equation

$$U(\psi; Z) = H(\psi)(Z - E(Z))$$

$$\text{where } H(\psi) = Y - \gamma(a; \psi)$$

Set the estimating equation to 0  
and solve for  $\psi$

Set  $E[U(\psi; Z)] = 0$  and solve for  $\psi$ ; for continuous outcomes,

the solution is:

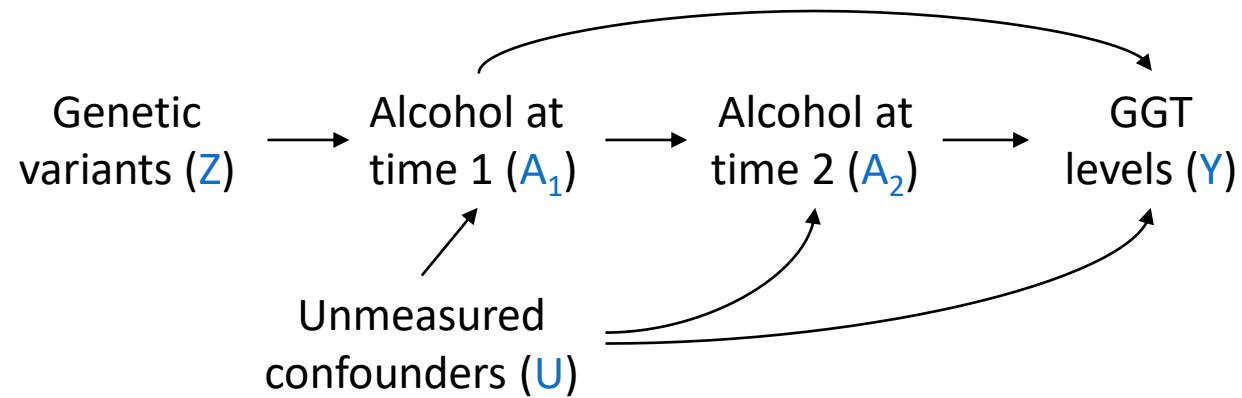
$$\hat{\psi} = \frac{\sum_{i=1}^n Y_i(Z_i - E[Z])}{\sum_{i=1}^n A_{m,i}(Z_i - E[Z])}$$



# APPLICATION: OVERVIEW.

**Goal:** use data from the Framingham Heart Study (FHS) to estimate the **period effect**\* of shifting one's **alcohol intake trajectory** upwards by 1 drink/day on **gamma-glutamyl transferase (GGT) levels**

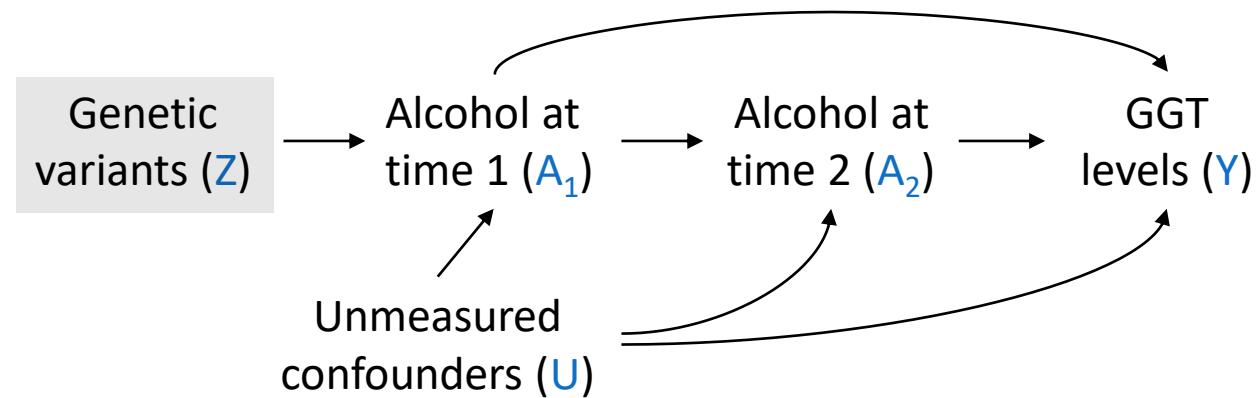
\*The period was defined to be over the duration of follow-up



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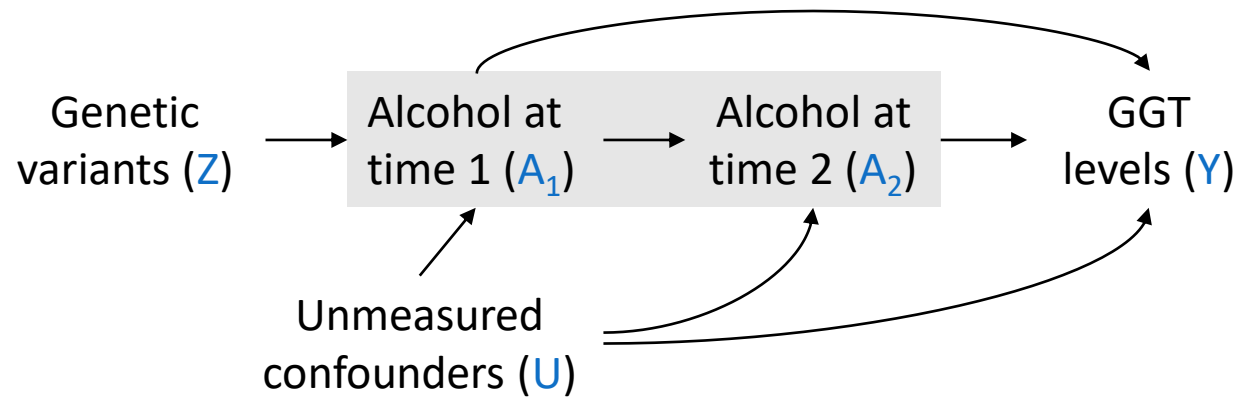


**INSTRUMENT:** 26 genetic variants identified from prior studies that were combined in different ways to create multiple weighted allele scores;

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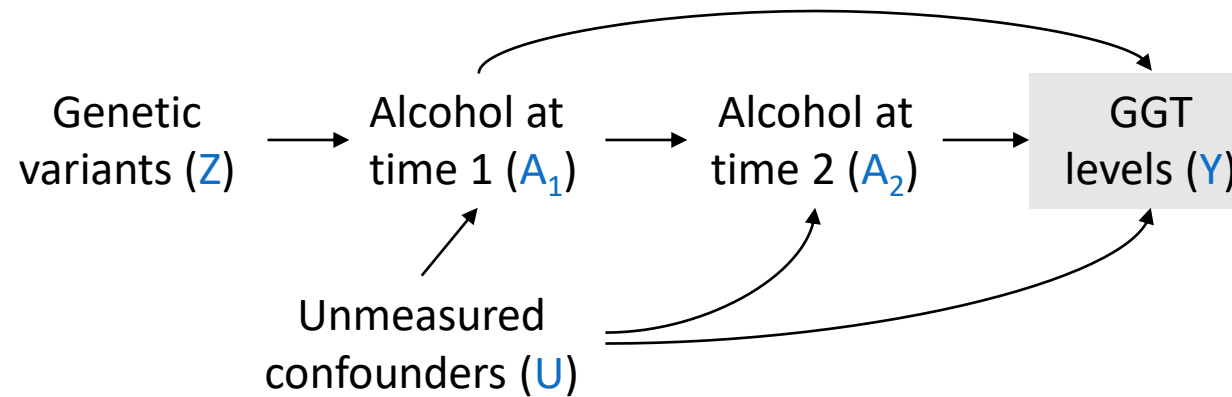


**EXPOSURES:** alcohol intake (via FFQ) at examination 1 and examination 2

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**Goal:** use data from the Framingham Heart Study (FHS) to estimate the **period effect**\* of shifting one's **alcohol intake trajectory** upwards by 1 drink/day on **gamma-glutamyl transferase (GGT) levels**

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**OUTCOME:** gamma-glutamyl transferase levels (measured in blood) at examination 2; marker for liver function

## APPLICATION: ANALYSIS.

Proposed two structural mean models

### Only consider a single exposure measurement

1. Exposure measured at examination 1
2. Exposure measured at examination 2
3. Average exposure across the two examination time points

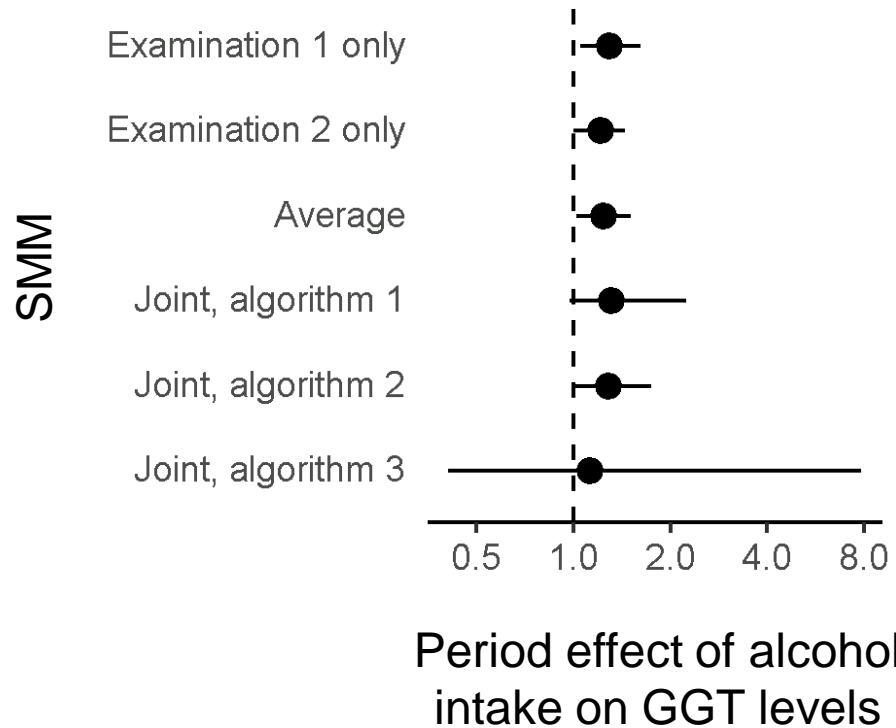
### Consider multiple exposure measurements

Estimated the parameters using different weighted allele scores

$$\text{i} \quad E[Y - Y^{\bar{0}} | A_{m-p}, \dots, A_{m-1}, A_m, Z] = \psi_1 A$$

$$\text{i} \quad E[Y - Y^{\bar{0}} | A_{m-p}, \dots, A_{m-1}, A_m, Z] = \sum_{j=1}^2 \psi_j A$$

# APPLICATION: RESULTS.



- Highlights from our data application:
- Similarity of results driven by limited number of exposure measurements
  - Precision of estimates

**Takeaway:** estimates were similar regardless of choice of model, although confidence intervals vary

## SUMMARY.



Possible **causal interpretations** of MR estimates and their assumptions

- Point effect
- Period effect



**G-estimation** of **structural mean models** to accommodate multiple measures of a time-varying exposure in an MR analysis.



**Advantages** of our proposed method:

- Include >2 time points
- Model non-linear outcomes
- Include other covariates into the model

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- Bernard Rosner

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# QUESTIONS.