



LifeCycle

Early life stressors and LifeCycle Health

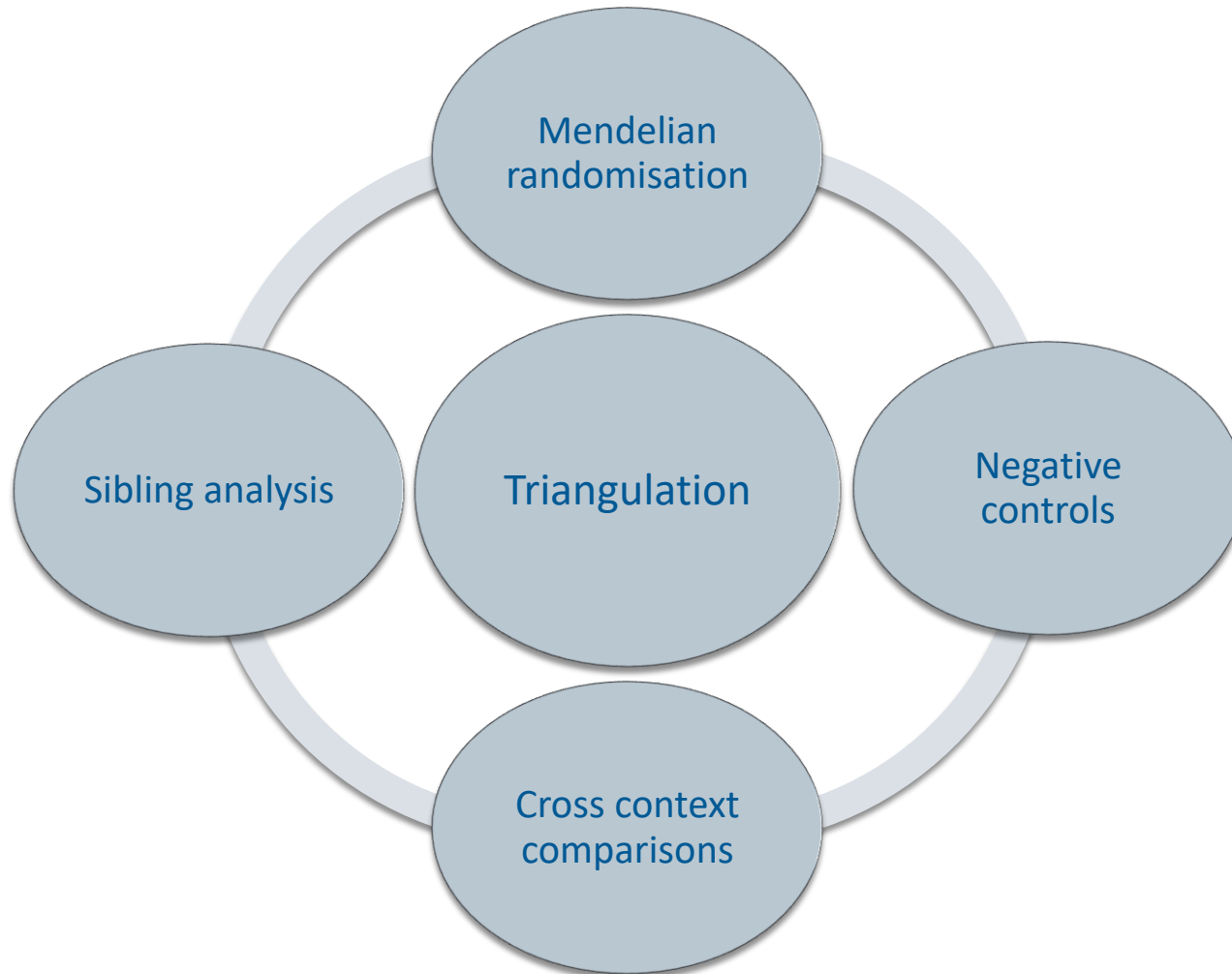
TRIANGULATION TUTORIAL

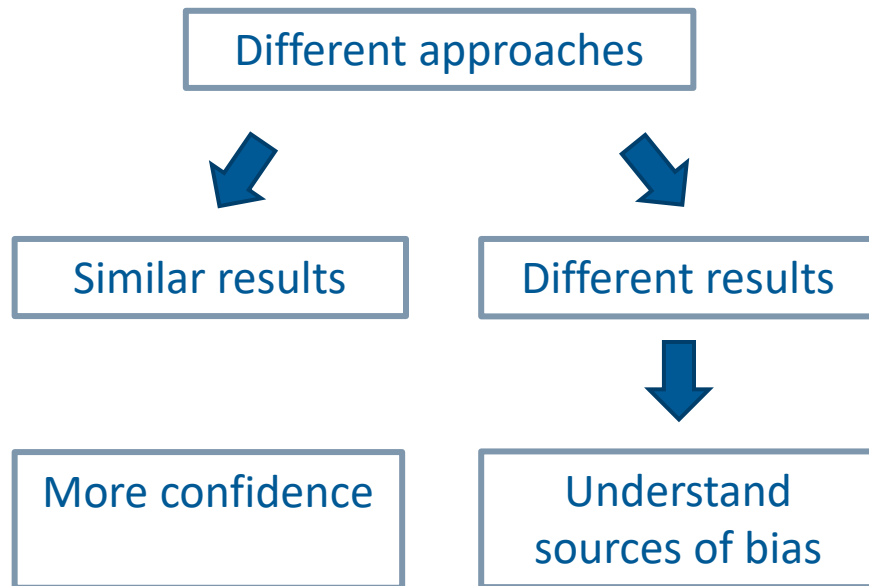
Q3 2022



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Plurality of approaches





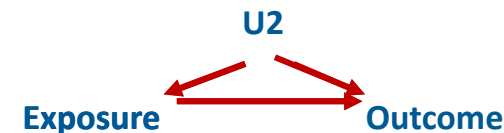
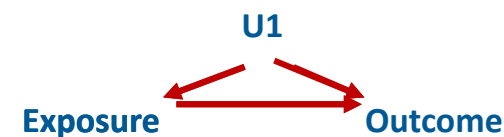
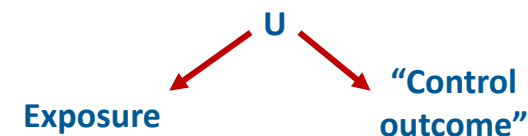
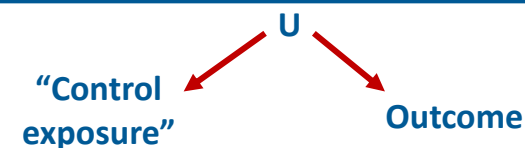
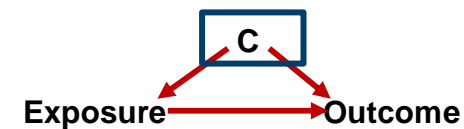
Lawlor, Tilling, Davey Smith IJE 2017

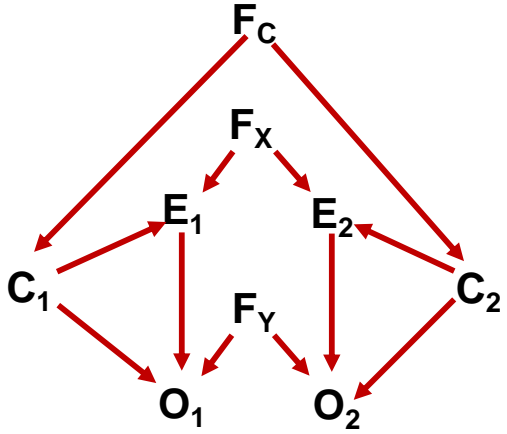
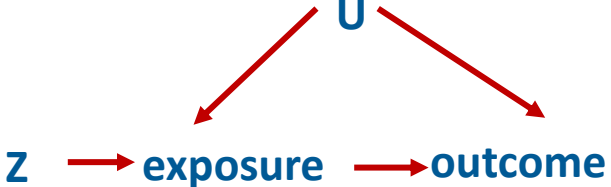
Minimum set of criteria:

- *Results from at least two, but ideally more, different approaches, with differing and unrelated key sources of potential biases, are compared (better if potential biases are in opposite directions);*
- *The different approaches address the same underlying causal question;*
- *For each approach:*
 - *Account for duration and timing of exposure*
 - *Acknowledge key sources of bias*
 - *Be explicit about the expected direction of all key sources of potential bias (where feasible)*



Method	Key assumptions
Multivariable regression, G-estimation, inverse probability etc.	<ul style="list-style-type: none"> All confounders measured and fully controlled for No reverse causality (confounding by prevalent disease)
Negative control study	<ul style="list-style-type: none"> No effect of negative control exposure on real outcome (negative exposure control); No effect of real exposure on negative control outcome Confounders same for negative control exposure/outcome as for real
Cross context	<ul style="list-style-type: none"> Marked differences in confounders between contexts (populations) No effect modification by context/population



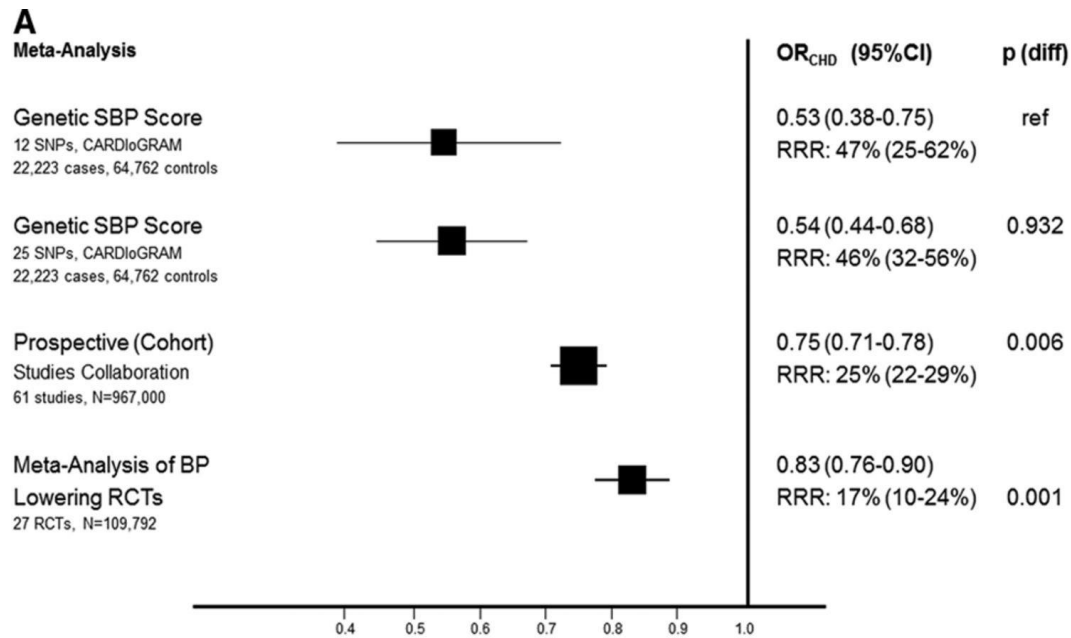
Method	Key assumptions	
Within sibship (or other matched designs)	<ul style="list-style-type: none"> • Within sibling pairs observed and unobserved confounders matched • No or little residual individual confounding • No contamination between discordant sibs 	 <p>A causal diagram for within sibship designs. At the top is a common confounder F_C. Below it are two sibling-specific confounders, F_X and F_Y. F_X influences two exposures, E_1 and E_2. F_Y influences E_1 and E_2. E_1 influences two outcomes, O_1 and O_2. E_2 influences O_1 and O_2. Additionally, F_C influences O_1 and O_2. There are also causal links from C_1 to O_1 and from C_2 to O_2.</p>
Instrumental variables	<ul style="list-style-type: none"> • IV is robustly associated with exposure • No common causes of Z-Y • IV is not associated with outcome by any other path than via the exposure 	 <p>A causal diagram for instrumental variables. A variable Z influences exposure, which in turn influences outcome. A common cause U influences both exposure and outcome. There is no direct path from Z to outcome.</p>

Triangulation in practice

- **Specific** research question
- Publish protocol / analysis plan before starting analyses
- (e.g. <https://osf.io/e4t8c/> and <https://osf.io/s6jv4/>)
- Identify methods/approaches and data sources based on criteria for triangulation
- **Specific** assessment of sources and risk of bias and likely direction
- Complete main analyses
- Complete sensitivity analyses related to assumptions / sources of bias
- **Compare** results from different methods



Example 1: SBP and CHD



Ference BA, Julius S,
Mahajan N, et al.
Hypertension 2014;
63(6): 1182-8

- NOTE: Paper does not refer to Triangulation. Focus is largely on MR with prospective cohort and RCT analyses mentioned only briefly at end of methods but highlighted in results and discussion substantially
- Specific policy relevant research question related higher SBP in early life influencing age-related increase in SBP and hence arterial damage and risk of CHD

Example 1: SBP and CHD

A

Meta-Analysis

Genetic SBP Score

12 SNPs, CARDIoGRAM
22,223 cases, 64,762 controls

Genetic SBP Score

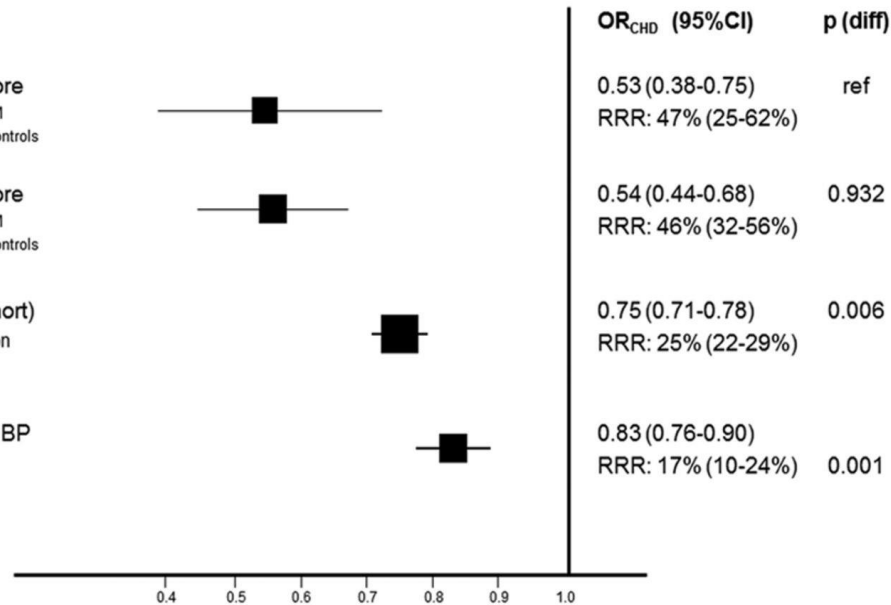
25 SNPs, CARDIoGRAM
22,223 cases, 64,762 controls

Prospective (Cohort)

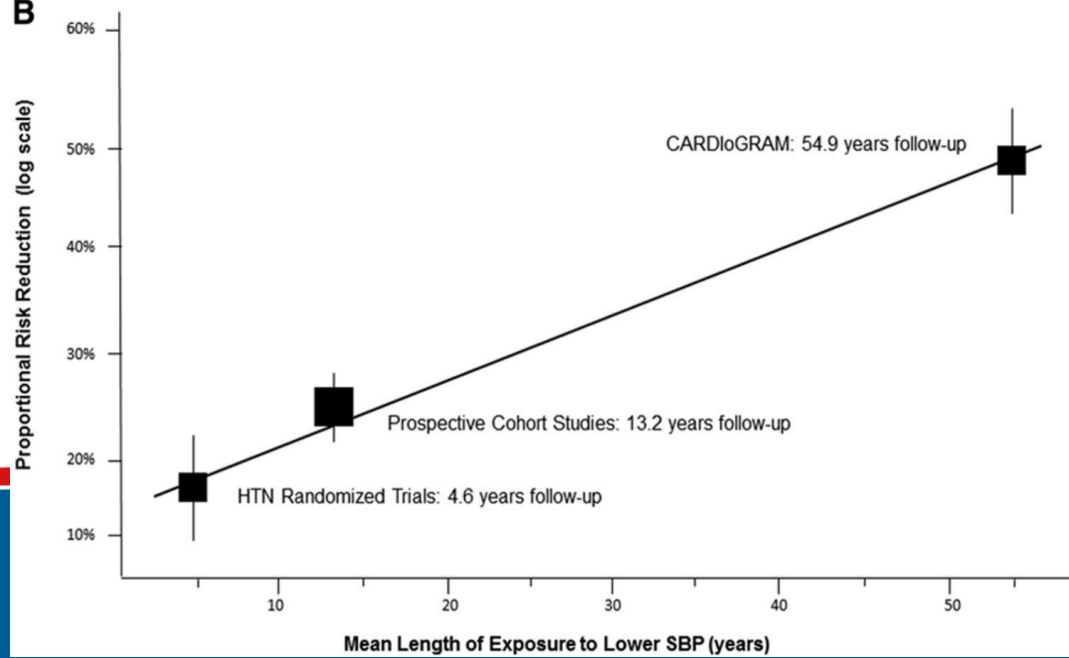
Studies Collaboration
61 studies, N=967,000

Meta-Analysis of BP

Lowering RCTs
27 RCTs, N=109,792



B



Method	Description	Key source of bias & direction
Two-sample MR	Two sample MR. Genetic variants from ICBP that had reached genome-wide levels of statistical significance were used for SBP. CARDIoGRAM used for sample 2 (22 223 fatal or non-fatal CHD cases and 64,762 controls). Ference et al. used MA of wald ratios.	On the basis of sensitivity analyses we did post hoc, we concluded these results were unlikely to have major bias if one outlier removed . But we could not quite replicate his results.
MV regression	Prospective Cohorts Collaboration: an individual participant meta-analysis of 958,074 adults (61 studies) aged 40-69 with no previous history of CVD. Exposure = SBP; Outcome = fatal CHD. Adjustment for age and sex only. Repeat SBP measurements in a large subgroup were used to adjust the association for regression dilution bias; the estimate of duration of exposure is therefore unlikely to be biased by this	Residual confounding, by adiposity and height, which would exaggerate any true positive causal effect.
IVs in RCTs	Systematic review and meta-analyses of 25 RCTs including 109,797 participants with no clinical evidence of cardiovascular disease prior to randomization. Authors of the original paper calculated ratios of difference in log odds CHD ÷ difference in BP by randomised group for each antihypertensive and meta-analysed these. Exposure = SBP & DBP together; outcome = fatal or non-fatal CHD.	Ference et al assumed the results represented a risk reduction in CHD for 10mmHg lower SBP, whereas the estimand = risk reduction in CHD for a 10mmHg lower SBP or 5mmHg lower DBP. Thus the (assumed) SBP effect is exaggerated in comparison to its true effect.

Example 2: Effect of maternal gestational smoking on fetal growth

Methods

- Multivariable regression
- Paternal Negative control
- Gene*smoking status interaction in Mendelian randomization framework

Data sources

- Generation R & Born in Bradford
- 8621 European liveborn singletons (Gen R 4682+ Born in Bradford 3939)
 - with repeat fetal USS and birth anthropometry
 - Genome-wide data
 - Smoking data on fathers at time of partners pregnancy.



Multivariable regression

Residual confounding due to measurement error due to harmonisation of confounders

Expectation **bias away from null**

Explore with sensitivity analyses, including here paternal negative control

Selection bias due to missing data

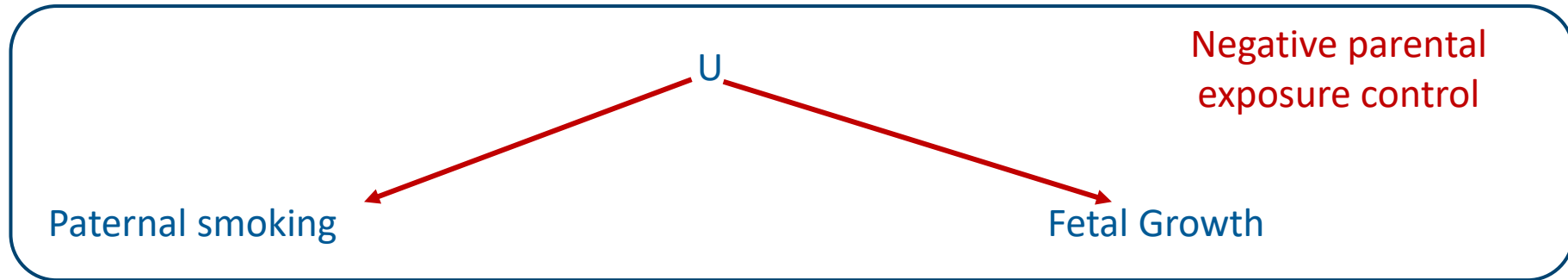
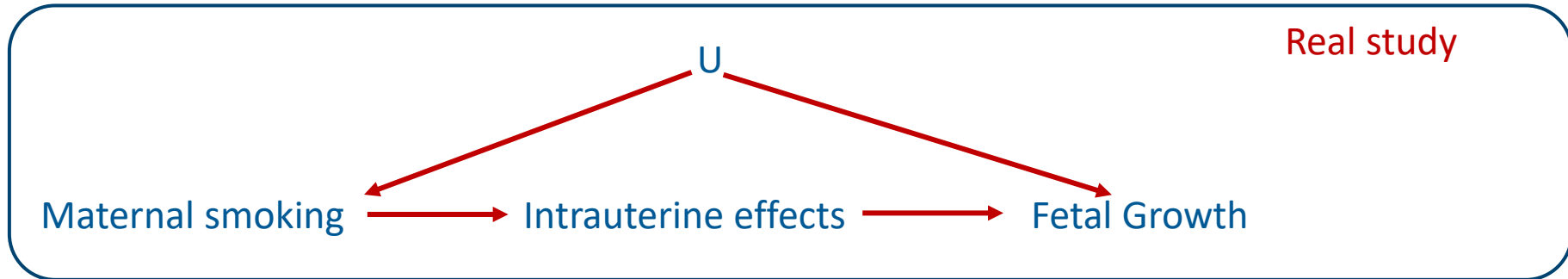
Use MLM and multiple imputation; assumes MAR if incorrect could be **bias in either direction**

Reporting bias – mothers under reporting smoking status & intensity

Expectation **bias towards null**

Explore with sensitivity analyses

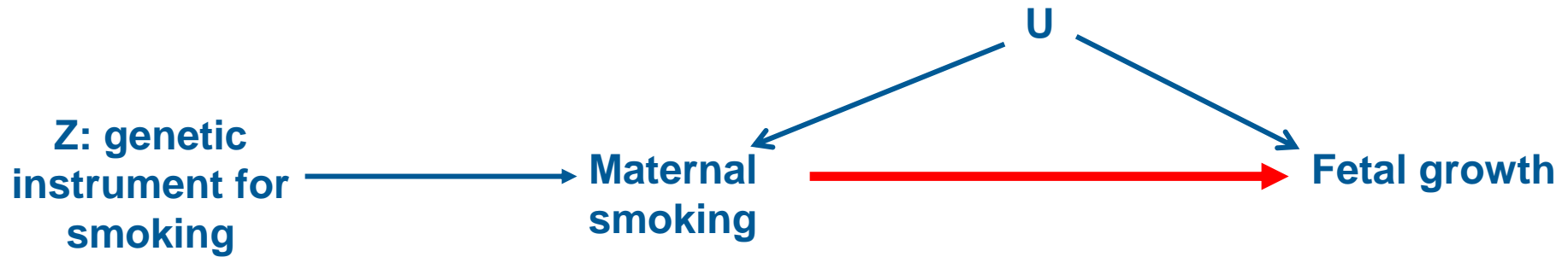


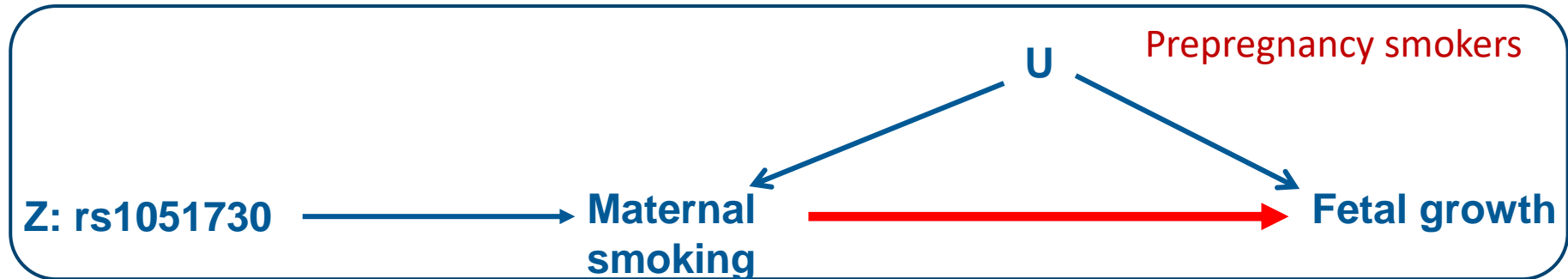
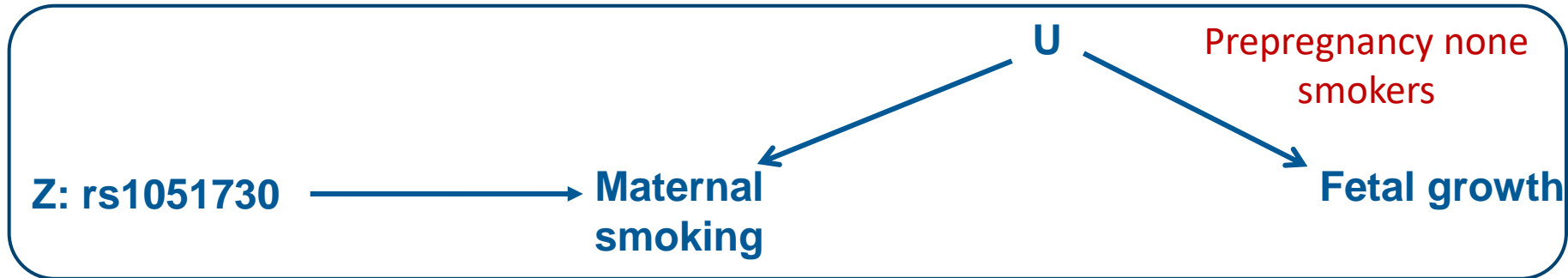


- **Confounders and measurement error similar** for mothers and fathers
- **Gen R mothers reported partners smoking** – could bias negative control towards that of mothers ‘real’ study. **BiB fathers reported own but sample size ~40%** reduces power to detect association – explore consistency between two studies
- **Fathers could influence fetal growth** via maternal passive smoking or epigenetics. Would expect mothers to be stronger and mutually adjust.



Mendelian randomization





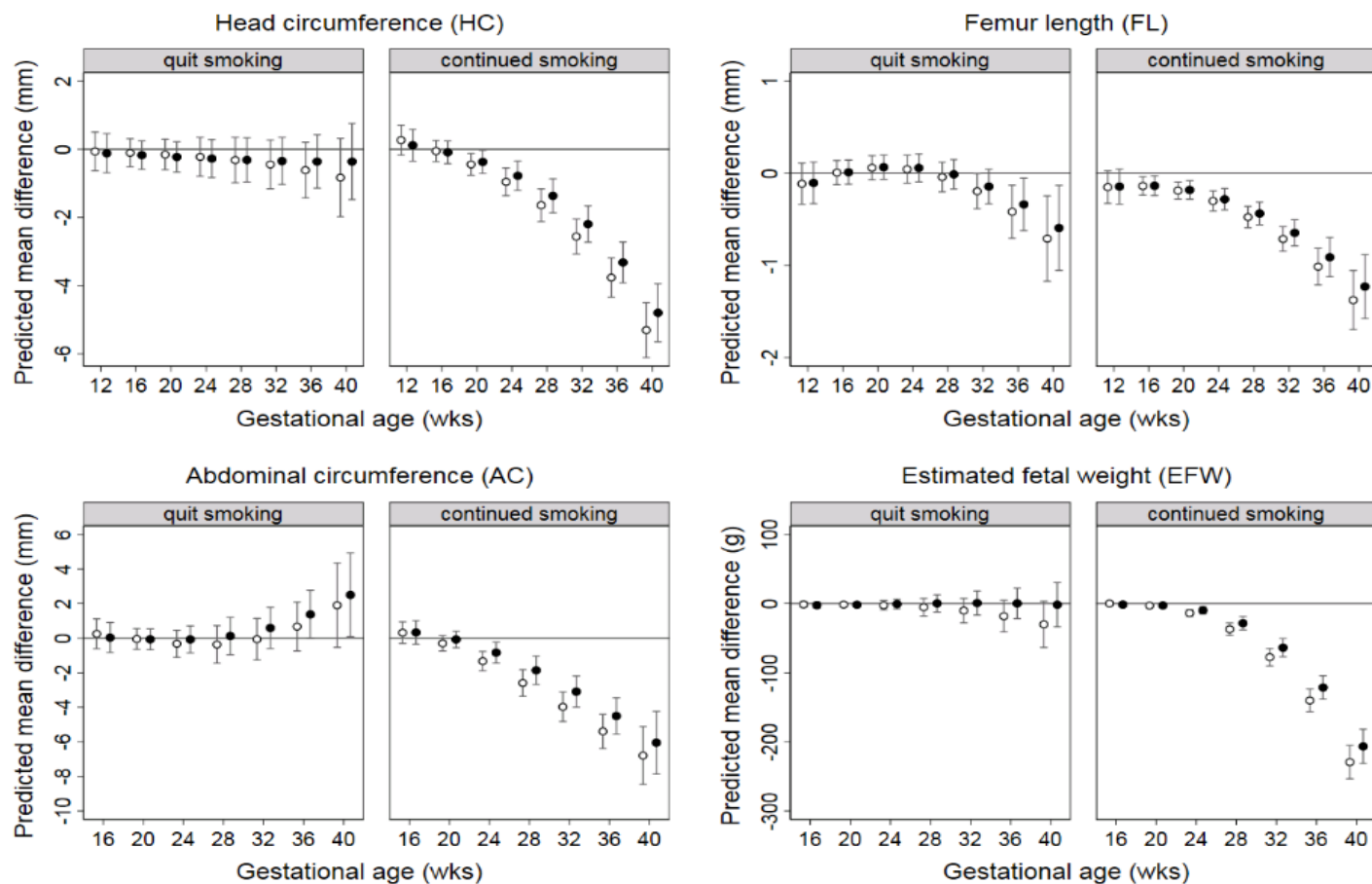
Horizontal pleiotropy: rs1051730 associates with BMI/adiposity (inc. in never smokers). As maternal BMI increased fetal growth this could bias inverse effects towards null.

Misreporting maternal smoking: could bias results such that never vs current smokers look more similar

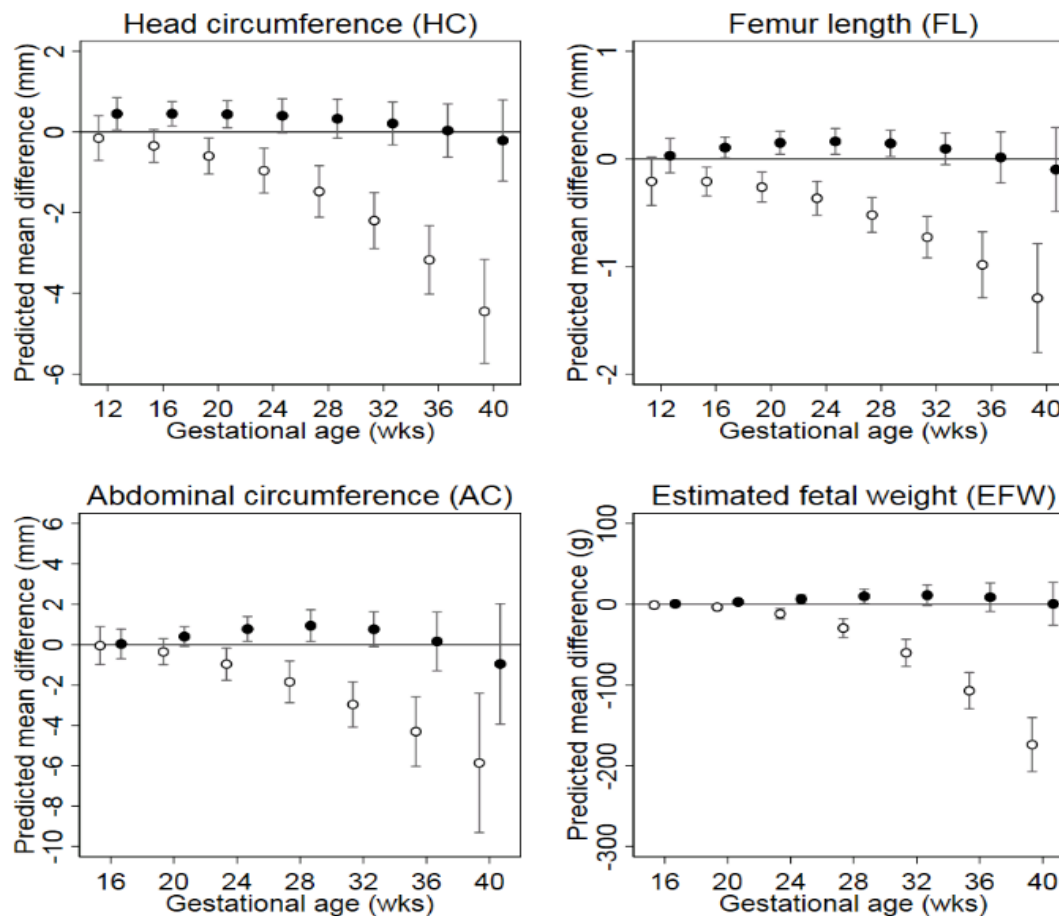
Collider bias: In main analyses actually compared results between never smokers, ever smokers who quit before/early pregnancy & ever smokers who continued



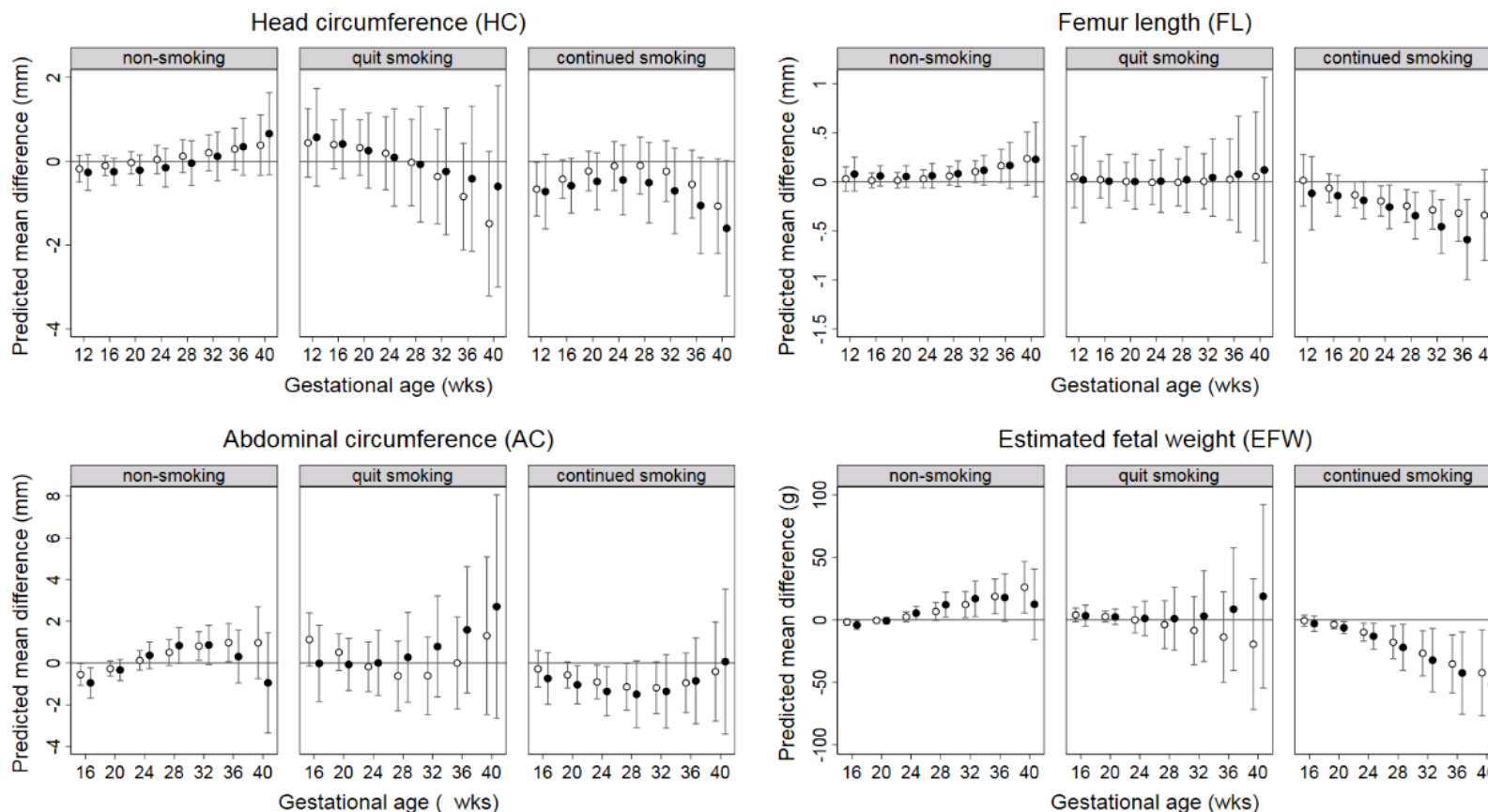
Multivariable regression maternal smoking status



Negative control paternal smoking during partner's pregnancy



Mendelian randomization; rs1051730 associations stratified by smoking status



RESEARCH ARTICLE

Associations of maternal quitting, reducing, and continuing smoking during pregnancy with longitudinal fetal growth: Findings from Mendelian randomization and parental negative control studies

Judith S. Brand^{1,2,3}, Romy Gaillard^{4,5}, Jane West^{2,3,6}, Rosemary R. C. McEachan⁶

- Pre-pregnancy smokers who continued smoking during pregnancy had a reduced fetal size from early gestation (12-16 wks) onwards.
- In pre-pregnancy smokers who gave up smoking early in pregnancy no overall growth deficit was observed, except for a smaller femur length towards the end of pregnancy.
- There was a dose-response
- These findings were supported by consistency across all 3 methods.
- Women who smoke in early pregnancy and quit once they realise they are pregnant can be reassured their smoking is unlikely to have adversely affected fetal growth.

• For women who find it difficult to quit smoking during pregnancy, stopped in

Going forward

- Triangulation has potential to improve causal inference
- **SHOULD have:**
 - specific causal questions
 - Prior publication Of analysis plan / protocol (iterative & can be changed with date and rationale)
 - Specific risk of assessment bias
- Currently, triangulation is mostly selected qualitative comparison
- There is a spectrum from that to fully open quantitative integration
- We are some way from the latter, with challenges including:
 - Time, effort vs current way academics are rewarded
 - Lack of methods / need to develop methods
 - Dealing with multiple sources of bias



THANK YOU

- All of you
- Chin Yang Shapland
- George Davey Smith
- Julian Higgins
- Kate Tilling
- Marcus Munafo

