

Power and instrument strength requirements for Mendelian randomization studies using multiple genetic variants

Tyler J. VanderWeele

Departments of Epidemiology and Biostatistics
Harvard School of Public Health

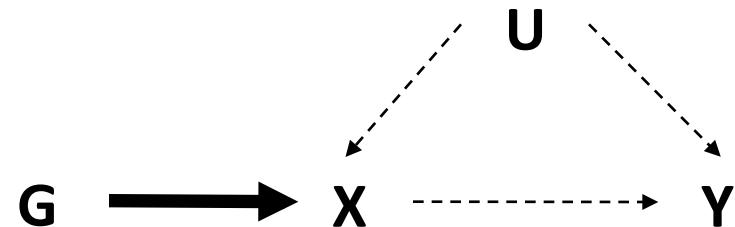
Paper and Collaborators

Pierce, B.L., Ahsan, H., and VanderWeele, T.J.
(2011). Power and instrument strength
requirements for Mendelian randomization
studies using multiple genetic variants.
International Journal of Epidemiology,
40:740-752.

Mendelian Randomization (MR)

Genes as instrumental variables

- **Goal of MR:** estimate causal effect of X on Y, using data on a known genetic determinant (G) of X
- Need data on G, X, and Y
 - But not U (if assumptions hold)
- Key MR assumptions: The IV (G) is
 - (1) associated with X
 - (2) independent of X-Y confounders (U)
 - (3) independent of Y given X and U (X-Y confounders)



What will be the implications for Mendelian Randomization of...

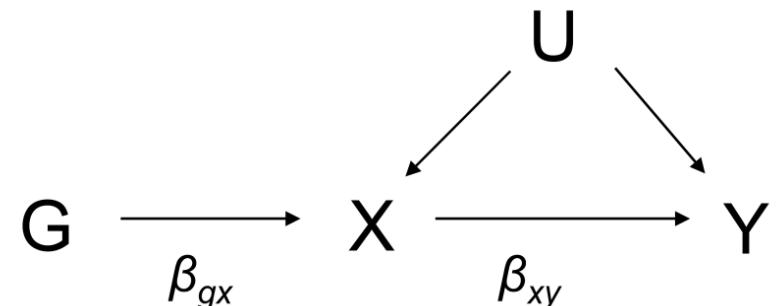
1. More potential IVs
2. Using knowledge of genetic architecture

Goal of this work:

Evaluate power and IV strength requirements for
MR studies that utilize multiple variants

Methods for Simulations

- Simulate data on a gene (G), exposure (X), and outcome (Y)
 - G is biallelic, X and Y $\sim N(0,1)$
 - With and without confounding (U)
 - 10,000 datasets



- Vary parameters:
 - $f(G)$, β_{gx} , β_{xy} , n, β_{ux} , β_{uy}

- Two-stage least squares regression (2SLS)

- Stage 1: regress X on G (the IV)
 - Stage 2: regress Y on fitted X values
 - Equivalent to the “Wald Estimator”

Wald Estimator:

$$\hat{\beta}_{MR} = \frac{\hat{\beta}_{gy}}{\hat{\beta}_{gx}}$$

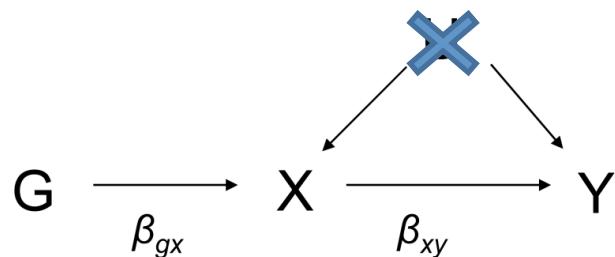
- Retain F statistic from the first-stage regression

- Rule of thumb: A “strong IV” has $F > 10$ (Stock et al, 2002)
 - Weak IVs bias towards the confounded OLS estimate

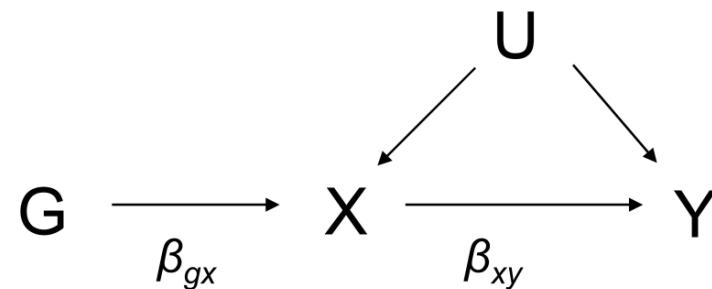
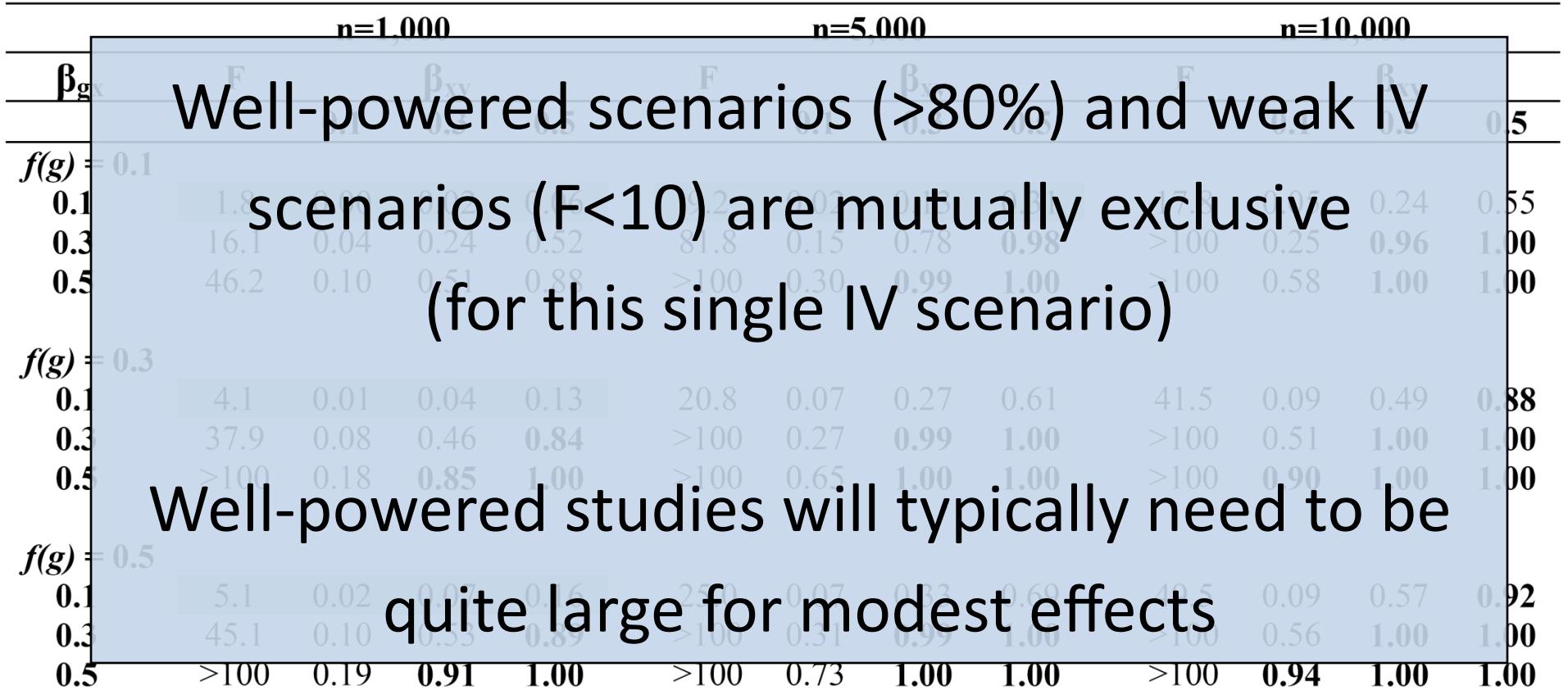
- Retain estimates and p-values from stage 2, determine empirical power

Power estimates for MR with a single IV

β_{gx}	F	n=1,000			n=5,000			n=10,000				
		β_{xy}			β_{xy}			β_{xy}				
		0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5		
$f(g) = 0.1$		→			→			→				
0.1	1.8	0.00	0.02	0.06	9.2	0.02	0.13	0.31	17.8	0.05	0.24	0.55
0.3	16.1	0.04	0.24	0.52	81.8	0.15	0.78	0.98	>100	0.25	0.96	1.00
0.5	46.2	0.10	0.51	0.88	>100	0.30	0.99	1.00	>100	0.58	1.00	1.00
$f(g) = 0.3$		↓										
0.1	4.1	0.01	0.04	0.13	20.8	0.07	0.27	0.61	41.5	0.09	0.49	0.88
0.3	37.9	0.08	0.46	0.84	>100	0.27	0.99	1.00	>100	0.51	1.00	1.00
0.5	>100	0.18	0.85	1.00	>100	0.65	1.00	1.00	>100	0.90	1.00	1.00
$f(g) = 0.5$		↓										
0.1	5.1	0.02	0.07	0.16	25.0	0.07	0.33	0.69	49.5	0.09	0.57	0.92
0.3	45.1	0.10	0.53	0.89	>100	0.31	0.99	1.00	>100	0.56	1.00	1.00
0.5	>100	0.19	0.91	1.00	>100	0.73	1.00	1.00	>100	0.94	1.00	1.00

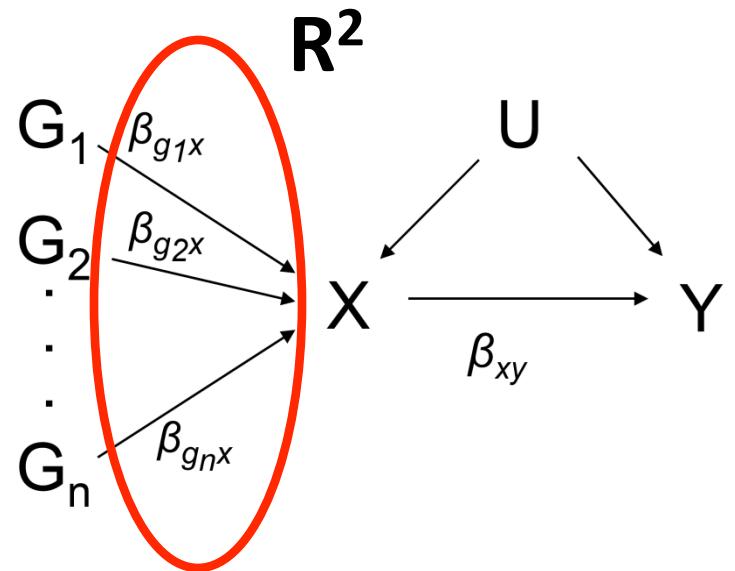


Power estimates for MR with a single IV

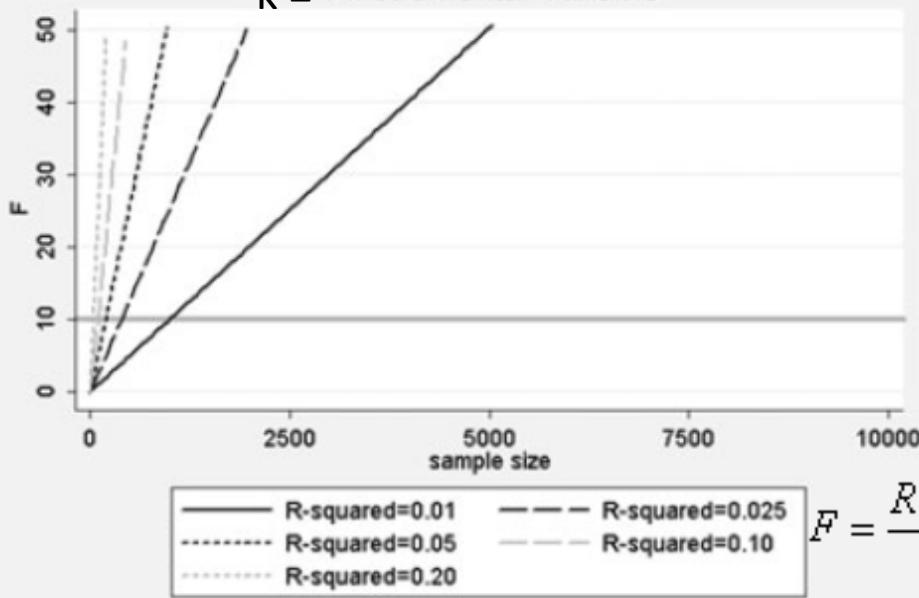


Multi-IV MR

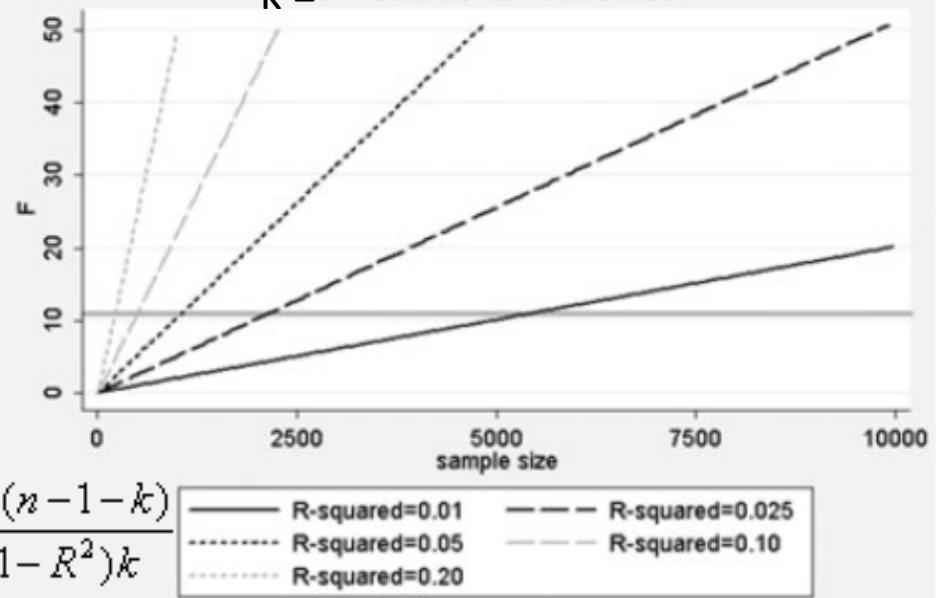
- Multiple IVs in the 2SLS regression
- R^2 as summary measure of the effects of Gs on X
- If n and β_{xy} are held constant, R^2 determines power



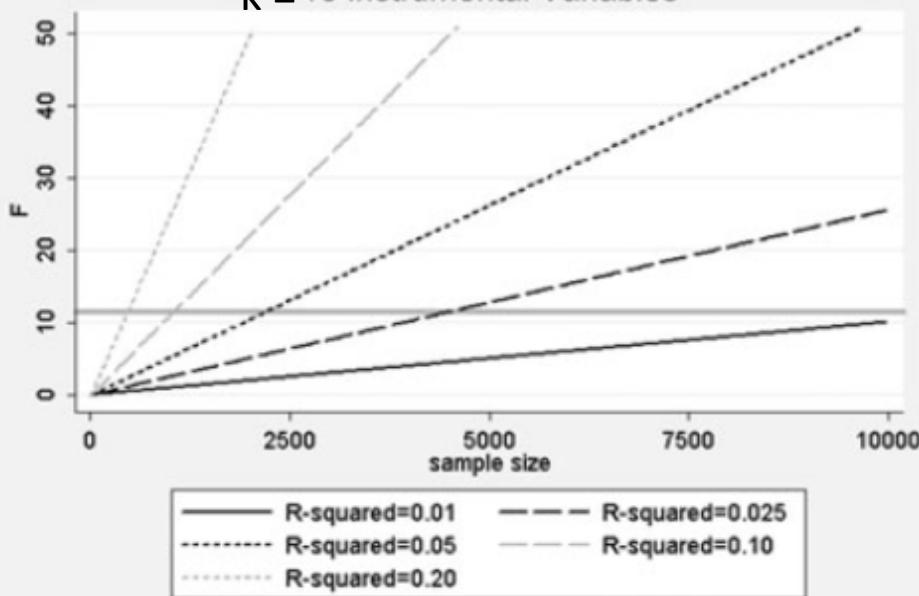
$k = 1$ Instrumental Variable



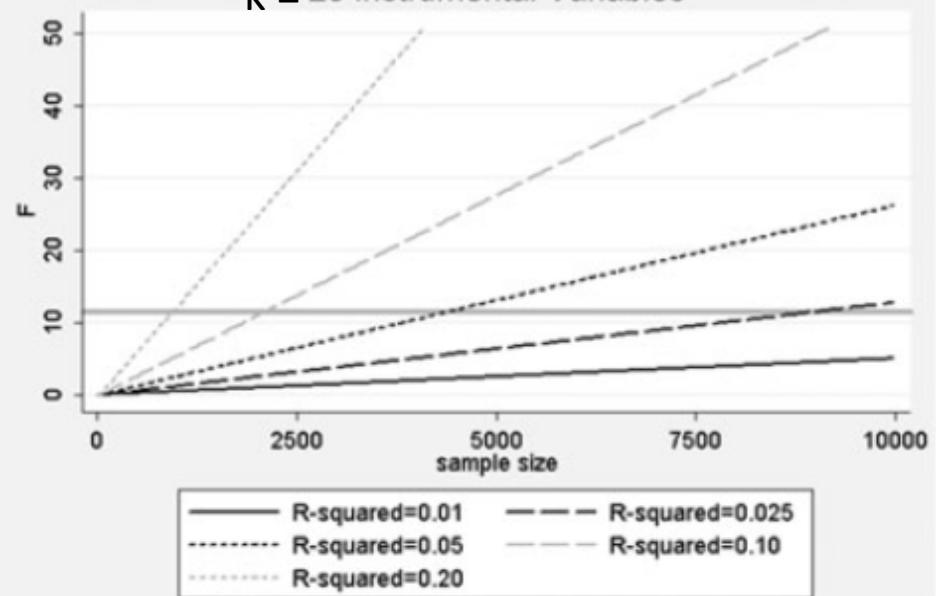
$k = 5$ Instrumental Variables



$k = 10$ Instrumental Variables

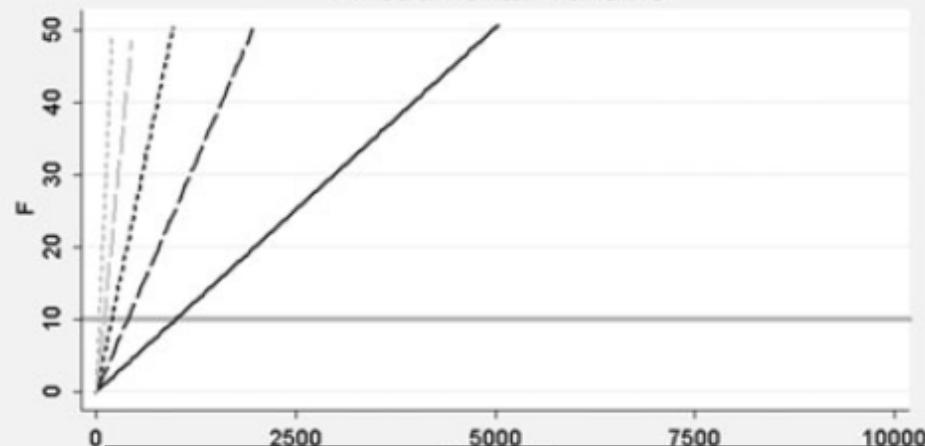


$k = 20$ Instrumental Variables

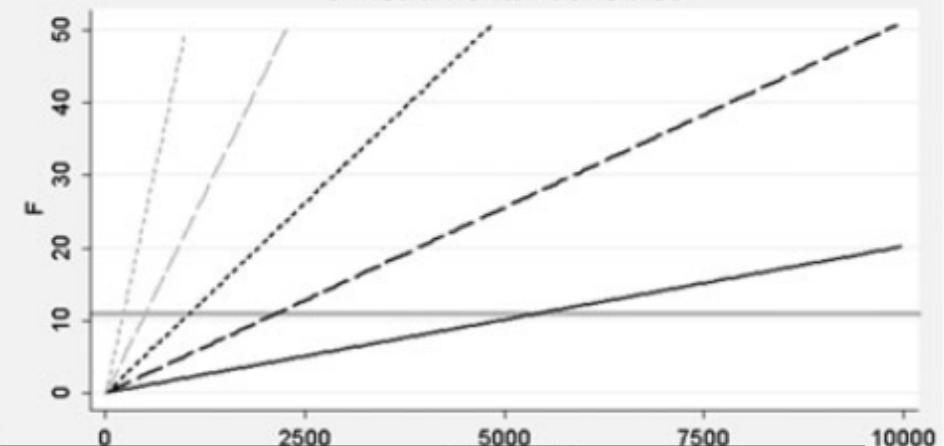


$$F = \frac{R^2(n-1-k)}{(1-R^2)k}$$

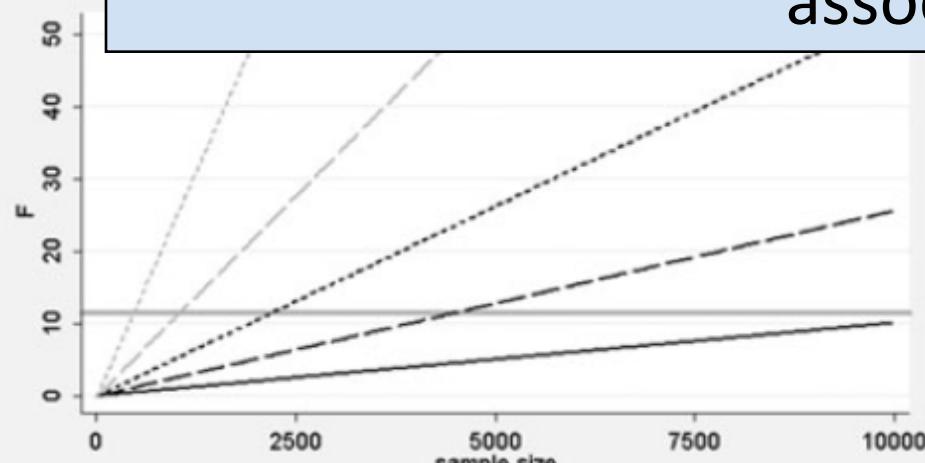
1 Instrumental Variable



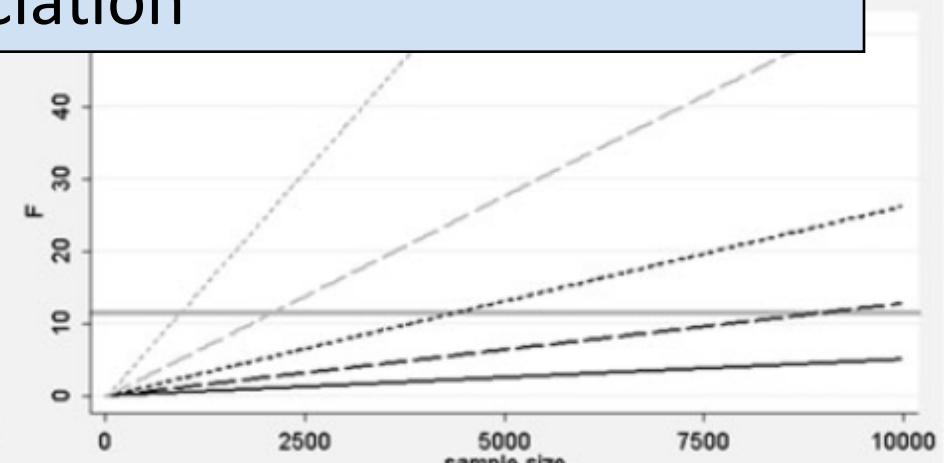
5 Instrumental Variables



Using many IVs will result in low F values, resulting in an MR estimate that is biased towards the confounded association



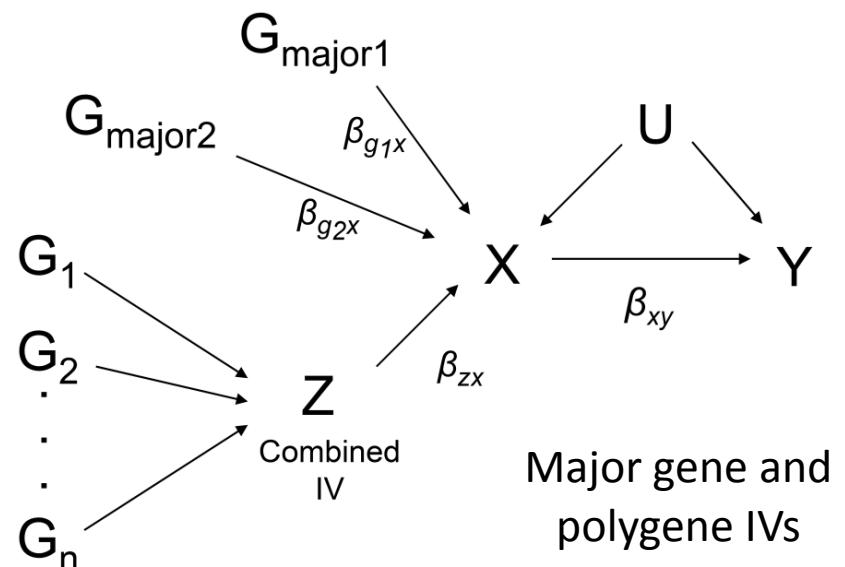
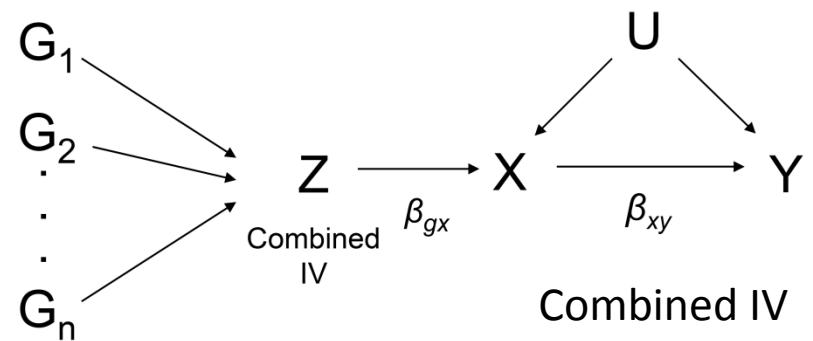
R-squared=0.01	R-squared=0.025
R-squared=0.05	R-squared=0.10
R-squared=0.20	



R-squared=0.01	R-squared=0.025
R-squared=0.05	R-squared=0.10
R-squared=0.20	

Reducing the number of IVs

- Combined IVs could take several forms:
 - allele count
 - weighted allele count
 - major gene/polygene
- Goal: maximize R^2 , while maintaining acceptable F values



A continuum of effects

No. of variants	IV(s)	Power Estimates					
		β_{gx}	R ²	F	0.1	0.3	
A continuum of effects (n=1,000)							
5 variants							
5 IVs	0.189	0.055	11.6	0.10	0.61	0.93	
Allele count	0.189	0.045	47.2	0.09	0.56	0.89	
Weighted count	0.189	0.051	53.5	0.11	0.58	0.92	
10 variants							
10 IVs	0.134	0.060	6.3	0.11	0.64	0.95	
Allele count	0.134	0.045	46.5	0.09	0.53	0.90	
Weighted count	0.134	0.051	53.7	0.11	0.57	0.93	
20 variants							
20 IVs	0.094	0.069	3.6	0.14	0.71	0.98	
Allele count	0.094	0.045	47.0	0.10	0.53	0.89	
Weighted count	0.094	0.051	53.7	0.11	0.58	0.92	

- Weighted count outperforms allele count (R² and F)
- Model misspecification decreases R² and F

Major gene/polygene model

No. of variants	IV(s)	β_{gx}	R^2	F	Power Estimates		
					0.1	0.3	β_{xy}
2 main effects + 8 polygenes (n=500)							
10 variants							
10 IVs		0.081	0.118	6.6	0.13	0.67	0.96
Allele count		0.081	0.063	33.6	0.07	0.42	0.79
Weighted count		0.081	0.102	57.0	0.10	0.60	0.94
2 major IVs + allele count		0.081	0.105	19.7	0.11	0.62	0.94

- Major-gene/polygene has slightly higher R^2 than the weighted count, lower F (but acceptable)
- Allows flexibility in model assumptions

Conclusions

- R^2 , power are maximized when using one IV per variant. But...
- For fixed R^2 , IV strength (F) decreases as # of IV increases
- Constructing optimal IV set is a balancing act:
 - Maximize R^2 , power
 - Minimize bias (adequate F values)
- Weighted allele counts may accomplish this
- GWAS-based MR requires careful treatment of weak IV problem
- BUT... with multiple instruments, we have multiple exclusion restrictions