

Causation in (Quantitative) Science

Ask Questions at any Time!!!

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What is SCIENCE?

- Science is the measurement of reproducible effect.
- Science allows society and individuals to benefit and plan their existence using reproducible effect.
- To measure reproducible effect – We need to reduce Bias
- Bias:
 - Selection Bias – Need to sample representatively of the population
 - Measurement Error – Keep accurate Measurements (*As the Label on the Jar Says*)
 - Random Chance – Insufficient sample size.
 - Confounding Bias

Reducing Counfounding Bias

Randomised Control Trials
(RCTs):

Randomly allocating
Interventions to balance
confounders between trial
groups to reduce bias.

Observational Studies:

Descriptive and
interventional: Need to
adjust for confounding
variables to reduce bias.

RCTs Not Always!



Sometimes Unethical



Balancing confounders is proportional to sample size. Small RCTs don't actually balance for all confounders.



Treatment non-compliance : Intention to Treat vs As Treated



Cost



Inflexibility: Compares few interventions to few outcomes.
New Chemotherapy drug every month. Oh Oh!



Cannot personalise treatment to patients.



Too clean: - cohort is not representative, too many exclusions, too strict inclusion criteria



More Internal consistency, but reduced Generalisability



Challenges in psychotherapy research due to varying therapist client "fit".

RCT Not
Always!

Observational studies

No RCT

Can't Balance for Confounders. **So What to Do!!!**

Literature
Review

Gather Evidence from Multiple Sources. From tall mountains to small pebbles!

Draw DAG

Directed Acyclic Graph: Draw a mechanism of Causation between predictor and outcome.



Science Awareness: Accurately portrays the science to the scientist and the reader.(After a good Literature review)



Measuring Causation: By Reducing confounding bias.

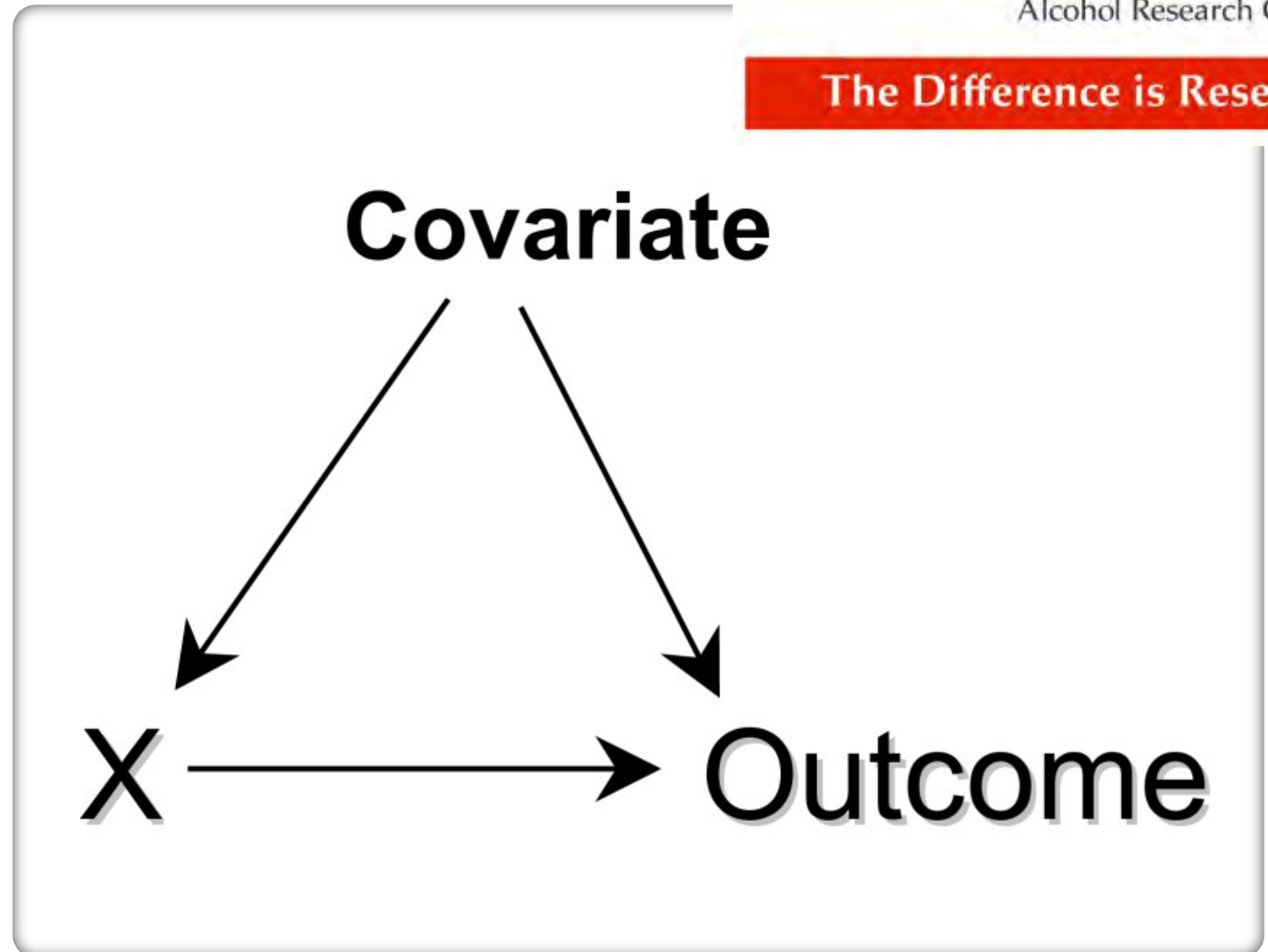


Efficiency Gain: DAGs show least confounders required to make causal inference.

Why the DAG!

Confounding the DAG way

- Predicts both the treatment (X) and the outcome.
- Does not lie on the causal pathway between treatment and outcome (i.e not a Mediator)
- In a DAG arrows only go one way. This causes that. (more details later)



Instrumental Variables: Adjusting For The Unmeasured!

Hang On!

We didn't measure or don't know what the confounders are.
Instrumental Variables to the Rescue. Assumptions:

Not on the causal pathway between treatment and outcome.

Does Not predict confounders.

Predicts outcome ONLY through treatment.

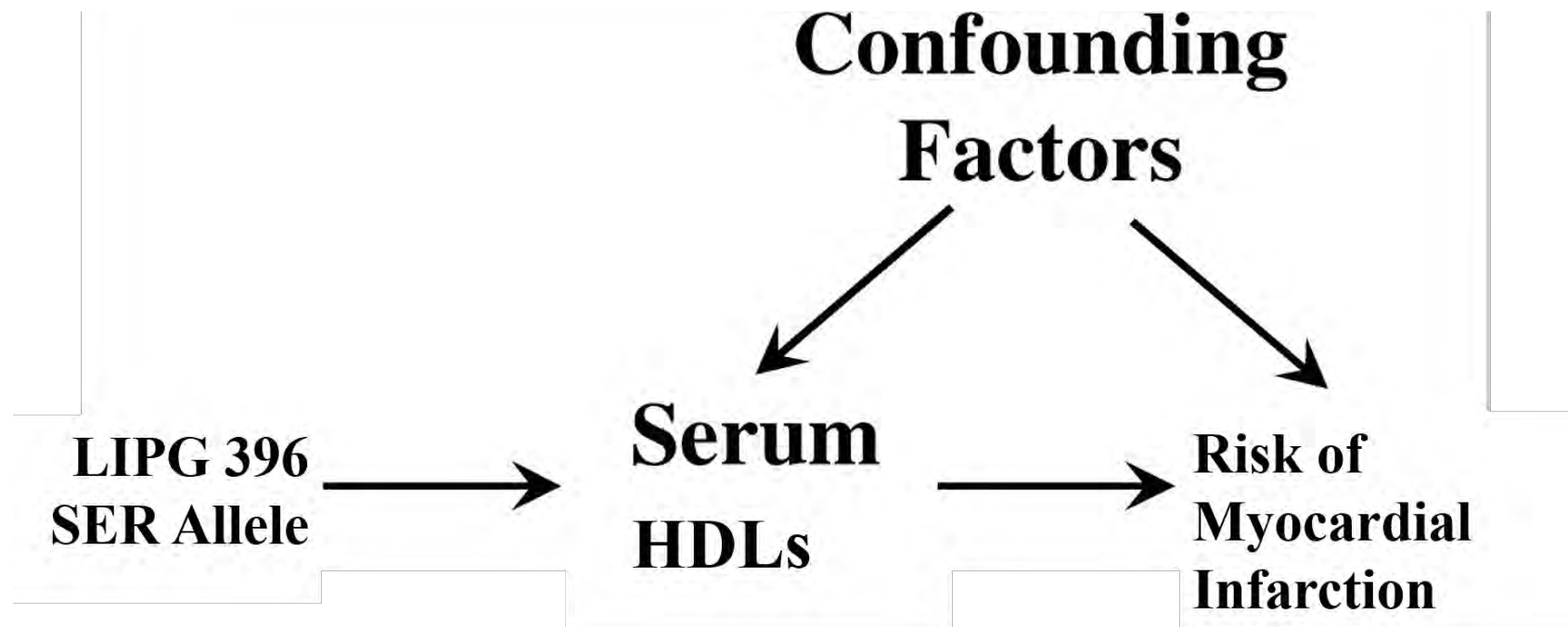
Beware: Sample size required is higher for instrumental variables.

Instrumental Variables In Action

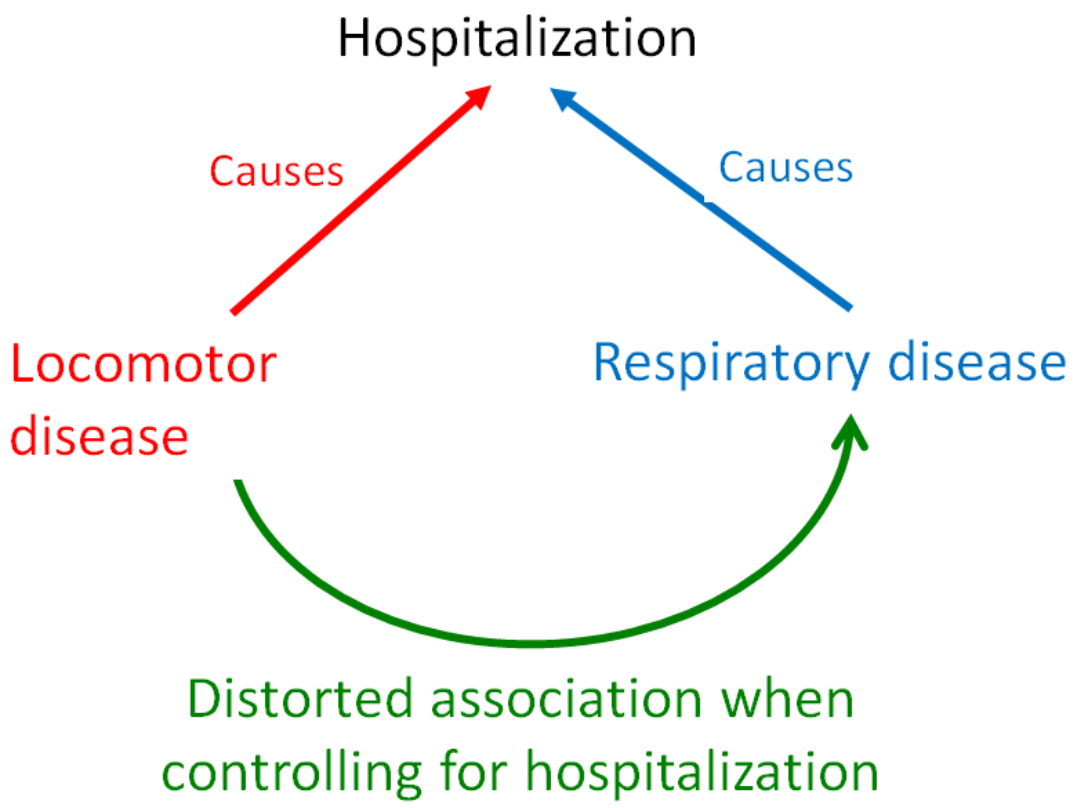
The Difference is Research

No association between HDL and Risk of MI.

Voight BF, Peloso GM, Orho-Melander M, Frikke-Schmidt R, Barbalic M, Jensen MK, et al. Plasma HDL cholesterol and risk of myocardial infarction: a mendelian randomisation study. *The Lancet*. 2012;380(9841):572-80.



No instruments! – Adjusting for measured confounders. Collider Bias: traps for young players



Disease X and Outcome Y might be causally linked.
But adjusting for a collider → increases bias between X & Y.

Hx: That Locomotor Disease reduces mobility and leads to respiratory disease

Both cause increased rate of hospitalisation.

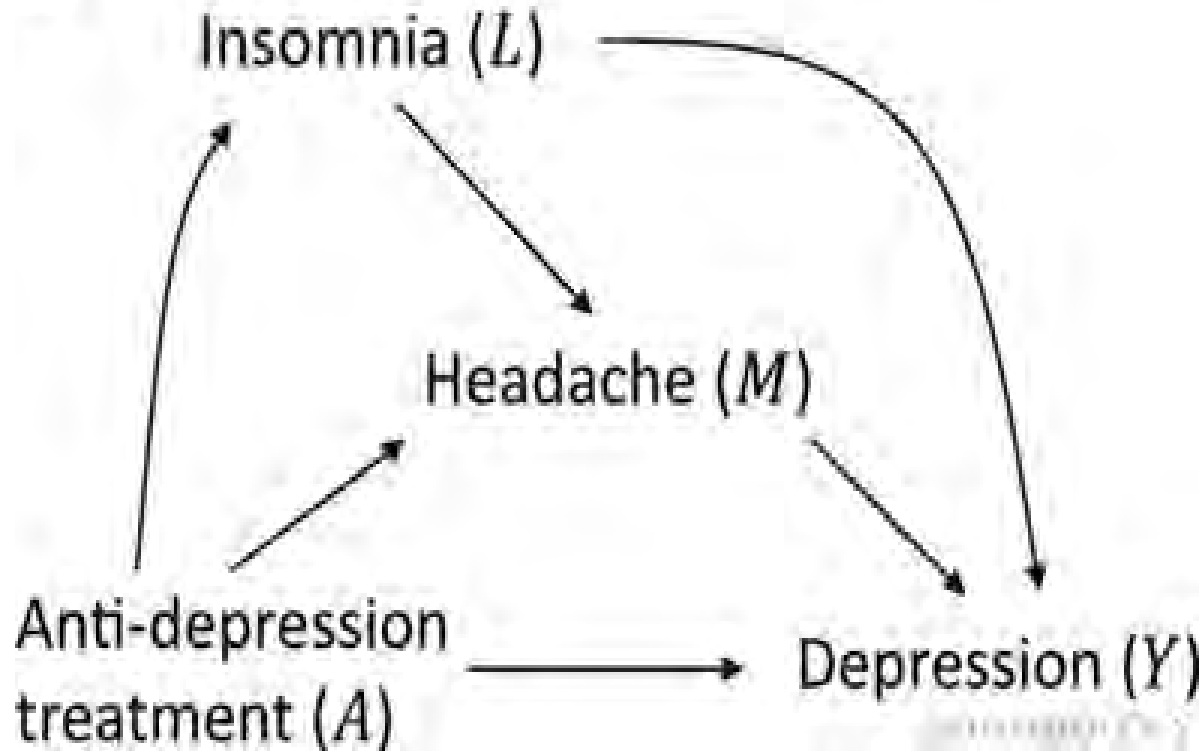
Sampling only in hospitals creates a biased association for Hx.

No link seen in general population.

Similar issue seen in general population when adjusting for hospitalisation

Effectiveness Of Antidepressants: An Artificial Scenario

B

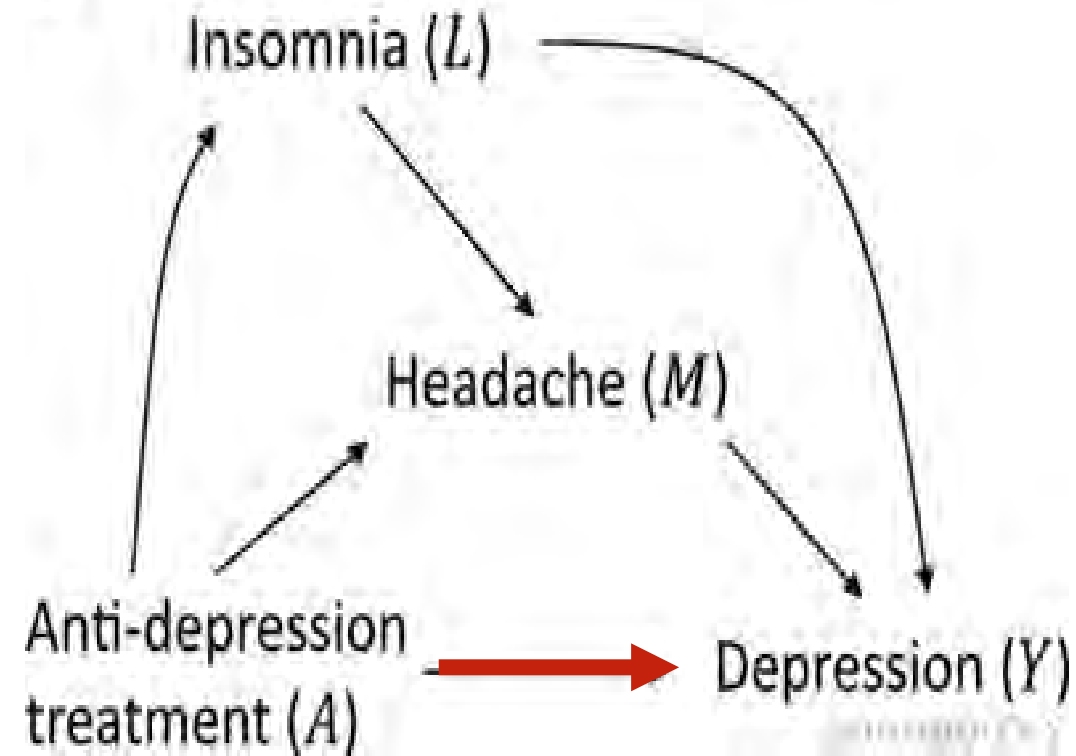


A, Y, L, M are all binary variables (Yes or No)

- Antidepressants **Reduce** Depression
- Antidepressants **Increase** Headache
- Headache **Increases** Depression
- Antidepressants **Increase** Insomnia
- Insomnia **Increases** Depression
- Insomnia **Increases** Headache
- Headache **Increases** Depression

Interventional (I/V) (in)Direct Effects

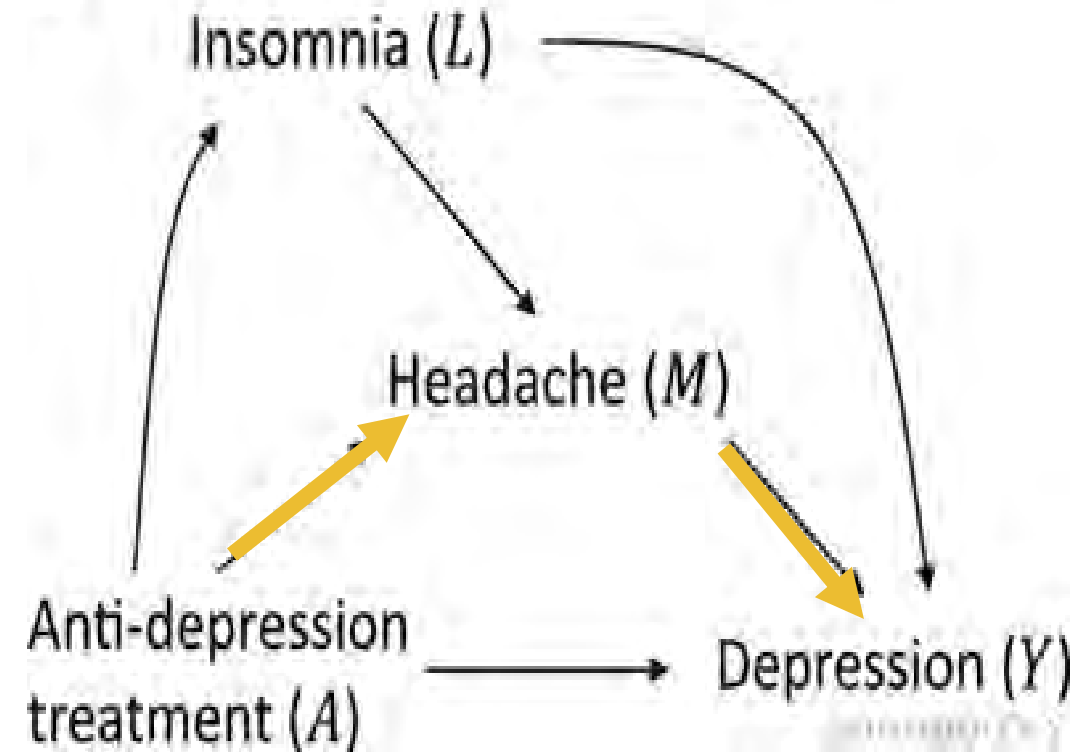
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- **Path 1)** Antidepressant to Depression
A to Y: Interventional Direct Effect
- Path 1 is negative as taking Antidepressants reduce Depression
- Path 1 is the effect of Antidepressants in those who don't have side-effects.

Interventional (I/V) (in)Direct Effects

B



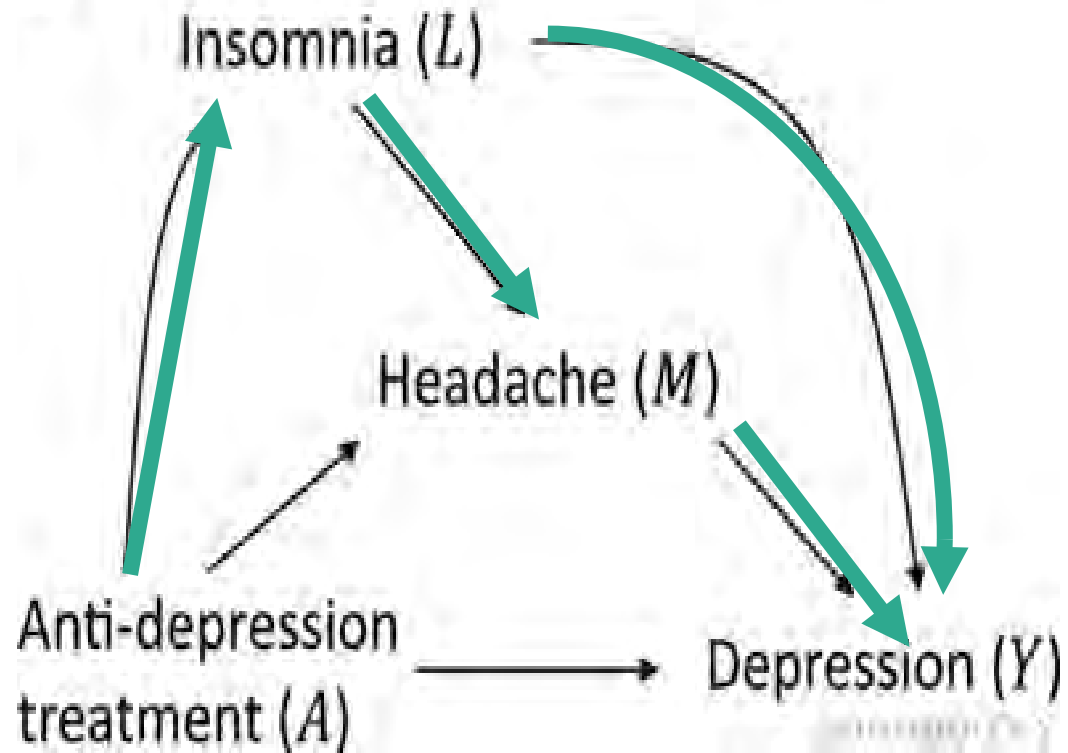
- **Path 2)** Effect Antidepressant on Depression *via Headache*

A to M to Y: Interventional In-Direct Effect

- Path 2 is positive as Headaches are a side-effect of Antidepressants and headaches increase depression
- Path 2 > 0

Interventional (I/V) (in)Direct Effects

B



- Path 3) $A \rightarrow L \rightarrow Y$ and $A \rightarrow M \rightarrow L \rightarrow Y$

- Path 3 has 2 components:

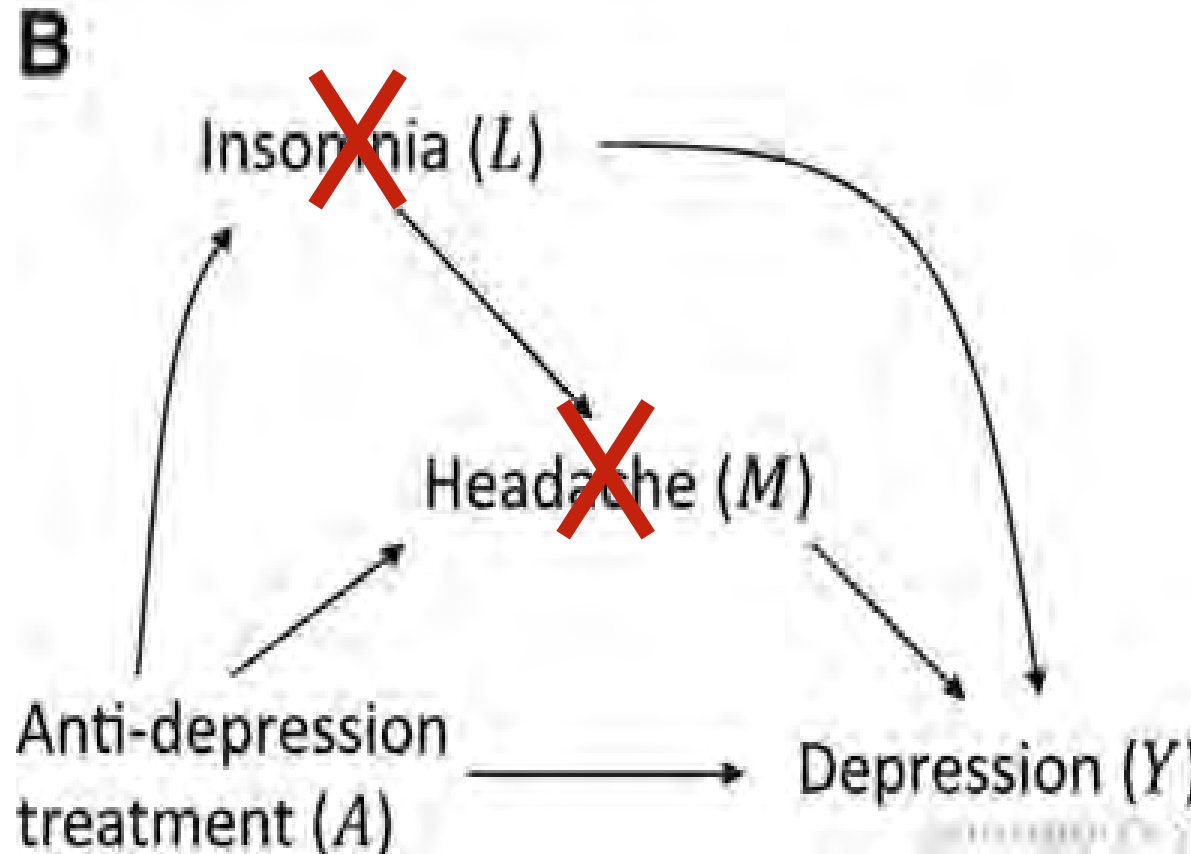
- Antidepressants lead to insomnia. Insomnia leads increases to Depression

- Also: Insomnia makes Headaches worse. Headaches increases Depression

- Total Effect: Path 1 + Path 2 + Path 3

Direct effect: Path 1 ($A \rightarrow Y$)

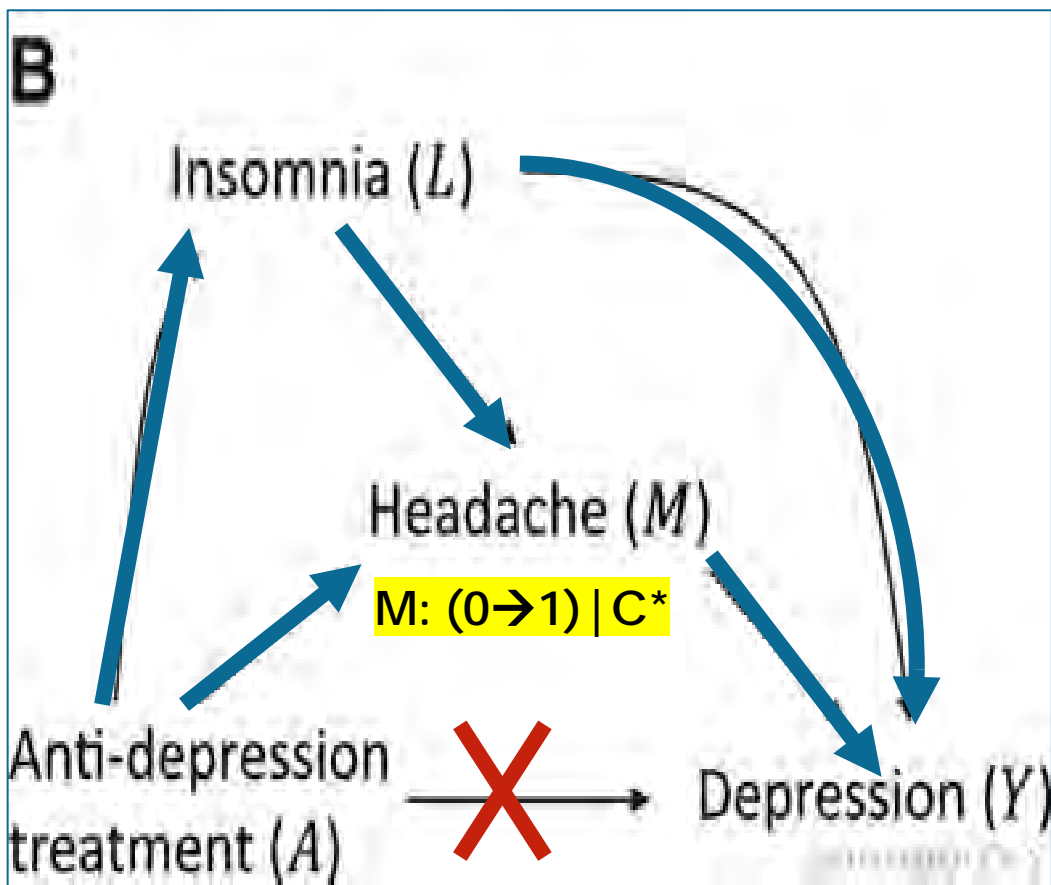
- Fixing $M=0$ and $L=0$ gives direct effect $A \rightarrow Y$.
- Effect of Antidepressants on Depression in Patients without the side-effects of insomnia and headache.



A: (0→1)

Indirect effect: via Mediators M(headache) I(insomnia) i.e

Path 2 & 3:



Effect of Headaches and Insomnia on Depression in treated patients.

(Fix A=1)

Effect of Headache (Yes | No) on Depression (Yes | No) for every combination of covariates. (done via bootstrapping)

M: (0→1) | C*

Total Effect = Indirect Effect + Direct Effect

Fix A=1: Only Treated Patients

Effect Decomposition

The Difference is Research

PATHWAYS	Abbreviation	Odds Ratio
1) Antidepressant to Depression	AY	0.28
2) Antidepressant to Headache to Depression	AMY	1.12
3) Antidepressant to Insomnia to +/- Headache to Depression	ALY & ALMY	1.87
Total Effect	1) + 2) + 3)	0.47
Treating Insomnia	1) + 2)	0.25
Treating Headache	1) + 3)	0.42
Treating Headache and Insomnia	1)	0.28

REFERENCES

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