Quantitative Social Research II

Workshop 3: Path Analysis and the Causal Framework

Jose Pina-Sánchez

Workshop Aims: Recap

- Last week we contrasted two model building strategies
  - Data driven (inductive, seeking to predict)
  - Theory driven (deductive, seeking to explain)
- Question: Why is the former not good at explaining?

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- Last week we contrasted two model building strategies
  - Data driven (inductive, seeking to predict)
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- Question: Why is the former not good at explaining?
  - Over-fitted models leading to problems of multicollinearity, etc.
  - Arbitrary selection of variables, p-hacking
- We need to pre-identify the variables to be included in the model
  - To test hypotheses (e.g. judges in the Crown Court discriminate against Muslim offenders)
  - To describe a causal mechanism (e.g. compliance with the law is caused by the perceived legitimacy of authorities)
  - To do so (to identify the right variables) we need theory
  - And a few important concepts from the causal framework

Research Aims

- The causal framework offers a systematic approach to interpret the theoretical role of different variables
  - Cause and effect
  - but also confounders, colliders, mediators and moderators
- We should be careful as to how/where they should be included
  - And how they are related to each other
- We'll present these concepts now and in the workshop we will practice them using data from
  - The Labour Force Survey
  - 'Pathways to Desistance'

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  - Problems with the modelling strategy (collider effects) or the research design (measurement error, missing data, etc.)

Cross-Sectional Data

- We can rule out the presence of reverse causality and confounding effects using experiments
  - We compare subjects in similar (randomised) groups before and after we intervene in one of those groups
  - No confounders, the two groups are identical because subjects are allocated to the 'intervention' or 'control' group at random
  - No reverse causality, we control the timing of the intervention and compare results from before and after
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    Question: Do you remember why?

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    Question: Do you remember why?
- We can explore reverse causal paths using longitudinal data
  - The problem of confounding effects is still present though
- When we have cross-sectional data we have to rely on a series of assumptions
  - The causal framework is just a tool to help us formalise those assumptions

Causal Framework

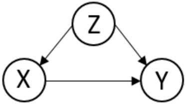
- Representing the relationships between our variables before we run our models
- Using graphs (DAGs) variables can be considered as
  - Parents (cause, explanatory variables)
  - Descendants (effect, outcome variables)
- Allows us to theorise additional roles of different variables in complex causal relationships
  - Confounders
  - Colliders
  - Mediators
- Which should be considered when building our model

Confounders

- Variables that cause both the outcome and an explanatory variable
  - Higher salaries (Y) for older (X) workers are confounded by experience (Z)
  - Longer sentences (Y) for male (X) offenders are confounded by their rehabilitation potential (Z)
  - Higher number of car crashes (Y) are recorded for bigger drivers (X), which is confounded by their sex (Z)
- We should include all potential confounders
  - Otherwise the relationship between X and Y will be biased

Modelling Confounders

Causal relationship



Modelling Confounders

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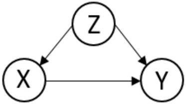

Bad model

$$Y = \alpha + \beta X + e$$

Modelling Confounders

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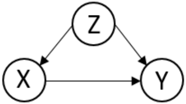

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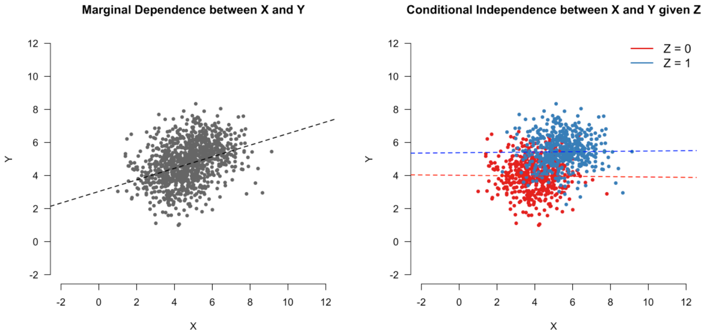
Good model

$$Y = \alpha + \beta_1 X + \beta_2 Z + e$$

Confounder Effect



Source: Fabian Dablander

Confounder Effect

- The assumptions of the linear regression model:
  - Normality: $N \sim (0, Var(e))$
  - Homoskedasticity: $Var(e_i) = Var(e)$
  - Independence: $Cov(e_i, e_j) = 0$
  - **No endogeneity**: $Cov(X_i, e_i) = 0$
  - Perfectly measured variables
  - No missing data (other than missing at random)
  - **No omitted relevant variables**
  - No multicollinearity
  - Linearity

Confounder Effect: Mathematically

- Variability in the dependent variable that is not controlled for the explanatory variables included in the model is captured by the error term
  - true model: $Y = \beta_0 + \beta_1 X + \beta_2 Z + e$
  - our model: $Y = \beta_0 + \beta_1 X + e^*$
  - then our residuals: $e^* = e + \beta_2 Z$

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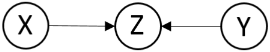
  - true model: $Y = \beta_0 + \beta_1 X + \beta_2 Z + e$
  - our model: $Y = \beta_0 + \beta_1 X + e^*$
  - then our residuals: $e^* = e + \beta_2 Z$
- If Z is a confounder (causing Y but also associated to X)
  - $Cov(X, Z) \neq 0$ and $Cov(X, e^*) \neq 0$
- Then $\hat{\beta_1}$, the estimated effect of X on Y is biased
  - $\hat{\beta_1^*} = \overbrace{\frac{Cov(Y, X)}{Var(X)}}^{\hat{\beta_1}} + \overbrace{\beta_2 \frac{Cov(Z, X)}{Var(X)}}^{bias}$

Colliders

- Confounders which are not a cause but an effect of the outcome variable
  - The duration of a custodial sentence (Y) will determine whether the sentence is reviewed by the Parole Board (Z), which is also determined by the seriousness of the case (X)
  - Being attractive (X) and being intelligent (Y) are two unrelated traits, but they are both -probably- related to being in a couple (Z)
- We should not condition on any colliders (or their descendants)
  - Otherwise the relationship between X and Y will be biased

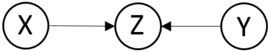
Modelling Colliders

Causal relationship



Modelling Colliders

Causal relationship



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Modelling Colliders

Causal relationship

$$X \rightarrow Z \leftarrow Y$$

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Good model

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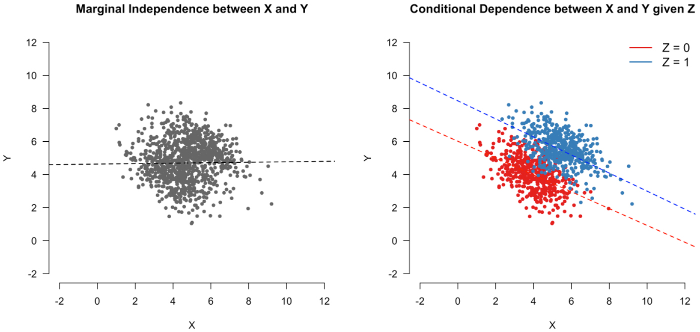
Collider Effect



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Mediators

- A variable Z through which X has a causal effect on Y
  - *Full mediation*, as in $X \rightarrow Z \rightarrow Y$
  - *Partial mediation*, when X also has a direct effect on Y
  - E.g. grades $\rightarrow$ happiness, mediated by self-esteem
  - Question: Are there mediating paths in the gender gap model?
  - The procedural justice model
  - When a variable Z modifies the effect of X on Y we call it a *moderator* (aka interaction)

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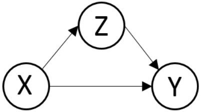
  - When a variable Z modifies the effect of X on Y we call it a *moderator* (aka interaction)
- If we want to disentangle the different (*direct* and *indirect*) effects of X on Y,
  - We need to specify the potential *mediating (indirect)* effects
  - Otherwise we will be estimating its *total* effect, as a whole, or just its *direct* effect

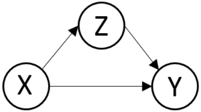
Modelling Mediators

Causal relationship (partial mediation)



Modelling Mediators

Causal relationship (partial mediation)



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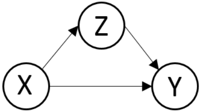

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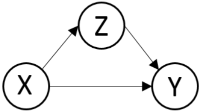

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Better model (we estimate the total effect, although the direct and indirect effects are not disentangled)

$$Y = \alpha + \beta_1 X + e$$

Better model (we estimate the direct effect, and the indirect effect through a second model)

$$Z = \alpha + \beta_1 X + e$$
$$Y = \alpha + \beta_2 X + \beta_3 Z + e$$

$$\text{Total Effect}_X = \overbrace{\beta_1 \beta_3}^{\text{Indirect Effect}} + \overbrace{\beta_2}^{\text{Direct Effect}}$$

- We have learnt useful model building strategies when we seek to *explain*
  - To approximate the causal relationship between two variables more accurately we need to control fo confounding factors
  - Introducing all the variables in a model in order to 'control' for them is not the right approach
  - Rather we need to think carefully about the underlying causal relationships (avoid collider bias)
  - If interested in the total (direct + indirect) effect of a given variable you might want to consider potential mediating effects
- To learn more read:
  - van der Weele (2011) 'Causal diagrams for empirical legal research: A methodology for identifying causation, avoiding bias and interpreting results'
- In Workshop 8 we will learn how to use longitudinal data to model reverse causal effects