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, exploratory, seeking to predict)
  - theory driven (deductive, confirmatory, seeking to explain)
- Question: Why is the former not good at explaining?

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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 right variables to be included in the model if we want to
  - test hypotheses
  - describe causal mechanisms
- To do so (to identify the right explanatory variables) we need theory
  - and a few important concepts from the causal framework

Workshop 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 more
- 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 and put them in practice using data from
  - The Labour Force Survey
  - Pathways to Desistance

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  - $Z \rightarrow X, Y$, a third variable (a *confounder*) might be causing both the alleged cause and effect
  - also, due to problems of data quality (e.g. measurement error, non-response) or research design (e.g. coverage error)

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    Question: do you know 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

- Use theory to represent the expected causal relationships between our variables before we run our models
- Create a causal diagram (a DAG) where the variables involved are considered either
  - parents (cause, explanatory variables)
  - descendants (effect, outcome variables)
- But also consider additional roles of those variables in more complex causal relationships
  - confounders
  - colliders
  - mediators

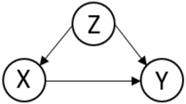
Confounders

- Variables that cause both the outcome and an explanatory variable
  - higher salaries (Y) paid to older (X) workers are confounded by experience (Z)
  - longer sentences (Y) for male (X) offenders are confounded by their rehabilitation potential (Z)
  - shorter sentences (Y) for remorseful offenders (X) are confounded by legal representation (Z)
  - higher number of car crashes (Y) are recorded for taller drivers (X), which is confounded by their sex (Z)
- We should include (control for) all potential confounders
  - otherwise the relationship between X and Y will be biased

Modelling Confounders

Causal relationship

(e.g. shorter sentences, Y, for remorseful offenders, X, are confounded by legal representation, Z)



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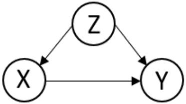

Bad model

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

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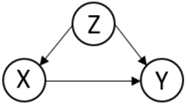

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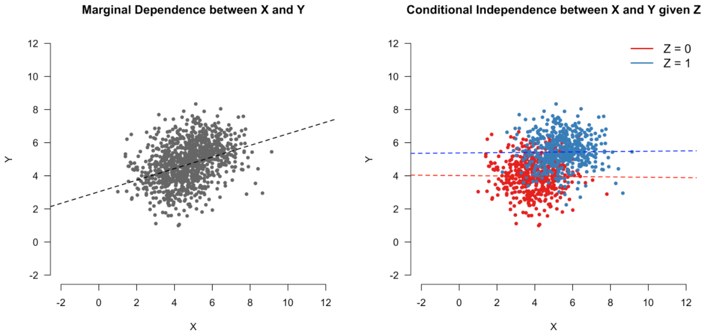
$$Y = \alpha + \beta X + e$$

Good model

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

Confounder Effect

(e.g. taller drivers have more car crashes)



Source: Fabian Dablander

Confounder Effect

- Assumptions in the linear regression model ($Y = \alpha + \beta_k X_k + e$):
  - normality: residuals are normally distributed
  - homoskedasticity: the variance of the residuals is constant
  - independence: residuals are independent of each other
  - no multicollinearity
  - perfectly measured variables
  - no missing data (other than missing at random)
  - **no unobserved confounders**: we control for all common causes of X_1 and Y
  - no reverse causality: Y does not cause X_1
  - linearity: the effect of X_1 on Y is the same across the range of X_1

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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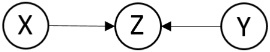
  - true model: $Y = \beta_0 + \beta_1 X + \beta_2 Z + e$
  - our model: $Y = \beta_0 + \beta_1 X + e^*$
  - then our residuals: $e^* = e + \beta_2 Z$
- If Z is a confounder (causing Y but also associated to X)
- Then $\hat{\beta}_1$, the estimated effect of X on Y is biased
  - $\hat{\beta}_1^* = \overbrace{\frac{Cov(Y,X)}{Var(X)}}^{\hat{\beta}_1} + \overbrace{\beta_2 \frac{Cov(Z,X)}{Var(X)}}^{bias}$

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- inversely related for those in a couple (Z) (e.g. Megan Fox voted the worst and most attractive actress)
  - obesity (X) is negatively related to life expectancy (Y) but positively amongst people with diabetes (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

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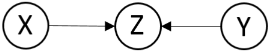

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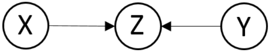

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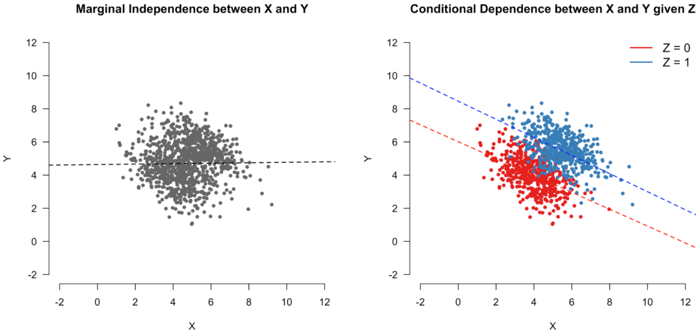
Collider Bias

(e.g. beauty and talent are unrelated, except for movie starts)



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Mediators

- A variable Z through which X has a causal effect on Y
  - *full mediation*, X only has an indirect effect on Y, as in $X \to Z \to Y$
  - *partial mediation*, when X also has a direct effect on Y
  - e.g. grades $\to$ happiness, mediated by self-esteem
  - Question: are there mediating paths in the gender gap model?

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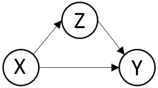
  - e.g. grades $\rightarrow$ happiness, mediated by self-esteem
  - Question: are there mediating paths in the gender gap model?
- If we want to disentangle the different (*direct* and *indirect*) effects of X on Y,
  - we need to specify the potential *mediating (indirect)* effects
  - otherwise we will be estimating its *total* effect (i.e. its *direct* + *indirect* effect) if we do not control for Z, and only the direct effect if we do

Modelling Mediators

Causal relationship (partial mediation)

(e.g. the gender gap in academia with Z being academic ranking)



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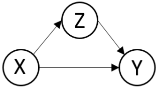

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$$\begin{tikzcd} & Z \arrow[dr] & \\ X \arrow[ur] \arrow[rr] & & Y \end{tikzcd}$$

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

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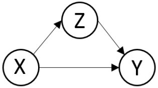

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Better model (we estimate the total effect, although the direct and indirect effects are not disentangled)

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Even better model (we estimate the direct effect, then 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 for 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
  - if interested in disentangling direct and indirect effects 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