Longitudinal Data Analysis

methods@manchester summer school

Day 3 | morning session

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30/06—04/07

Today

Reverse causality and reciprocal relationships

- What is reverse causality *really*?
- The traditional cross-lagged panel model
- Reverse causality and/vs. reciprocality
- Estimating CLPMs using `lavaan`

Reverse causality and reciprocal effects

Reverse causality?

When conducting empirical research, we sometimes want to examine the effect of X on Y but are afraid that Y might also affect X

- ⇝ Effect of policing (X) on crime (Y)
  - More police might be deployed in high-crime areas
- ⇝ Effect of education (X) on income (Y)
  - People from higher-income families may be more likely to pursue education
- ⇝ Effect of social media (X) on mental health (Y)
  - People with poor mental health may use social media more

We may be interested in:

→ *Controlling* for reverse causality

→ *Discovering* the direction of the association

→ *Discovering* a reciprocal relationship*

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Reciprocality

What are reciprocal effects *really*?

- **The world is recursive** (Pearl, 2009)
  - There are no simultaneous effects
- Usually a time problem, either:
  - Ambiguity from theory (i.e., reciprocality is substantive)
  - Competing theory when they are specific (i.e., empirical adjudication problem)
  - Purely empirical problem due to repeated observations
    - reciprocality is a nuisance
    - reality and theory operate at one pace, but we observe data at another
- Separate theoretical and methodological concerns

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Reverse causality: a motivating example


Untangling the Relationship Between Fear of Crime and Perceptions of Disorder: Evidence from a Longitudinal Study of Young People in England and Wales

Ian Brunton-Smith

The British Journal of Criminology, Volume 51, Issue 6, November 2011, Pages 885–899, https://doi.org/10.1093/bjc/azr064

Published: 19 August 2011

- Brunton-Smith (2011) wanted to study the relationship between fear of crime and perceptions of disorder
  - H_1 : fear of crime $\longrightarrow$ perceptions of disorder
  - H_2 : perceptions of disorder $\longrightarrow$ fear of crime
- Interesting question: which one is causing which?
  - Can we use empirical data to answer it?

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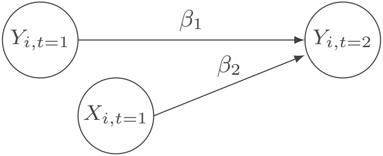
- Panel data allows us to model changes in various ways
  - e.g. including **autoregressive** parameters

$$Y_{it} = \alpha + \beta_1 \cdot Y_{i,t-1} + \beta_2 \cdot X_{i,t} + \varepsilon$$



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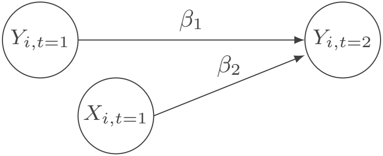

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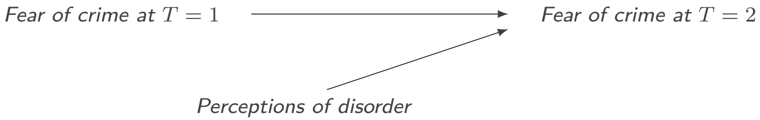
- Good! So we can assess the association between perceptions of disorder and *changes* in fear of crime:



- But perceptions of disorder also vary in time, so we can **also** assess the association between fear of crime and *changes* in disorder perceptions:

Reverse causality: a motivating example

- Good! So we can assess the association between perceptions of disorder and *changes* in fear of crime:

$$\begin{tikzcd}
\textit{Fear of crime at } T=1 \arrow[rr] & & \textit{Fear of crime at } T=2 \\
& \textit{Perceptions of disorder} \arrow[ur] &
\end{tikzcd}$$

- But perceptions of disorder also vary in time, so we can **also** assess the association between fear of crime and *changes* in disorder perceptions:

$$\begin{tikzcd}
\textit{Disorder perception } T=1 \arrow[rr] & & \textit{Disorder perception } T=2 \\
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\end{tikzcd}$$

$\Rightarrow$ What if we draw on the SEM framework and estimate both at the same time?

The cross-lagged panel model

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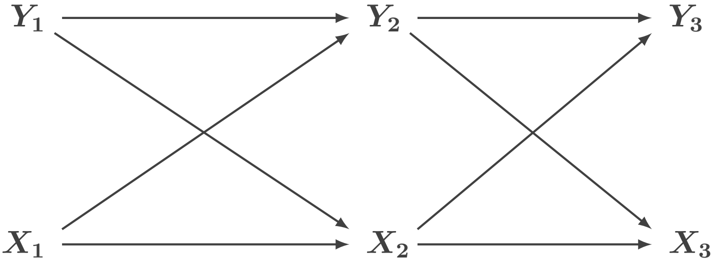

Cross-lags enforce temporal order

The cross-lagged panel model

$$Y_{i,t} = \alpha + \beta_1 \cdot Y_{i,t-1} + \beta_2 \cdot X_{i,t-1} + \varepsilon$$
$$X_{i,t} = \mu + \beta_3 \cdot X_{i,t-1} + \beta_4 \cdot Y_{i,t-1} + \upsilon$$

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- CLPM allows us to model reciprocal relationships
- Estimated using the Structural Equation Modelling (SEM) framework
- Temporal order: very useful in social research

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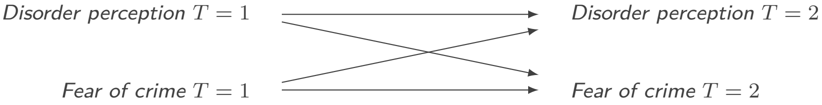

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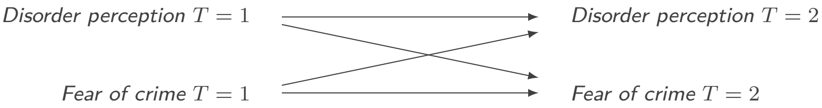

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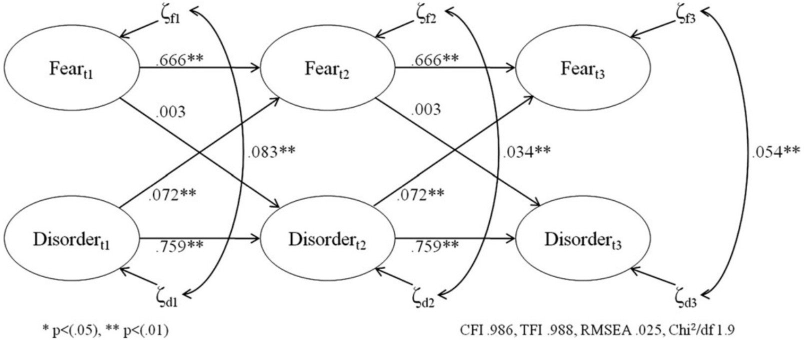

FIG. 2 Cross-lagged panel model (age 16–25).

⇝ Brunton-Smith (2011) estimated a CLPM

- Changes in perceptions of disorder lead to changes in fear of crime
- Changes in fear of crime **do not** lead to changes in perceptions of disorder

The cross-lagged panel model

Some technical details...

Y at $T = 1$	Y at $T = 2$	Y at $T = 3$
X at $T = 1$	X at $T = 2$	X at $T = 3$

The cross-lagged panel model

Some technical details. . .

⇝ **Autoregressive** and **cross-lagged** parameters are *conventionally* constrained to equality

$$
\begin{tikzcd}
Y \text{ at } T = 1 \arrow[r, "\beta_{a1}"] & Y \text{ at } T = 2 \arrow[r, "\beta_{a1}"] & Y \text{ at } T = 3 \\
X \text{ at } T = 1 \arrow[r, "\beta_{a2}"] & X \text{ at } T = 2 \arrow[r, "\beta_{a2}"] & X \text{ at } T = 3
\end{tikzcd}
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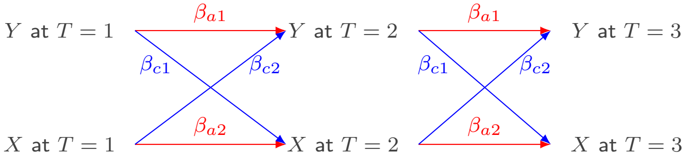

The cross-lagged panel model

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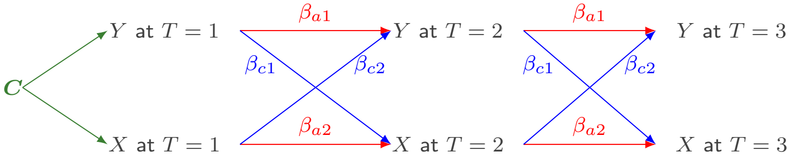
- **Autoregressive** and **cross-lagged** parameters are *conventionally* constrained to equality
- Time-constant covariates are included as predictors of both initial states (i.e., $X_{i,t=1}$ and $Y_{i,t=1}$)



The cross-lagged panel model

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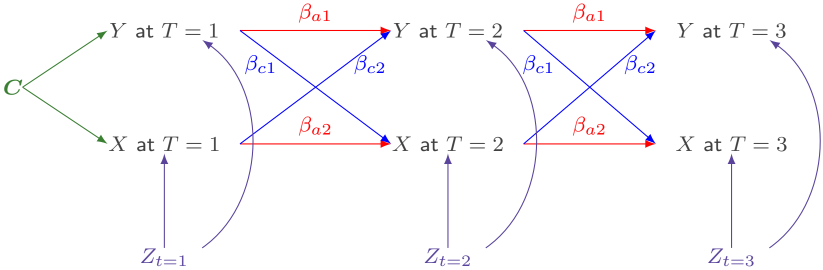
- **Autoregressive** and **cross-lagged** parameters are *conventionally* constrained to equality
- Time-constant covariates are included as predictors of both initial states (i.e., $X_{i,t=1}$ and $Y_{i,t=1}$)
- Time-varying covariates are included as predictors of each X_{it} and each Y_{it}



CLPM using `lavaan`

Estimating CLPMs in R

CLPMs can be easily estimated using the `lavaan` package

- Dataset in the **wide** format
- Assume we have variables y and x, each measured at three occasions
- Assume we also have one time-varying covariate z and two time-constant covariates w and v

In R:

```
> my_clpm <- ' y3 ~ a*y2 + b*x2 + z3
               y2 ~ a*y1 + b*x1 + z2

               x3 ~ c*x2 + d*y2 + z3
               x2 ~ c*x1 + d*y1 + z2

               y1 ~ z1 + w + v
               x1 ~ z1 + w + v

               x1 ~~ y1
               x2 ~~ y2
               x3 ~~ y3
             '
> fit.my_clpm <- sem(my_clpm, estimator =  "ML", data = my_data)
> summary(fit.my_clpm, fit.measures = TRUE, standardized = TRUE)
```

Thank you!

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REFERENCES

Brunton-Smith, I. (2011). Untangling the relationship between fear of crime and perceptions of disorder: Evidence from a longitudinal study of young people in England and Wales. *The British Journal of Criminology 51*(6), 885–899.

Pearl, J. (2009). *Causality*. Cambridge University Press.