Longitudinal Data Analysis

methods@manchester summer school

- Thiago R. Oliveira
- Lecturer in Quantitative Criminology, University of Manchester
- 30/06-04/07

About me

- ♣ Hi, I'm Thiago!
- Lecturer, University of Manchester
 PhD in Social Research Methods
- ্রতি I am a quantitative criminologist
- Into longitudinal data analysis, causal inference, and other hard drugs...



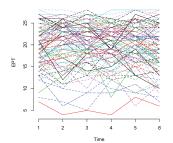
How about you?

About the course

This is a course about longitudinal data analysis

Specifically, we are going to cover three topics:

- How to model change over time and estimate individual trajectories
 Keyword: Growth curve models
- How to handle reverse causality and reciprocal relationships
 Keyword: Cross-lagged panel models
- How to leverage longitudinal data to make causal conclusions
 Keyword: Difference-in-differences estimators



Course structure

We will adopt a hands-on approach:

Lectures introducing theoretical concepts, followed by lab sessions using R applying concepts with real datasets

Morning session (9am—12:30pm)

→ 9:00—10:30: Lecture Coffee break in The Hive

→ 11:00—12:30: Lab session using R.

Afternoon session (1:30—5pm)

→ 1:30—3:00: Lecture Coffee break in The Hive

→ 3:30—5:00: Lab session using R

12:30—1:30pm: Lunch in The Hive

Longitudinal Data Analysis

Course outline (short version)

- > Monday: Introduction to longitudinal data and R
- > Tuesday: Latent trajectories and growth curve models
- > Wednesday: Reverse causality and cross-lagged panel models
- > Thursday: Difference-in-differences and causal inference with panel data
- > Friday: Recent advancements in causal inference with panel data

- > Monday: Introduction to longitudinal data and I
 - → Housekeeping
 - → What is longitudinal data?
 - → Wide vs. long datasets
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 - → Dealing with longitudinal data in F

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> Tuesday: Latent trajectories and growth curve models

- --> Morning session: a multilevel approach
 - Introduction to multilevel models
 - · Growth curve models: a multilevel approach
 - · Estimating growth curve models using 1me4
- → Afternoon session: a structural equation modelling approach
 - Introduction to SEM
 - · Latent Growth Curve Analysis: a SEM approach
 - · Estimating LGCA models using lavaan

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> Wednesday: Reverse causality and cross-lagged panel models

- --> Morning session: traditional cross-lagged panel models
 - · What is reverse causality *really*?
 - · Reverse causality and/vs. reciprocality
 - · The traditional cross-lagged panel model
 - Estimating CLPMs using lavaan
- → Afternoon session: modern cross-lagged panel models
 - · Recent advancements in cross-lagged panel models
 - · The Random Intercepts Cross-Lagged Panel Model
 - · The Dynamic Panel Model with fixed effects
 - · Estimating RI-CLPM models using lavaan
 - Estimating DPMs using dpm

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> Thursday: Difference-in-differences and causal inference with panel data

- --> Morning session: Basic intuition for causal inference with panel data
 - · Causality and the potential outcomes framework
 - Leveraging longitudinal data to identify average causal effects
 - · Difference-in-differences in a two-period scenario
 - · Simple difference-in-differences analysis in R
- → Afternoon session: Difference-in-differences regression estimators
 - · Using linear regression in the two-period scenario
 - · Multi-period difference-in-differences
 - · Two-way fixed effects regression estimator
 - · Using regression in difference-in-differences analysis in R

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- > Friday: Recent advancements in causal inference with panel data
 - → Issues with TWFE estimator
 - → Staggered difference-in-differences
 - Difference-in-differences when treatment status switches on and off
 - → Discussion of projects

Introduction to longitudinal data

Idea of longitudinal data

What is longitudinal data?

- → How is it different from cross-sectional data?
- → How is it different from time series data?

- ⇒ Repeated observations of the same units over time
 - \rightarrow Intuitively: Large N, small T

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- Modelling change over time, controlling for variables measured at different points in time
- Modelling effects on change, focusing on within-unit change over time only
- Modelling time to event, focusing on distal outcomes or probability of event happening (survival models, event-history, marginal structural models, ...)

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Imagine we conduct a survey with a sample of 100 individuals and collect information on 5 variables:

age, gender, income, education, employment status

This gives us a dataset with

100 rows (individuals) and 5 columns (variables)

This is a typical cross-sectional dataset

In standard regression analysis, we often assume observations are *i.i.d.* — independent and identically distributed.

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Repeated measurements - what changes?

Now imagine we go back one year later and collect the same 5 variables from the same 100 individuals

How should we organise the new data?

Option A - Wide format

One row per individual, now with 10 columns (e.g., income_t1, income_t2)

Option B – Long format

One row per observation (i.e., person-year): 200 rows \times 5 variables + a time column

These are two ways of structuring longitudinal data: wide and long

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Wide vs Long format

	Wide Format	Long Format
Structure	One row per individual	One row per individual-time point
Columns	One variable per time point (e.g., income_t1, income_t2)	One outcome column, plus a time indicator (e.g., income, wave)
Pros	Maintains individuals as the unit of analysis	Much more flexible and efficient
Cons	Inefficient and static	Violates i.i.d. assumptions

 $\Rightarrow {\sf Different\ modelling\ strategies\ require\ different\ longitudinal\ datasets}$

Coffee break

SEMINAR REFRESHMENTS!



Nothing says "We are confident this seminar will be intellectually stimulating for you" like a table full of things to help you stay awake.

Thank you!

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