Session 7:

Peer effects: measuring social spillovers

Andreas Bjerre-Nielsen

Agenda

Session on peer effects

1. Introduction
2. Reflection problem
3. Selection problem
4. Random assignment
5. Other identification strategies

Info

- Projects
- Evaluation
- Moving teaching

Causality

Are machine learning parameters causal?

- In general, no. Moreover, estimates are also not unbiased.

Recap

What have you learned about networks?

- Clustering Coefficient
- Average Path Length
- Degree (in/out)

Social effects

What spreads on a networks? How are you affected by your friends?

- Public health
- Information, immitating behavior, emotion

Introduction to peer effects

What is a peer effect

Impact of social interactions on current/future outcomes

- Do healthy friends make your healthier?

What is a peer effect

Finding influence from person(s) to person

- These questions date far back in sociology and social psychology
- We take an econometric angle

Other examples - from exercise:

- Are you affected by number of bilingual pupils in your school class?
- Do roommates matter for academic success, drinking?

Who are peers?

We often distinguish between meausring peer effects:

- from policy assignment
  - these may be voluntary and involuntary choices
  - e.g. colleagues at work, classmates in school
  - network structure based on shared institution/foci (bipartite graph)
- from friendships
  - these are voluntary choices
  - network structure where edges are friendships

Why should we care?

Through policies we can affect outcomes by manipulating social structures

- Suppose that exposure to able peers matters for own achievements, consequence:
  - Class room composition matters for achievements
  - Can we raise social mobility by pairing low achievers with high achievers?

There is inherent value in knowing about causal social effects.

Measuring peer effects

We face two main problems in identifying peer effects:

- separating endogenous and exogenous effects
- picking out sorting/homophily effects

Reflection problem

Who affects whom?

How can we measure the impact of a group's behavior on a member's behavior?

How can we measure peer effects?

Reflection problem - [Manski (1993) (https://www.jstor.org/stable/2298123?seq=1#page_scan_tab_contents)](https://www.jstor.org/stable/2298123?seq=1#page_scan_tab_contents) decomposes group effects into three categories of effects:

- *Exogenous/contextual*: behavior is affected by group exogenous characteristics
    - example: parents income, number of bilingual.
- *Endogenous*: individual unobserved behavior, beliefs (to analyst)
    - e.g. study effort, distraction etc.
- *Correlated*: non-social, i.e. unobserved selection
    - people behave in the same way because they are similar
    - people face same unobservable background variables, e.g. teachers, class facilities, neighborhood

Linear-in-means - components

Suppose we are interested in making a model of an outcome ω_{ig}, e.g. alcohol drinking in college dorm.

The following factors affect ω_{ig}:

- x_i: observed individual factor, e.g. individual high-school alcohol.
- y_g: observed group factors, e.g. mean dorm high-school alcohol.
    - **exogenous** effect
- m_{ig}^e: individual expectation/perception of others' behavior, e.g. drinking by dorm-mates.
    - **endogenous** effect which can create feedback loops
- ϵ_i: idiosyncratic error

Linear-in-means - model

Suppose individual behavior follows this rule:

$$\omega_{ig} = k + cx_i + \underbrace{dy_g}_{exogenous} + \underbrace{Jm^e_{ig}}_{endogenous} + \underbrace{\varepsilon_i}_{error}$$

Assume that every individual has complete knowledge of the model (but not errors of others, i.e. ε_j). It follows that:

$$\begin{aligned} m^e_{ig} &= \mathbb{E}_{x_i}[\mathbb{E}[\omega|x_i, g]] \\ &= k + c\mathbb{E}[x|g] + dy_g + Jm^e_{ig} \\ m^e_{ig} &= \frac{k + c\bar{x}_g + dy_g}{1 - J} \end{aligned}$$

If we re-insert that into the model and isolate:

$$\omega_{ig} = \tfrac{k}{1-J} + cx_i + \tfrac{cJ}{1-J}\bar{x}_g + \tfrac{d}{1-J}y_g + \varepsilon_i$$

Linear-in-means - identification

Suppose that we assume that exogenous characteristics are $y_g = \bar{x}_g$. This implies the model solution is:

$$\omega_{ig} = \frac{k}{1-J} + cx_i + \frac{cJ+d}{1-J}\bar{x}_g + \varepsilon_i$$

Thus we cannot disentangle d and J! That is, the parameters are **not identified**.

Note, much empirical literature have tried to identify a model of only exogenous effects:

$$\omega_{ig} = \pi_0 + \pi_1 x_i + \pi_2 y_g + \varepsilon_i$$

Overcoming reflection

The reflection problem is often solved in practice because it relies on y_g being a linear function of $\bar{x}_g$.

Some solutions:

- Network structure (Bramouellé et al. 2009 (https://www.sciencedirect.com/science/article/pii/S0304407609000335))
  - Effect of friends can be measured by indirect effect from friends of friends (instrumentation)
  - Requires assumption of no correlated effects!!
- Non-linear structure, dynamics - see Blume et al. (2011) (https://www.sciencedirect.com/science/article/pii/B9780444537072000013)

A note on policy

[Hoxby, Weingarth (2005) (https://www.pausd.org/sites/default/files/pdf-faqs/attachments/TakingRaceOutOfTheEquation.pdf)](https://www.pausd.org/sites/default/files/pdf-faqs/attachments/TakingRaceOutOfTheEquation.pdf) argues that if peer effects are *linear and homogenous* then reshuffling students implies that mean GPA is constant!

- There will still be redistributing effect.
- Non-linearities has first order effects: Suppose "bright" students "less bright" students ability more than they do for "bright". Can raise mean GPA by redistributing!

Selection problem

Peer effects in obesity

Question: can we measure peer effects of friends obesity? This problem is studied by [Christakis and Fowler (2007) (https://www.nejm.org/doi/full/10.1056/NEJMsa066082)](https://www.nejm.org/doi/full/10.1056/NEJMsa066082)

- They have a large friendship network and measure individual obesity.
- They conclude that having more obese friends increase your own obesity.

Unobserved similarity or cause?

Is obesity contagious?

- No. There are multiple competing explanations.
- A fundamental problem: are we friends because we are similar or similar because we are friends?
    - Homophily: we tend to self-select into friendships and schools with people who are similar to us.

General impossibility

- Cosma and Shalizi (2011) (https://journals.sagepub.com/doi/abs/10.1177/0049124111404820): without imposing structure we cannot separate homophily and peer effects
- Also problematic in schools, work place - "sorting" by skill

Random peers

Antidote for handling selection: *"No causation without manipulation"*, Holland (1986) (https://www.jstor.org/stable/2289064)

- Idea: Use random allocation of students to rooms to remove correlated (selection) effect.

Some evidence

- Sacerdote 2001 (https://academic.oup.com/qje/article-abstract/116/2/681/1904199) examines effect of random allocation of roommates (exercise)

Work place studies

- Being in a shift with a high productive person raises own productivity [Falk, Ichino (2007) (https://www.journals.uchicago.edu/doi/abs/10.1086/497818)](https://www.journals.uchicago.edu/doi/abs/10.1086/497818); [Mas, Moretti (2009) (https://www.aeaweb.org/articles?id=10.1257/aer.99.1.112)](https://www.aeaweb.org/articles?id=10.1257/aer.99.1.112)
- Working with someone rather than being alone raises your own productivity, see [Falk, Ichino (2007) (https://www.journals.uchicago.edu/doi/abs/10.1086/497818)](https://www.journals.uchicago.edu/doi/abs/10.1086/497818)

Adverse consequences?

[Carrell, Sacerdote, West (2013) (https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10168)](https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA10168) investigates random assignment into classes. They estimated a positive effect for those expected to be low performers of being paired with high performers.

- They implemented a programme with **negative sorting** such that low and high performers were in class separate from medium performers.
- Results was that low performers were WORSE off!
- Explanation: low and high performers did not interact within class!

If negative sorting is bad could **positive sorting** work?

- Evidence suggest that students benefit from being seperated with other low ability students. Separating school cohorts by ability is known as **tracking**. See [Duflo, Dupas, Kremer (2011) (https://www.aeaweb.org/articles?id=10.1257/aer.101.5.1739)](https://www.aeaweb.org/articles?id=10.1257/aer.101.5.1739), [Leuven et al 2017 (https://www.dropbox.com/s/o4jlzdg264nx1k7/ability_final.pdf?dl=0)](https://www.dropbox.com/s/o4jlzdg264nx1k7/ability_final.pdf?dl=0).

Other identification strategies

Cohort variation within schools

- [Hoxby (2000) (https://www.nber.org/papers/w7867.pdf)](https://www.nber.org/papers/w7867.pdf) uses random variation of race, gender across cohorts within school
    - Finds evidence of boys performance increase when exposed to more girls.
- Other studies - exerises today.

Exogenous individual variation

Exploiting natural variation

- Aral, Nicolaides (2018) (https://www.nature.com/articles/ncomms14753):
  - Use variation in weather's effect on work out > fitness peer effect
- Andersen, Bjerre-Nielsen, Glavind (ongoing):
  - Use incoming text message as shock to smartphone usage > measure social impact

Similar ideas are being attempted with adverse shocks, e.g. unemployment, family member dies.

Exogenous individual variation

Interventions

- Kramer, Guillory, Hancock (2014) (https://www.pnas.org/content/111/24/8788):
    - Intervene on pictures shown in news feed to affect emotion > measure effect on peers

Structural modelling

If we model network formation correctly we can hope to identify friendship selection.

- See for instance Goldsmith-Pinkham, Imbens (2013) (https://www.tandfonline.com/doi/abs/10.1080/07350015.2013.801251)
- Next session about network formation