Longitudinal Data Analysis

methods@manchester summer school

Day 3 | afternoon session

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30/06—04/07

Today

Reverse causality and reciprocal relationships

- ⇝ A critique of the cross-lagged panel model
- ⇝ Three common problems
- ⇝ Some potential solutions
- ⇝ Estimating RI-CLPMs and DPMs

A critique of the cross-lagged panel model

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A Critique of the Cross-Lagged Panel Model

Ellen L. Hamaker and Rebecca M. Kuiper
Utrecht University

Raoul P. P. P. Grasman
University of Amsterdam

The cross-lagged panel model (CLPM) is believed by many to overcome the problems associated with the use of cross-lagged correlations as a way to study causal influences in longitudinal panel data. The current article, however, shows that if stability of constructs is to some extent of a trait-like, time-invariant nature, the autoregressive relationships of the CLPM fail to adequately account for this. As a result, the lagged parameters that are obtained with the CLPM do not represent the actual within-person relationships over time, and this may lead to erroneous conclusions regarding the *presence*, *predominance*, and *sign* of causal influences. In this article we present an alternative model that separates the within-person process from stable between-person differences through the inclusion of random intercepts, and we discuss how this model is related to existing structural equation models that include cross-lagged relationships. We derive the analytical relationship between the cross-lagged parameters from the CLPM and the alternative model, and use simulations to demonstrate the spurious results that may arise when using the CLPM to analyze data that include stable, trait-like individual differences. We also present a modeling strategy to avoid this pitfall and illustrate this using an empirical data set. The implications for both existing and future cross-lagged panel research are discussed.

Keywords: cross-lagged panel, reciprocal effects, longitudinal model, trait–state models, within-person dynamics

(Hamaker et al., 2015)

Socius
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SAGE journals

Original Article

Maximum Likelihood for Cross-lagged Panel Models with Fixed Effects

Paul D. Allison[1], Richard Williams[2], and Enrique Moral-Benito[3]

Abstract
Panel data make it possible both to control for unobserved confounders and allow for lagged, reciprocal causation. Trying to do both at the same time, however, leads to serious estimation difficulties. In the econometric literature, these problems have been solved by using lagged instrumental variables together with the generalized method of moments (GMM). Here we show that the same problems can be solved by maximum likelihood (ML) estimation implemented with standard software packages for structural equation modeling (SEM). Monte Carlo simulations show that the ML-SEM method is less biased and more efficient than the GMM method under a wide range of conditions. ML-SEM also makes it possible to test and relax many of the constraints that are typically embodied in dynamic panel models.

Keywords
panel data, dynamic panel model, fixed effects, cross-lagged model, generalized method of moments, GMM, Arellano-Bond, FIML, SEM, structural equation model, maximum likelihood, predetermined variable, sequentially exogenous variable, xtdpdml, instrumental variable

(Allison et al., 2017)

A critique of the cross-lagged panel model

Common issues have emerged recently

- ⇝ Correct specification of temporal lags (Vaisey and Miles, 2017)
- ⇝ Unobserved stable heterogeneity (Hamaker et al., 2015; Allison et al., 2017)
- ⇝ Low inter-temporal variation (Hamaker et al., 2015)

Temporal order

Temporal Order

As illustrated by Vaisey and Miles (2017), if. . .

- $\rightsquigarrow$ True model: $y = \beta \cdot x_t + \alpha_i + \epsilon_{it}$
- $\rightsquigarrow$ Estimated model: $y = \beta^* \cdot x_{t-1} + \alpha_i + \epsilon_{ei}$
- $\rightsquigarrow$ Resulting bias: $\mathbb{E}(\beta^*) = -0.5 \cdot \beta$

$\Rightarrow$ Incorrect temporal order **can reverse signs**

Temporal Order

Problem: we cannot know whether we have the correct specification of temporal lags!

⇒ *Probably the most underappreciated issue as it may produce misleading results*

Solution

- Use strong theory to get timing right!
- Think carefully about time processes
  - e.g., alcohol to disinhibition
- Be *very* suspicious of unexpected reversed signs
- Vaisey and Miles: estimate both lagged and contemporaneous effects
  - If no contemporaneous effect, only lagged, you're probably fine
  - If contemporaneous shows up, you can't definitively determine direction of contemporaneous effect

Unobserved stable heterogeneity

Unobserved stable heterogeneity

Point is relatively simple: the autoregressive parameter alone is not sufficient!

- It does not fully capture all time-constant traits
- Therefore, the model does not properly model change over time

Solution: use some recently developed robust estimator:

- Hamaker's (2015) **Random Intercepts-Cross-lagged panel model** (RI-CLPM)
  - Inspired by random effects models, it explicitly partitions the variance in *between-unit* variation and *within-unit* variation
- Allison et al.'s (2017) **dynamic panel model with fixed effects** (DPM)
  - Inspired by econometric models, considered the most robust approach by Vaisey and Miles (2017)

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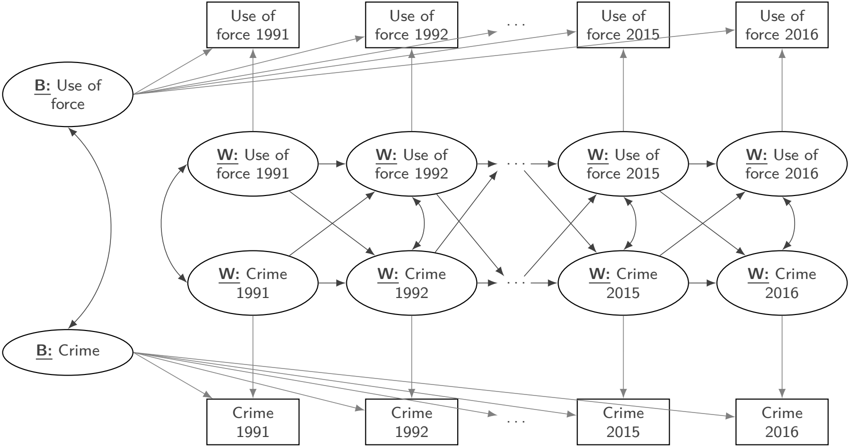
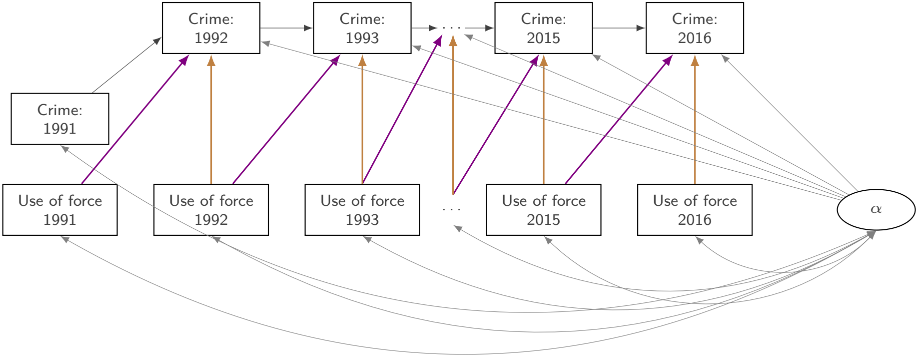
Hamaker et al's RI-CLPM



Allison et al.'s dynamic panel model



Pros: properly controls for unobserved stable heterogeneity, dismisses the threat of reverse causality, and properly models change over time

Cons: reciprocal effects cannot be simultaneously estimated, still sensitive to the correct specification of temporal lags

Low inter-temporal variation

Low inter-temporal variation

- ⇝ Error and bias become proportionally larger components
- ⇝ Intuition: not enough variation to explain!
- ⇝ Common with short observation times and stable constructs
- ⇝ Psychological constructs can be very stable over time

Solution:

- ⇝ This is first and foremost a data problem, so you want to attack it during design of data collection if possible
- ⇝ If you can't collect new data, look at different aggregations or wave skips

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Summary

- Cross-lagged panel models are a powerful method that permits
  - modelling reciprocal relationship
  - establishing temporal order
  - handling reverse causality
- In general, default to more robust estimators
  - Hamaker et al.'s RI-CLPM
  - Allison et al.'s DPM
- Models are *very* sensitive to the correct specification of temporal lags
  - Not something that can be solved empirically. Think carefully about the phenomenon you are studying...
- Now let's see how to estimate those models using `R`!

Thank you!

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