Cross-Lagged Panel Models

MuSt Zurich: Intro to Dynamic SEM
Day 1

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March 2021

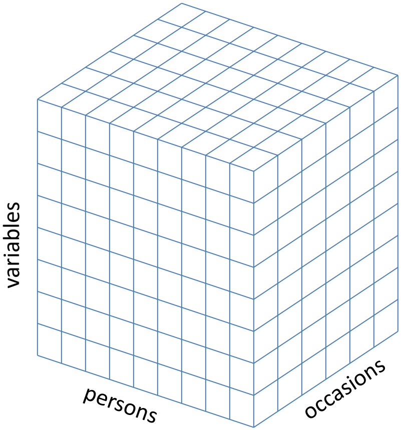
This Workshop

Aim: Introduce you to the basic principles behind "Dynamic SEM" and the estimation of these models (in Mplus)

Broadly:

- A way of modeling change over time / longitudinal data / repeated measures of the same variables
- Models based on estimation of *lagged regression* models: X now predicts X later
- Viewed through the lens of SEM / path models
- Similar principles can be used in different contexts, with some similarities, and some differences

Cattell's Data Box



This Workshop

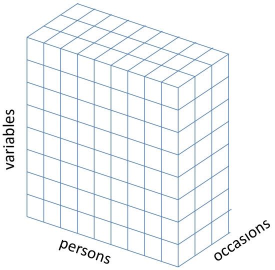
Day 1: Panel Data

- Many people, relatively few measurements, spread out over a long period of time

Typically used to:

- Investigate (developmental) trends (e.g. growth curve modeling)
- Investigate **cross-lagged relations**

Our focus: (Random Intercept) Cross-Lagged Panel Models and extensions



This Workshop

Day 2: Intensive Longitudinal Data

- Many repeated measures, spaced closely together in time

Two parts:

- $N = 1$: Time-Series Analysis
- $N =$ many: Multilevel Time-Series Models. ***DSEM*** in Mplus

Our focus: (Multi-level) Vector Auto-Regressive Models

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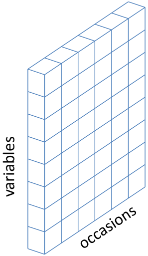

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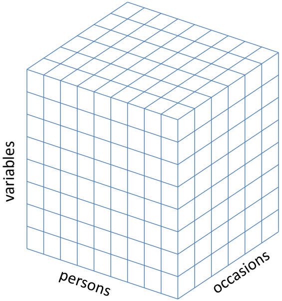


This Workshop

Day 1 & Day 2: Lecture followed by $\sim$ 1 hr practical session

- Practicals in Mplus (8.0.0 and higher)
- Other software possible.
- Solutions Provided

Day 3: Open Discussion Session

- General questions
- Reflecting on exercises

Getting to know each other

I am a postdoctoral researcher at the Department of Methodology & Statistics, Utrecht University, The Netherlands

Originally from Ireland (hence, “Oisín” $\rightarrow$ [Uh-sheen])

Research focuses on Dynamical Systems and Causal Modeling in (Clinical) Psychology

PhD supervisor: Ellen Hamaker

Who are you? Why are you here?

Universiteit Utrecht

Outline

- **SEM refresher**
- Cross-Lagged Panel Model (CLPM)
- Interpreting and fitting the CLPM
- Trait-like stability: Random-Intercept (RI-) CLPM
- Extensions: Trends, Measurement Error, Mediation and Time-Intervals
- Discussion/Lab

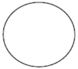
Structural Equation Modeling (SEM) consists of analyzing:

- **covariance structure**
- **mean structure**

SEM in a nutshell:

- Express our theory using a (graphical) model
- Relationships generally assumed linear and variables Gaussian (normally distributed)
- Model(s) assessed w.r.t their *fit*
- Interpret/compare model estimated parameters

Observed variable



Latent (unmeasured) variable
(or factor)

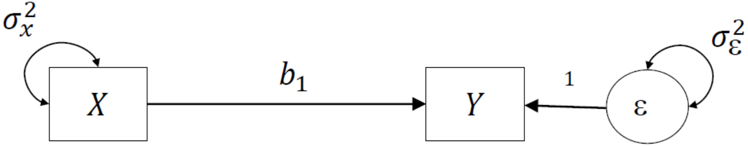
Regression
(Theoretical) Causal effect *
Direct Effect *

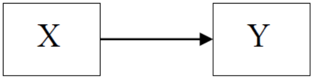
Covariance or Variance
(no causal hypothesis)

$$Y_i = b_0 + b_1 * X_i + \varepsilon_i$$

$$\varepsilon \sim N\,(0, \sigma_\varepsilon^2)$$

$$X_i \sim N(\mu_x, \sigma_x^2)$$



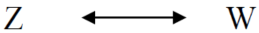


Y ON X

Regress the outcome variable Y on the predictor variable X

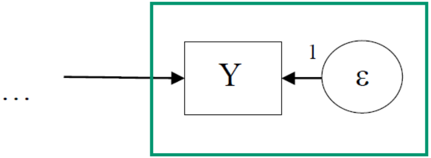
F BY Y

The factor F is measured by the observed variable Y



Z WITH W

Z and W covary with each other (can be observed, latent, error of Z and W)



[DEFAULT]

No need to specify error variables like other latent variables – will be done by default in Mplus.

Chi-Square test of model fit

- Compare more complex with simpler (less parameters) nested model
- $H0$ is the specified or simpler model
- $p < .05 \rightarrow$ simpler model fits worse than more complex model

RMSEA

- Rule of thumb: Should be $< .08$, “Good fit” $< .05$

CFI/TLI

- Rule of thumb: Should be $> .90$, “Good fit” $> .95$

AIC/BIC

- Can be used to compare non-nested models estimated with ML

DIC

- Information Criteria for Bayesian Models*

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Why Cross-Lags?

A **central question** in many disciplines is:

How is **change** in one domain **related to change** in another?

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How is **change** in one domain **related to change** in another?

For instance, we may want to know:

- does feminization of professions lead to lower pay, or does lower pay result in more women in a profession?
- do deviant friends lead to delinquency, or vice versa?
- does higher national income lead to higher subjective wellbeing or is it the other way around?
- how do maternal depression and children's externalizing behavior affect each other?
- do husbands and wives affect each other equally?
- are increases in language skills necessary for increases in math performance?
- does having more friends come before being more sociable or is it the other way around?

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- does having more friends come before being more sociable or is it the other way around?

Causal questions, but **experiments** typically not feasible

Why Cross Lags?

Basic Idea: Instead of intervening in the system, observe and model how current X predicts future Y

- Since future cannot effect the past, rule out one possible explanation for statistical dependence
- Interpretation: Cross-lagged parameters reflect (Granger) “causal dominance”

Why Cross Lags?

Basic Idea: Instead of intervening in the system, observe and model how current X predicts future Y

- Since future cannot effect the past, rule out one possible explanation for statistical dependence
- Interpretation: Cross-lagged parameters reflect (Granger) “causal dominance”

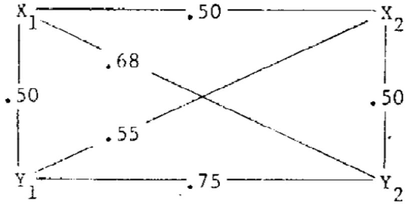
Disclaimer: The models we study in this workshop are not guaranteed to yield causal insights

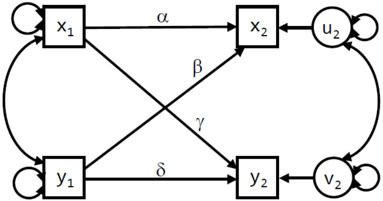
- Statistical models cannot solve the problem of **unobserved confounding** and **model misspecification**
- Pointless to pretend we don’t interpret parameters causally when discussion sections use parameters to suggest interventions
- Some developments and extensions of these models only make sense when we have very specific ideas about the causal system of interest

Panel data and cross-lagged relationships have been around a long time

Pre-1980:

- Cross-lagged panel design: measure same people on the same variable **at least twice**
- Goal: study causality
- Compute cross-lagged **correlations**

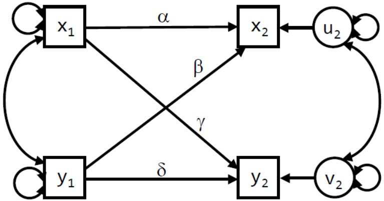




Cross-lagged panel model (for 2W2V design):

$$x_2 = c_{x2} + \alpha x_1 + \beta y_1 + u_2$$
$$y_2 = c_{y2} + \gamma x_1 + \delta y_1 + v_2$$

The Cross-Lagged Panel Model (CLPM) : Rogosa (1980)



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$$x_2 = c_{x2} + \alpha x_1 + \beta y_1 + u_2$$
$$y_2 = c_{y2} + \gamma x_1 + \delta y_1 + v_2$$

Where:

- α and δ are autoregressive parameters
- β and γ are cross-lagged parameter

At the time...

Rogosa (1980): When there are **different degrees of stability**, comparing CLC may:

- **fail** to detect relationships
- **erroneously** detect relationships
- select the wrong variable as being **causally dominant**

Message that stuck:

We need to **correct/control for stability**, and we do this by using the CLPM, which includes **autoregressive relationships.**

Outline

- SEM refresher
- Cross-Lagged Panel Model (CLPM)
- **Interpreting and fitting the CLPM**
  - Basic CLPM model
  - Investigating stability of means (i.e. trends)
  - Investigating stability of lagged parameters
- Trait-like stability: Random-Intercept (RI-) CLPM
- Extensions: Trends, Measurement Error, Mediation and Time-Intervals
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Empirical example

Soenens, Luyckx, Vansteekiste, Duriez, and Goossens (2008, Merrill-Palmer Quarterly) studied the relationship between:

- parental psychological control
- adolescents' depressive symptomatology

The data:

- 396 students
- three annual measurements
- here: using summary statistics (not the raw data)

The goal is to investigate whether:

- adolescents become depressed if their parents are over-controlling
- parents become more controlling when their child is depressed
- both mechanisms are at work

Part 1: Basic CLPM Input

```
VARIABLE:   NAMES ARE PsCon1 PsCon2 PsCon3
            Resp1 Resp2 Resp3 BeCon1
            BeCon2 BeCon3 Dep1 Dep2 Dep3;
            USEVARIABLES = PsCon1 Dep1 PsCon2 Dep2 PsCon3
            Dep3;

MODEL:      ! Specify the lagged effects
            PsCon2 Dep2 ON PsCon1 Dep1;
            PsCon3 Dep3 ON PsCon2 Dep2;

            ! Make wave 1 “endogenous”
            PsCon1;
            Dep1;

            ! Allow the residuals (dynamic errors) at
            ! subsequent waves to be correlated
            Dep2 WITH PsCon2;
            Dep3 WITH PsCon3;

OUTPUT:     TECH1 SAMPSTAT STDYX MOD(4) TECH3;
```

Output: Lagged parameter estimates

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
PSCON2 ON				
PSCON1	0.678	0.039	17.201	0.000
DEP1	0.012	0.004	3.065	0.002
DEP2 ON				
PSCON1	2.548	0.447	5.698	0.000
DEP1	0.322	0.046	7.051	0.000
PSCON3 ON				
PSCON2	0.699	0.038	18.332	0.000
DEP2	0.018	0.004	4.381	0.000
DEP3 ON				
PSCON2	2.043	0.442	4.623	0.000
DEP2	0.406	0.048	8.490	0.000

Remember that our goal is to assess something like ‘causal dominance’ - is one effect stronger than the other or are they approximately the same?

We want to do this by **comparing** cross-lagged regression coefficients. But, often, psychological variables measured on an **arbitrary** scale

Regression coefficients are a function of the **variance.** So, comparisons between parameters are thought to be more “fair” if the **standardized** regression coefficients are used.

Output: Standardized lagged parameter estimates

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
PSCON2 ON				
PSCON1	0.657	0.030	21.558	0.000
DEP1	0.117	0.038	3.070	0.002
DEP2 ON				
PSCON1	0.268	0.046	5.859	0.000
DEP1	0.331	0.045	7.378	0.000
PSCON3 ON				
PSCON2	0.668	0.029	22.911	0.000
DEP2	0.160	0.036	4.388	0.000
DEP3 ON				
PSCON2	0.216	0.046	4.699	0.000
DEP2	0.396	0.044	9.080	0.000

Output: Standardized covariances (correlations)

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
DEP2 WITH				
PSCON2	0.136	0.049	2.766	0.006
DEP3 WITH				
PSCON3	0.221	0.048	4.635	0.000
DEP1 WITH				
PSCON1	0.370	0.043	8.531	0.000

Note: These with statements for waves 2 and 3 are covariances (correlations) between the **residuals**, not the variables themselves.

Note also: The covariance (correlation) for wave 1 is only reported because we **explicitly asked for it**.

Output: Other parameters

MODEL RESULTS				Two-Tailed
	Estimate	S.E.	Est./S.E.	P-Value
Means				
PSCON1	1.940	0.032	61.356	0.000
DEP1	9.450	0.309	30.567	0.000
Intercepts				
PSCON2	0.509	0.075	6.760	0.000
DEP2	0.520	0.854	0.609	0.543
PSCON3	0.471	0.072	6.534	0.000
DEP3	1.277	0.836	1.528	0.126
Variances				
PSCON1	0.396	0.028	14.071	0.000
DEP1	37.850	2.690	14.071	0.000
Residual Variances				
PSCON2	0.210	0.015	14.071	0.000
DEP2	27.051	1.922	14.071	0.000
PSCON3	0.205	0.015	14.071	0.000
DEP3	27.638	1.964	14.071	0.000

Output: R-square (part of STDYX output)

R-SQUARE

Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
PSCON2	0.502	0.035	14.148	0.000
DEP2	0.247	0.038	6.560	0.000
PSCON3	0.554	0.033	16.631	0.000
DEP3	0.270	0.038	7.078	0.000

Note: Model misfit concerns the **entire covariance structure** (i.e., of all six variables); hence, even when significant amounts of variance are explained, the model may not provide a good fit.

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
ON Statements				
PSCON2 ON PSCON3	33.917	-0.450	-0.450	-0.471
DEP2 ON PSCON3	6.107	-3.944	-3.944	-0.447
DEP2 ON DEP3	7.255	-0.371	-0.371	-0.381
PSCON3 ON PSCON1	40.589	0.320	0.320	0.297
DEP3 ON PSCON1	6.516	-1.487	-1.487	-0.152
DEP3 ON DEP1	12.306	0.167	0.167	0.167
WITH Statements				
PSCON3 WITH PSCON2	37.286	-0.095	-0.095	-0.456
DEP3 WITH DEP2	4.843	-8.163	-8.163	-0.299
PSCON1 WITH PSCON3	39.256	0.103	0.103	0.360
PSCON1 WITH DEP3	15.890	-0.758	-0.758	-0.229
DEP1 WITH PSCON3	5.220	-0.305	-0.305	-0.109
DEP1 WITH DEP3	17.950	6.557	6.557	0.203

Note: Not all of these parameters make sense (substantively).

Part 2: Investigating the mean structure

Typically, the mean structure is **not explicitly modeled.**

This implies we estimate:

- **means** for the first wave
- **intercepts** thereafter

For the **first wave** we have:

$$x_{i1} = \mu_{x1} + u_{i1}$$
$$y_{i1} = \mu_{y1} + v_{i1}$$

For the **second wave** we have:

$$x_{i2} = c_{x2} + \alpha_2 x_{i1} + \beta_2 y_{i1} + u_{i2}$$
$$y_{i2} = c_{y2} + \gamma_2 x_{i1} + \delta_2 y_{i1} + v_{i2}$$

where c_{x2} and c_{y2} are **intercepts**, not means!

Investigating the mean structure

We may want to investigate whether the **means are stable across time**, that is:

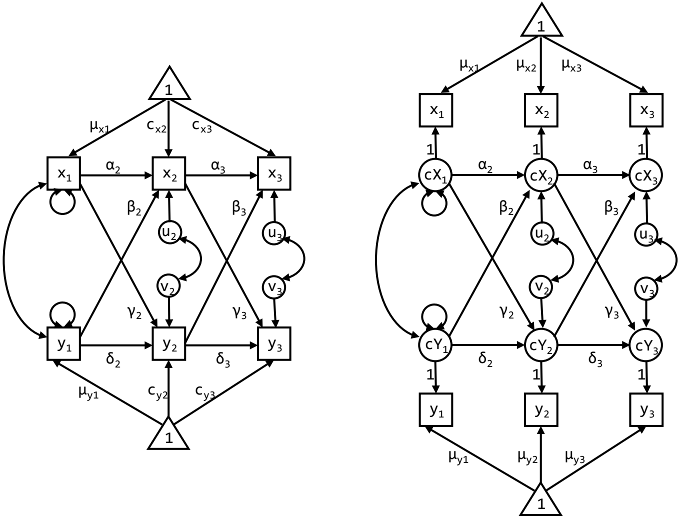
$$\mu_{xt} = \mu_x \text{ and } \mu_{yt} = \mu_y$$

In this model, the **means at wave 2** are functions of:

- the intercepts at wave 2
- the means at wave 1 weighted by the lagged parameters

So, it's not so easy to test whether the means are stable or not! Instead, we change the model specification to make use of *centered* variables

Two statistically equivalent versions of the CLPM



Note: **Triangles** are used to represent the mean structure.

Part 2: Investigate Stability of Means

```
MODEL:      ! Create grand mean centered variables
            cDep1 BY Dep1; cPsCon1 BY PsCon1;
            cDep2 BY Dep2; cPsCon2 BY PsCon2;
            cDep3 BY Dep3; cPsCon3 BY PsCon3;

            ! Constrain the group means per variable over time
            [Dep 1 Dep2 Dep3](MD);
            [PsCon1 PsCon2 PsCon3](MPs);

            ! Constrain the measurement error variances to zero
            PsCon1-Dep3@0;
```

Hence, the new variables cDep1 to cPsCon3 are **centered variables**: We will use these for the **lagged regressions** (see next slide).

As a result, we will estimate the **means of the observed variables** in this model (**instead of means and intercepts**).

(Continued)

```
! Specify the lagged effects between the grand mean centered variables
cPsCon2 cDep2 ON cPsCon1 cDep1;
cPsCon3 cDep3 ON cPsCon2 cDep2;

! Allow the grand mean centered variable at the first wave to be correlated
cDep1 WITH cPsCon1;

! Allow the residuals (dynamic errors) at
! subsequent waves to be correlated
cDep2 WITH cPsCon2;
cDep3 WITH cPsCon3;
```

Model fit for constant means model

Chi-square is 13.75 with 4 df, p=.0081.
RMSEA = 0.078
CFI = 0.990
TLI = 0.962
SRMR = 0.024

Hence, model fit is not good according to the chi-square test.

We can use the **Modification Indices** to see where the problem is:

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
Means/Intercepts/Thresholds				
[DEP1]	10.205	0.632	0.632	0.102
[PSCON3]	4.943	0.038	0.038	0.056

Output: Mean estimates

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Means				
PSCON1	1.949	0.029	66.936	0.000
DEP1	9.474	0.309	30.682	0.000
PSCON2	1.949	0.029	66.936	0.000
DEP2	8.526	0.258	33.104	0.000
PSCON3	1.949	0.029	66.936	0.000
DEP3	8.526	0.258	33.104	0.000

Results show that **depression at the first wave** was higher than depression at the second and third wave.

Part 2b: Constraining the means in the CLPM

```
MODEL:    ! Create grand mean centered variables
          cDep1 BY Dep1; cPsCon1 BY PsCon1;
          cDep2 BY Dep2; cPsCon2 BY PsCon2;
          cDep3 BY Dep3; cPsCon3 BY PsCon3;

          ! Constrain the group means per variable over time
          ! except for the mean of Dep1
          [Dep2 Dep3](MD);
          [PsCon1 PsCon2 PsCon3](MPs);

          ! Constrain the measurement error variances to zero
          PsCon1-Dep3@0;
```

We free the mean of Dep1, but otherwise keep the same constraints
This model fits better! (rest of model specification not shown)

Part 3: Investigating Stability of Lagged Parameters

We may also be interested in whether/which *lagged* regression parameters remain stable over time.

Does the way in which adolescent depression influences parental control stay the same each year, or does it change?

We can test this by constraining the lagged parameters to be equal *across time*

Part 3: Constrain lagged parameters across time

Instead of this:

```
! Lagged effects between the grand mean centered variables
cPsCon2 cDep2 ON cPsCon1 cDep1;
cPsCon3 cDep3 ON cPsCon2 cDep2;
```

we now specify this:

```
! Autoregressive effects between the grand mean centered variables
! (these effects are also constrained over time, but this is not necessary)
cPsCon2 ON cPsCon1 (a); cPsCon3 ON cPsCon2 (a);
cDep2 ON cDep1 (d); cDep3 ON cDep2 (d);

! Cross-lagged effects between the grand mean centered variables
! (these effects are also constrained over time, but this is not necessary)
cPsCon2 ON cDep1 (b); cPsCon3 ON cDep2 (b);
cDep2 ON cPsCon1 (c);cDep3 ON cPsCon2 (c);
```

Model comparison

Model	χ^2	df	p	$\Delta\chi^2$	Δ df	p	AIC	BIC
1	60.14	4	<.0001				9151	9242
2	63.08	7	<.0001	2.94	3	.40	9148	9227
3	66.18	11	<.0001	3.10	4	.54	9142	9206

Description:

- Model 1 is the initial CLPM
- Model 2 is CLPM with constraints on the means
- Model 3 is model 2 with constraints on the lagged parameters

Models are **increasingly more restrictive**, hence the misfit (chi-square) increases; does increase in misfit **outweigh** the decrease in complexity (parsimony)?

Rules of thumb for AIC and BIC:

- difference <2 no preference
- difference 2-6 some preference
- difference 6-10 substantial preference
- difference >10 overwhelming preference

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- **Trait-like stability: Random-Intercept (RI-) CLPM**
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The issue of stability

Motviation behind the CLPM (Rogosa, 1980):

We need to **correct/control for stability**, and we do this by using the CLPM, which includes **autoregressive relationships**.

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Autoregression **only controls for temporal stability**; it does **not** control for **trait-like, time-invariant stability** (= unobserved heterogeneity).

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Crux: Does everybody vary around the same mean (or trend), or do individuals have different means (or trends)?

Seperating Within and Between Variance

Hamaker, Kuiper, Grasman (2015): CLPM doesn't seperate within-person variance (over time) from between-person variance (differences in means/trends across individuals)

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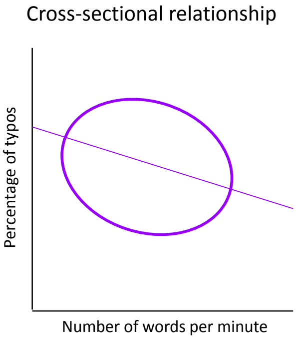
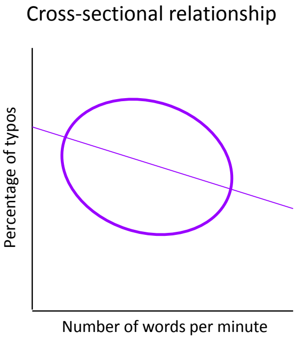
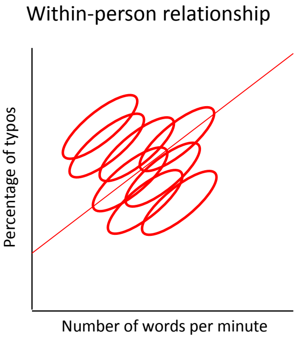


Seperating Within and Between Variance

Hamaker, Kuiper, Grasman (2015): CLPM doesn't seperate within-person variance (over time) from between-person variance (differences in means/trends across individuals)





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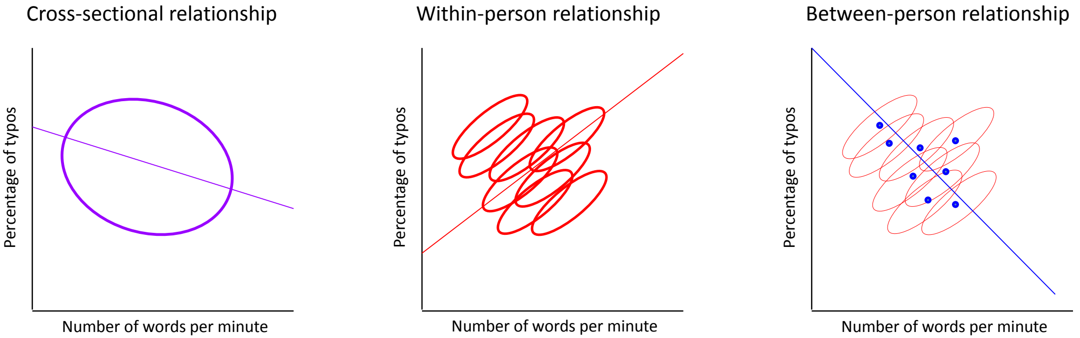
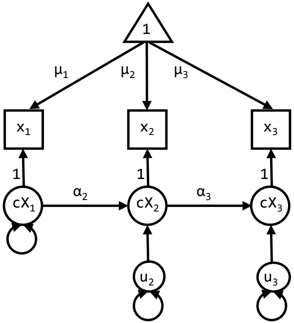
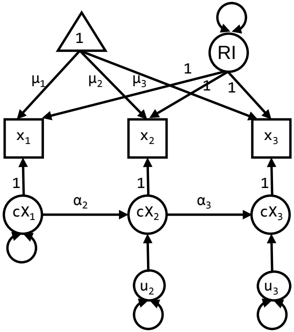


Univariate Models: Random Intercept

Solution: Allow the mean/trend to vary across individuals with a *Random Intercept*
Lagged parameters are *average within-person* parameters





Simplex model

$x_{it} = \mu_t + cX_{it}$

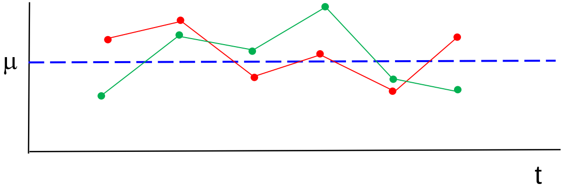
$cX_{it} = \alpha_t cX_{i,t-1} + u_{it}$

Alternative model

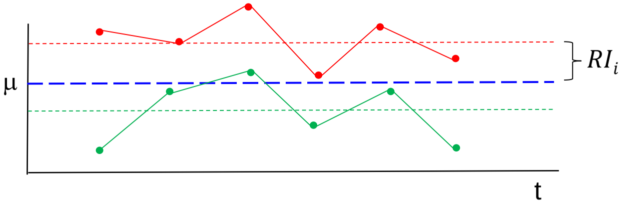
$x_{it} = \mu_t + RI_i + cX_{it}$

$cX_{it} = \alpha_t cX_{i,t-1} + u_{it}$

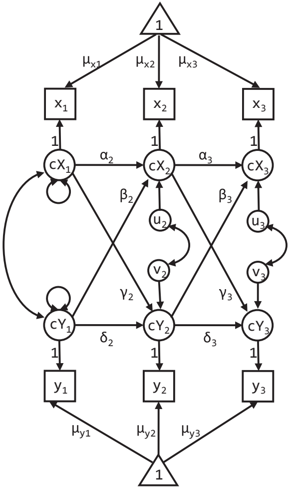
Simplex model: Autoregression = rank stability

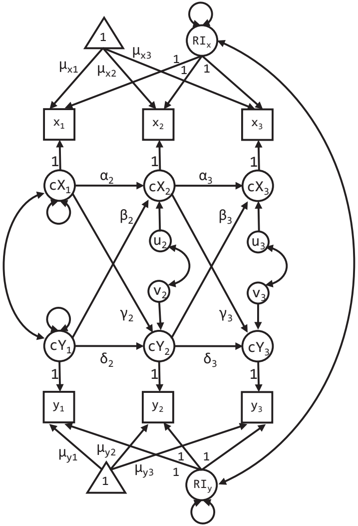


Random intercept AR model: Autoregression = carry-over

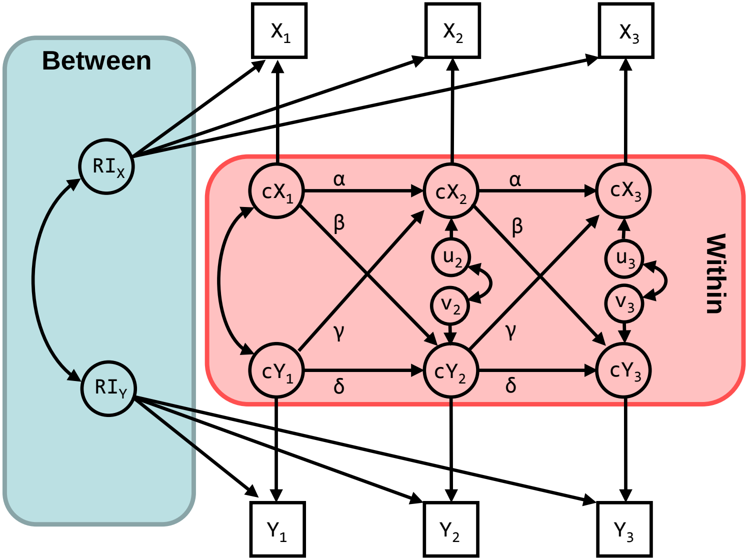


Bivariate models (based on Hamaker et al., 2015)





Simplified RI-CLPM (without the mean structure)

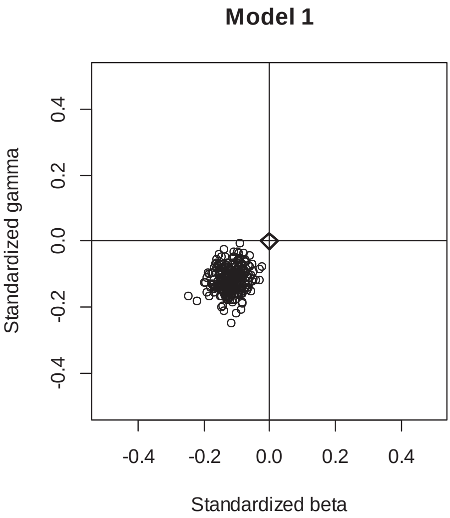


Three objectives in cross-lagged panel research:

- determine which cross-lagged effects are **significant**
- determine which cross-lagged effect is **stronger**
- determine the **sign** of significant cross-lagged effects

True RI-CLPM:
no cross-lagged parameters

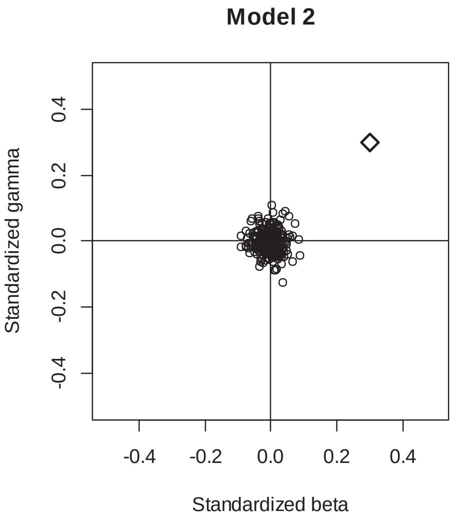
Estimated CLPM:
both cross-lagged parameters about -.1



Scenario 2: Failing to detect cross-lagged effects

True RI-CLPM:
cross-lagged effects about .3

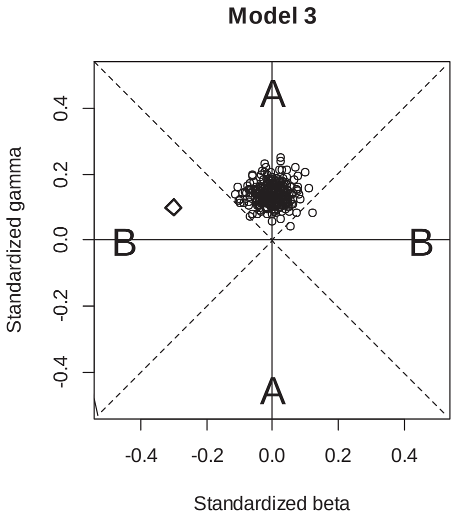
Estimated CLPM:
both cross-lagged parameters about 0



Scenario 3: Causal dominance incorrect

True RI-CLPM:
y is causally dominant

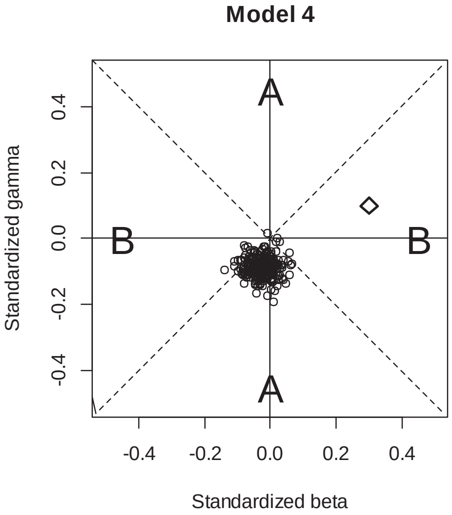
Estimated CLPM:
x is causally dominant



Scenario 4: Getting the sign wrong

True RI-CLPM:
γ is positive

Estimated CLPM:
γ is negative



To summarize

Using the traditional CLPM when the data are actually generated by the RI-CLPM, you may:

- find **spurious** relationships
- **fail** to detect relationships
- identify the **wrong variable** as being causally dominant
- obtain the **wrong sign** for an effect

Input for RI-CLPM

```
VARIABLE:   NAMES ARE PsCon1 PsCon2 PsCon3 Resp1 Resp2
            Resp3 BeCon1 BeCon2 BeCon3 Dep1 Dep2 Dep3;
            USEVARIABLES = PsCon1 Dep1 PsCon2 Dep2 PsCon3
            Dep3;

MODEL:      ! Create a random intercept for each variable
            RID BY Dep1@1 Dep2@1 Dep3@1;
            RIPC BY PsCon1@1 PsCon2@1 PsCon3@1;

            ! Create within-person (centered) variables
            cDep1 BY Dep1; cPsCon1 BY PsCon1;
            cDep2 BY Dep2; cPsCon2 BY PsCon2;
            cDep3 BY Dep3; cPsCon3 BY PsCon3;

            ! Constrain the measurement error variances to zero
            PsCon1-Dep3@0;
```

Input (continued)

```
! Specify the autoregressive and cross-lagged
! effects for the within-person variables
cDep2 cPsCon2 ON cDep1 cPsCon1;
cDep3 cPsCon3 ON cDep2 cPsCon2;

! Allow correlated within-person variables at wave 1
cDep1 WITH cPsCon1;

! Allow corrrelated residuals at subsequent waves
cDep2 WITH cPsCon2;
cDep3 WITH cPsCon3;

! Fix the correlation between the random intercepts and
! the other exogenous variables to zero
RID WITH cDep1@0 cPsCon1@0;
RIPC WITH cDep1@0 cPsCon1@0;
```

Or with constraints on means and lagged parameters

```
! Constrain the group means per variable over time
! except for the mean of Dep1
[Dep2 Dep3](MD);
[PsCon1 PsCon2 PsCon3](MPs);

! Autoregressive effects between the within-person centered variables
! (these effects are also constrained over time, but this is not necessary)
cPsCon2 ON cPsCon1 (a); cPsCon3 ON cPsCon2 (a);
cDep2 ON cDep1 (d); cDep3 ON cDep2 (d);

! Cross-lagged effects between the within-person centered variables
! (these effects are also constrained over time, but this is not necessary)
cPsCon2 ON cDep1 (b); cPsCon3 ON cDep2 (b);
cDep2 ON cPsCon1 (c); cDep3 ON cPsCon2 (c);
```

Model fit and comparison

Current model is an extension of the traditional CLPM; the models are nested.

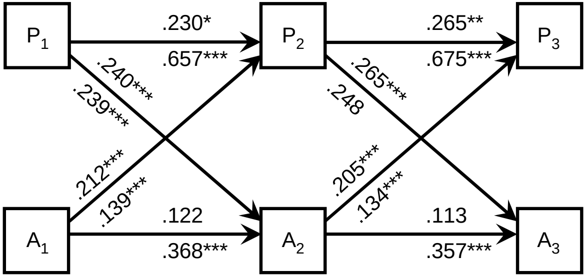
Model	χ^2	df	p	$\Delta\chi^2$	Δ df	p	AIC	BIC
RI-CLPM	9.85	8	.276				9092	9168
CLPM	66.18	11	<.0001	56.33	3	<.0001	9142	9206

Note: Using the chi-square difference test to determine whether variances are zero, is (slightly) problematic (cf. Stoel et al., 2006, Psychological Methods).

Empirical example based on Soenens

Standardized lagged relationships between:

- *Parental psychological control*
- *Adolescents' depressive symptomatology*

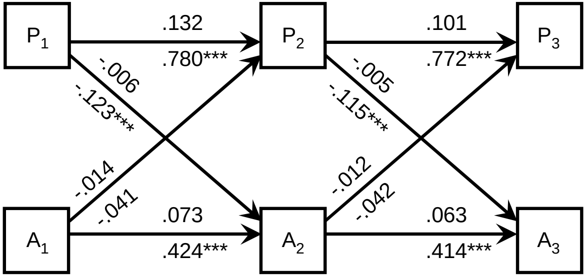


Conclusion (based on time-invariant lagged effects):

- CLPM (below arrows): $P_{t-1} \rightarrow A_t > A_{t-1} \rightarrow P_t$
- RI-CLPM (above arrows): the effects are **about equal**

Standardized lagged relationships between:

- *Parental responsiveness*
- *Adolescents' depressive symptomatology*



Conclusion (based on time-invariant lagged effects):

- CLPM (below arrows): $P_{t-1} \rightarrow A_t$ is **negative**
- RI-CLPM (above arrows): **no significant** cross-lagged effects

Conclusion Hamaker, Kuiper & Grasman (2015)

- We need to control for the **right kind** of stability
- CLPM does **not adequately control** for stability resulting from a trait
- When only 2 waves of data are available, the **CLPM is saturated** and no alternative model can be fitted; however, this does **not** mean that the problem does not exist!!!
- Researchers should gather **at least 3 waves** of data, and compare the CLPM to alternatives

Outline

- SEM refresher
- Cross-Lagged Panel Model (CLPM)
- Interpreting and fitting the CLPM
- Trait-like stability: Random-Intercept (RI-) CLPM
- **Extensions: Trends, Measurement Error, Mediation and Time-Intervals**
- Discussion/Lab

Trends in the RI-CLPM: $\mu_t \neq \mu$

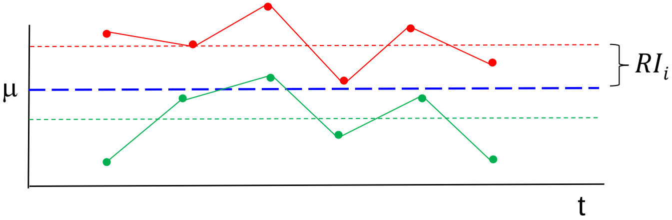
The RI-CLPM is not necessarily for **stationary processes.**

If the group mean μ_t changes over time, this implies that you can have all kinds of trends.

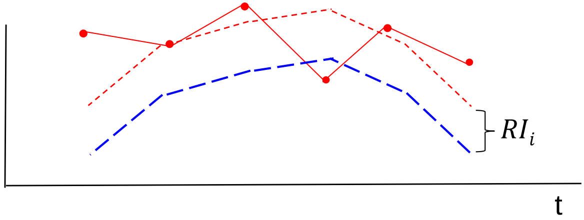
Each individual will be described by **a constant deviation** (i.e., RI_i) **from this group trend**, with the exact same shape as the average trend.

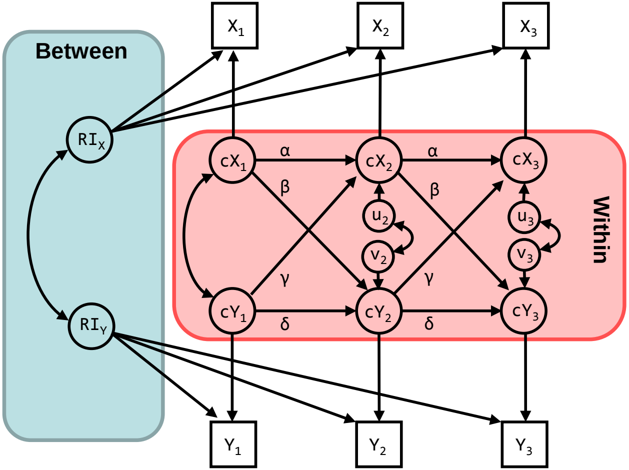
Trends in the RI-CLPM: $\mu_t \neq \mu$

Invariant mean over time



Varying mean over time




Between
Within
X1
X2
X3
RIX
RIY
cX1
cX2
cX3
cY1
cY2
cY3
u2
v2
u3
v3
α
α
β
β
γ
γ
δ
δ
Y1
Y2
Y3

Measurement vs Dynamic Error

RI-CLPM includes only **dynamic error**, which affects the current and future occassions (carries over)

Measurement model is used only for centering. Factor loading set to 1, and no measurement error variance. So, the model doesn't account for **measurement error** – error which affects only one occassion

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To estimate a measurement model we need either:

A Large number repeated measures **and** substantial autoregression (closely spaced in time) (Kenny and Zautra, 1995)

B Multiple indicators. But we must consider **factorial invariance.**

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Last option can be complicated: Many studies on decomposing **trait-** and **state-**variance, but typically do not include lagged relations

Some trait-state models (univariate construct)

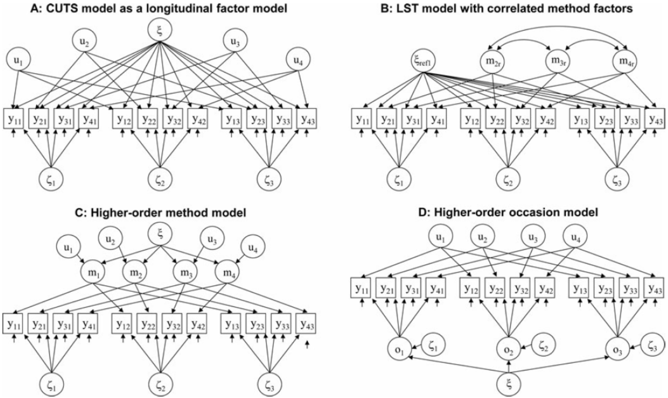


Figure 1. Four models for decomposing observed variances into trait and state components. Panel A contains the common and unique trait-state (CUTS) model presented in the current paper; panel B contains the latent state-trait (LST) model with correlated method factors as discussed by Geiser and Lockhart (2012), with indicator 1 as the reference indicator; panel C contains the higher-order method (HOM) model that includes the common trait as a second-order factor that links the method factors (i.e., the higher-order item model by Marsh and Grayson, 1994); panel D contains the higher-order occasion (HOO) model, which includes the common trait as a second-order factor that links the occasion factors (i.e., the higher-order time model by Marsh and Grayson, 1994).

Hamaker, Schuurman and Zijlmans (2017). Multivariate Behavioral Research, 52, 47-60.

Of course, (RI-)CLPM models can handle more than two variables!

Notably, Maxwell & Cole (2003) argue that *mediation* must be studied with lagged designs

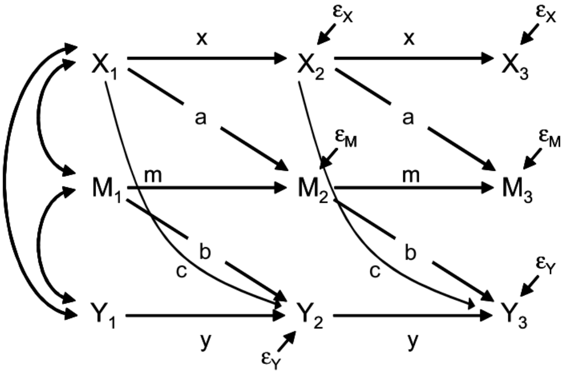


Figure from Maxwell, Cole, Mitchell (2011)

The “lag-problem”

As pointed out by Gollob and Reichardt (1987, Child Development), when studying lagged relationships, **results vary as a function of the interval** between cause and effect.

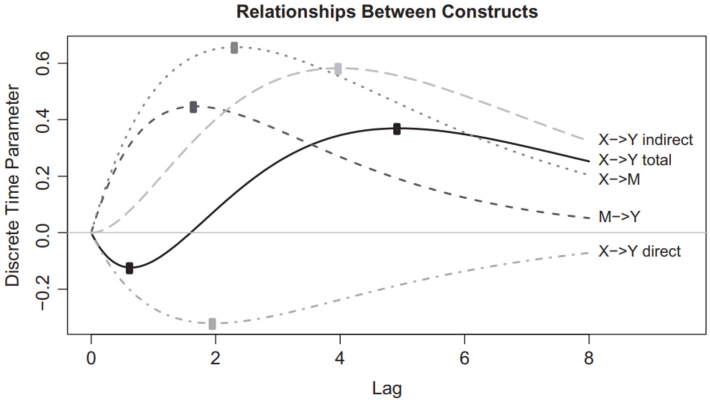
It is **very unlikely** that a particular cause **only** has an effect at a particular interval: It is more likely to have an increasing effect, to reach a maximum at some point, and then to decrease.

This is the idea underlying **continuous time modeling**.

Relating continuous and discrete time solutions

$$\boldsymbol{B}(\Delta t_i) = e^{\boldsymbol{A}\times\Delta t_i}$$

What you see is what you get!



Deboeck and Preacher (2016), Structural Equation Modeling, 23, p. 61-75.

Note: The **total effect** of X on Y is **negative at shorter intervals**, and **positive at longer intervals**; this is because the **direct effect is negative** and the **indirect effect is positive**, and they evolve differently over time.

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Thank you!

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References

Rogosa, D. (1980). A critique of cross-lagged correlation. Psychological Bulletin, 88(2), 245.

Soenens, B., Luyckx, K., Vansteenkiste, M., Luyten, P., Duriez, B., Goossens, L. (2008). Maladaptive perfectionism as an intervening variable between psychological control and adolescent depressive symptoms: a three-wave longitudinal study. Journal of Family Psychology, 22(3), 465.

Hamaker, E. L., Kuiper, R. M., Grasman, R. P. (2015). A critique of the cross-lagged panel model. Psychological methods, 20(1), 102.

Kenny, D. A., Zautra, A. (1995). The trait-state-error model for multiwave data. Journal of consulting and clinical psychology, 63(1), 52.

Cole, D. A., Maxwell, S. E. (2003). Testing mediational models with longitudinal data: questions and tips in the use of structural equation modeling. Journal of abnormal psychology, 112(4), 558.

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Maxwell, S. E., Cole, D. A., Mitchell, M. A. (2011). Bias in cross-sectional analyses of longitudinal mediation: Partial and complete mediation under an autoregressive model. Multivariate Behavioral Research, 46(5), 816-841.

Deboeck, P. R., Preacher, K. J. (2016). No need to be discrete: A method for continuous time mediation analysis. Structural Equation Modeling: A Multidisciplinary Journal, 23(1), 61-75.

Applications:

- Keijsers (2016) International Journal of Behavioral Development, 40, 271-281. Investigates the relationship between **parental monitoring** and **adolescent problem behaviors.** Compares traditional CLPM to RI-CLPM.
- te Poel, Baumgartner, Hartmann and Tanis (2016), Journal of Anxiety Disorders, 43, 32-40. Investigate **cyberchondria** using four waves of data. Does **online health information seeking** increase **health anxiety**, which subsequently leads to more health information seeking?

References: Similar Approaches

- Ormel, Rijsdijk, Sullivan, van Sonderen and Kempen (2002). Journal of Gerontology: Psychological Sciences, 57B, 338-347.
- Spinhoven, Penelo, de Rooij, Penninx and Ormel (2014). Psychological Medicine, 44, 337-348.
- Ousey, Wilcox and Fisher (2011) studied the relationship between **victimization** and **offending** in middle and high school students.
- Dorman and Griffin (2015), Psychological Methods, 20, p. 489-505.
- RI-CLPM can be related to the **latent curve model with structured residuals** (**LCM-SR**; Curran et al., 2014, Journal of Consulting and Clinical Psychology; Berry & Willoughby, 2017, Child Development), and the **autoregressive latent trajectory (ALT) model** (Bollen and Curren, 2004, Sociological Methods & Research). In both cases it is a version **without a slope factor**.
- Hamaker (2005) shows that when the ALT model is started up using certain constraints (i.e., trend stationarity), the two models are statistically equivalent.
- Jongerling and Hamaker, 2011, Structural Equation Modeling: A Multidisciplinary Journal, 18, 370-382. Describe behaviour of the ALT