Which Methods Do We Need for Intensive Longitudinal Data?

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The Transitional Aspect of Snow (Foreshadowing)

"Foreshadowing or guessing ahead is a literary device by which an author hints what is to come. Foreshadowing is a dramatic device in which an important plot-point is mentioned early in the story and will return in a more significant way. It is used to avoid disappointment. It is also sometimes used to arouse the reader".

Non-Intensive versus Intensive Longitudinal Data

- Non-intensive longitudinal data:
  - T small (2 - 10) and N large
  - Modeling: Auto-regression and growth
- Intensive longitudinal data:
  - T large (30-200) and N smallish (even $N = 1$) but can be $1,000$. Often $T > N$
  - Modeling: We shall see

Intensive Longitudinal Data Collection

- Ecological momentary assessment (EMA): a research participant repeatedly reports on symptoms, affect, behavior, and cognitions close in time to experience and in the participants' natural environment using smartphone, handheld computer, or GPS
- Experience sampling method (ESM): a research procedure for studying what people do, feel, and think during their daily lives
- Daily diary measurements
- Burst of measurement
- Ambulatory assessment (Trull & Ebner-Priemer, 2014. *Current Directions in Psychological Science*)

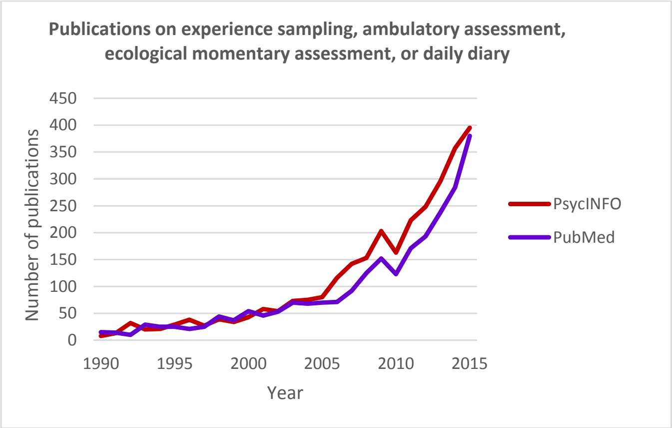
Examples of Intensive Longitudinal Data Sets

Data Sets	*N*	*T*
Trull data in Jahng et al. (2008)		
Mood:	84	76-186
Bergeman data in Wang et al. (2012)		
Positive and negative affect:	230	56
Shiffman data in Hedeker et al. (2013)		
Smoking urge:	515	34
Laurenceau data in Jongerling et al. (2015)		
Positive affect:	96	42

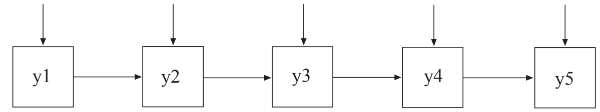
Publications on Analysis of Intensive Longitudinal Data

- Walls & Schafer (2006). *Model for Intensive Longitudinal Data*. New York: Oxford University Press.
- Bolger & Laurenceau (2013). *Intensive Longitudinal Methods: An Introduction to Diary and Experience Sampling Research*. New York: Guilford.
- Jahng, Wood & Trull (2008). Analysis of affective instability in ecological momentary assessment. Indices using successive differences and group comparison via multilevel modeling. *Psychological Methods*
- Wang, Hamaker & Bergeman (2012). Investigating inter-individual differences in short-term intra-individual variability. *Psychological Methods*
- Jongerling, Laurenceau & Hamaker (2015). A multilevel AR(1) model: Allowing for inter-individual differences in trait-scores, inertia, and innovation variance. *Multivariate Behavioral Research*

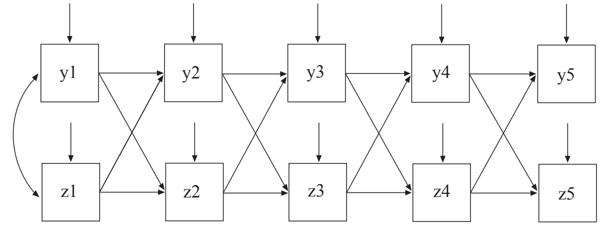
An Explosion of Intensive Longitudinal Data Articles



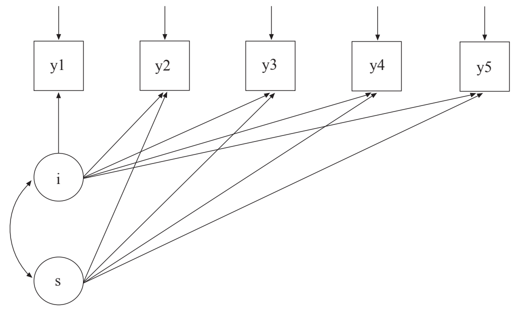
Common Methods for Non-Intensive Longitudinal Data N large and T small (2 - 10): (1) Auto-Regression Modeling

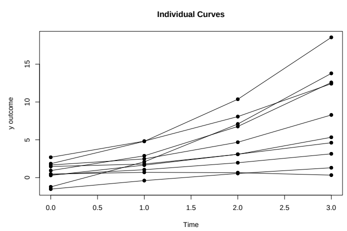


Cross-lagged modeling:

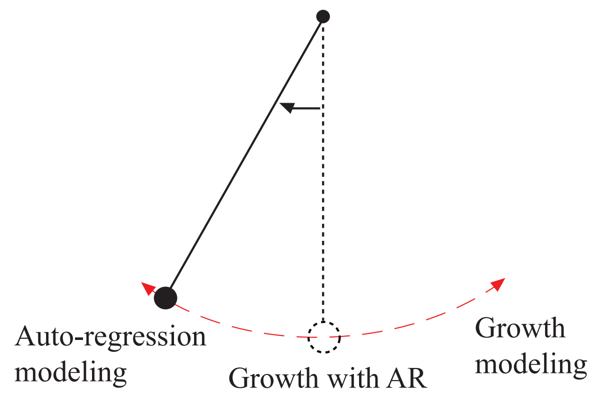


Common Methods for Non-Intensive Longitudinal Data: (2) Growth Modeling

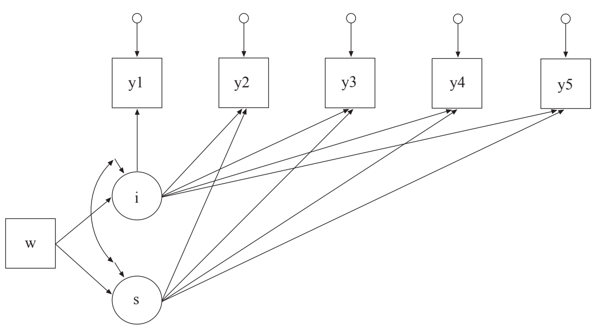




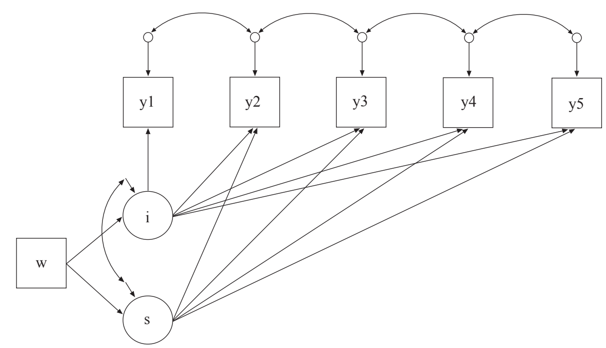
The Fashion Pendulum of Longitudinal Modeling



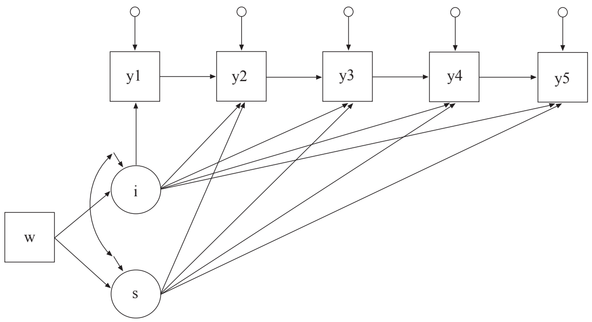
Growth Modeling using Single-level Wide Format



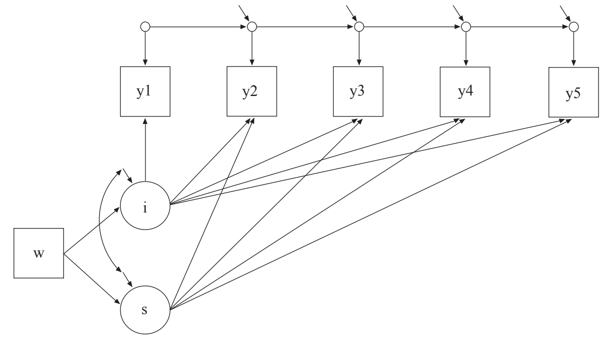
Growth Modeling Adding Correlated Residuals



Growth Modeling Adding Auto-Regression (ALT Model)



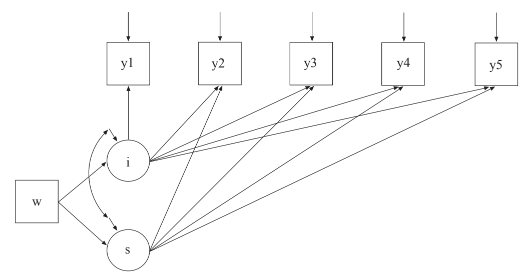
Growth Modeling Adding Auto-Regressive Residuals



Relating Auto-Regressive and Growth Modeling

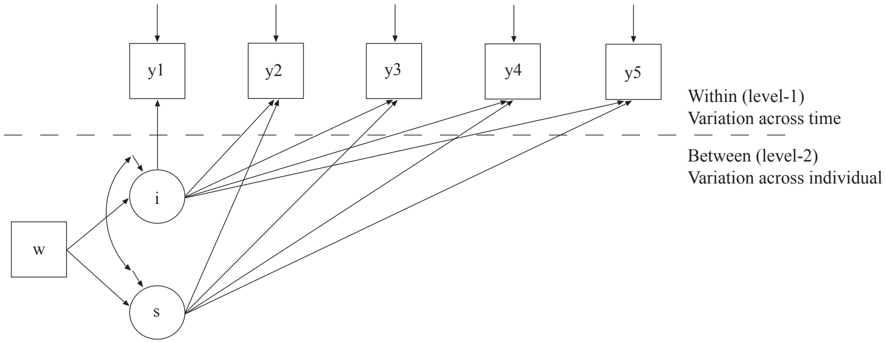
- Hamaker (2005). Conditions for the equivalence of the autoregressive latent trajectory model and a latent growth curve model with autoregressive disturbances. *Sociological Methods & Research*, 33, 404-416
- Jongerling & Hamaker (2011). On the trajectories of the predetermined ALT model: What are we really modeling? *Structural Equation Modeling*, 18, 370-382.

The Growth Model and Intensive Longitudinal Data (ILD)

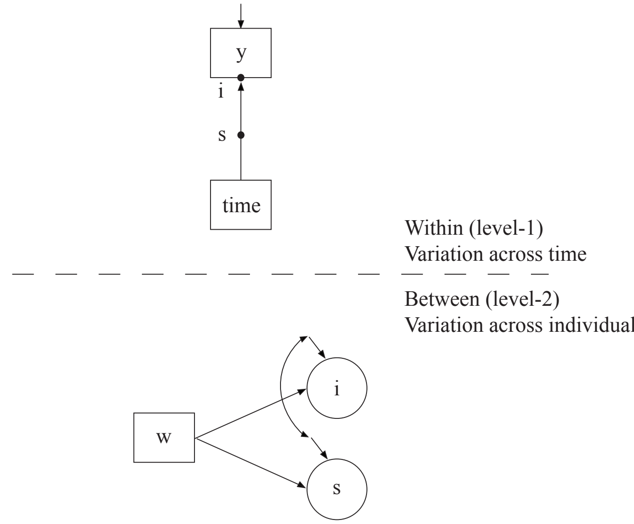


- Instead of $T = 5$, ILD has $T = 50$ or 100: Too wide for the single-level wide approach (and often $T > N$)
- Within-individual correlation across time is a nuisance in growth modeling but a focus of ILD analysis
- Development over time typically not as simple for ILD data as using a few random slope growth factors: seasonality, cycles

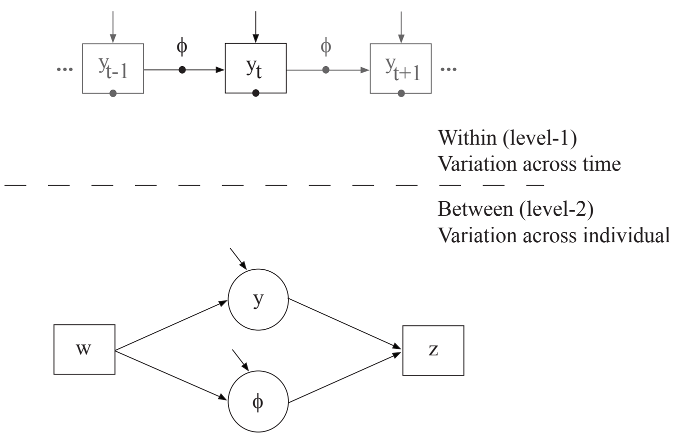
Growth Modeling from a Two-Level Perspective



Two-Level, Long Format Version



Two-Level, Time-Series Version

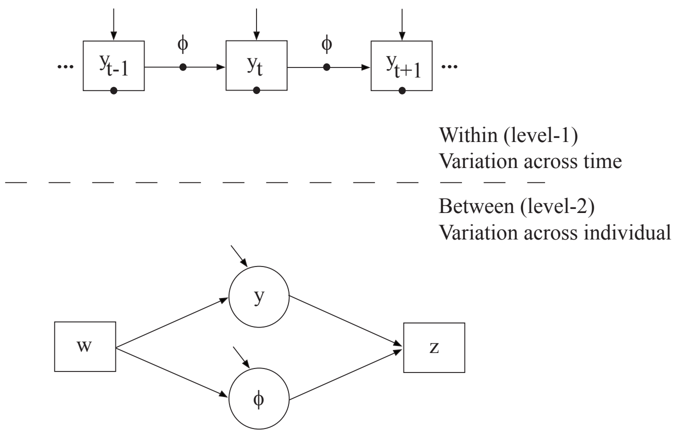


- 3 key features: Random mean (y), random autoregression (ϕ), random variance (not shown)

3 Key Features of Two-Level Time-Series Model: Inter-Individual Differences in Intra-Individual Characteristics

1. Random mean: Individual differences in level
2. Random autoregression: Inertia (resistance to change). Related to:
   - Neuroticism and agreeableness (Suls et al., 1998)
   - Depression (Kuppens et al., 2010)
   - Rumination, self-esteem, life satisfaction, pos. and neg. affect (gender)
3. Random variance: Innovation variance
   - Individual differences in reactivity (stress sensitivity) and exposure

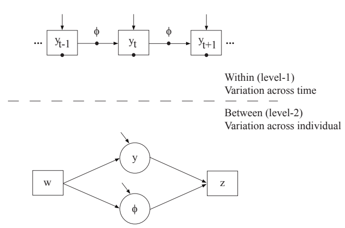
Two-Level Time-Series Analysis How Big do N and T Need to be?



Two-Level Time-Series Analysis: Monte Carlo Simulation Input for Mplus V8

```
MONTECARLO:   NAMES = y w z;
              NOBSERVATIONS = 5000;
              NREP = 1000;
              NCSIZES = 1;
              CSIZES = 100(50); ! N=100, T= 50
              LAGVARIABLES = y(1);
              BETWEEN = w z;
ANALYSIS:     TYPE = TWOLEVEL RANDOM;
              ESTIMATOR = BAYES;
              BITERATIONS = (1000);
              PROCESSORS = 2;
              ! MODEL MONTECARLO omitted
MODEL:        %WITHIN%
              phi | y ON y&1*0.5;
              y*1;
              %BETWEEN%
              ! w*1;
              y ON w*.3;
              y*0.09;
              phi ON w*.1;
              phi*.01; [phi*.3];
              z ON y*.5 phi*.7;
              z*0.0548;
```


Two-Level Time-Series Analysis: Monte Carlo Simulations in Mplus V8

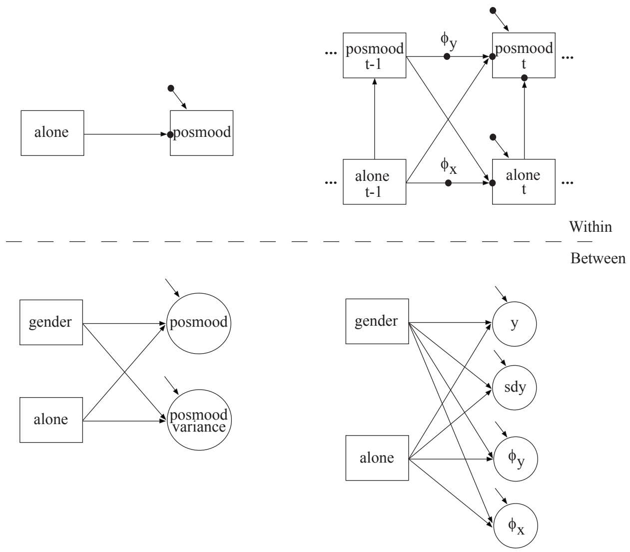


- E(ϕ) = 0.3, V(ϕ) = 0.02, 1000 replications. Ignorable bias, good coverage in all cases. Power results:
  - $N = 25$, $T = 50$: ϕ on $w = 0.73$, z on $\phi = 0.15$
  - $N = 50$, $T = 50$: ϕ **on** $w = 0.96$, z on $\phi = 0.32$
  - $N = 100$, $T = 50$: ϕ on $w = 1.00$, z on $\phi = 0.58$
  - $N = 200$, $T = 50$: ϕ on $w = 1.00$, **z on** $\phi = 0.87$

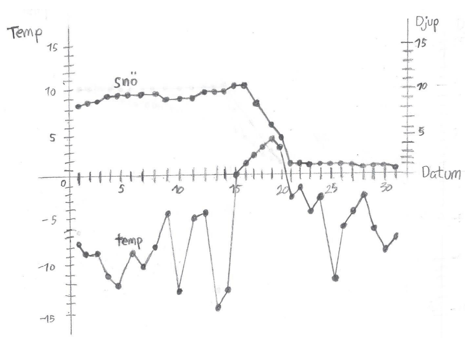
What About Other Methods for Intensive Longitudinal Data: Part 1. Multilevel Analysis

- Papers/talks:
  - Hedeker (2015): Keynote address at the 2015 M3 meeting
  - Hedeker, Mermelstein & Demirtas (2012). Modeling between-subject and within-subject variances in ecological momentary assessment data using mixed-effects location scale models. *Statistics in Medicine*
  - Hedeker & Nordgren (2013). MIXREGLS: A program for mixed-effect location scale analysis. *Journal of Statistical Software*
- Data from MIXREGLS:
  - Positive mood related to alone (tvc) and gender (tic), $N = 515$, $T = 34$ $(3 - 58)$

Two-Level Modeling of Hedeker Mood data: Hedeker's Model (Left) versus Time-Series Model (Right)



The Transitional Aspect of Snow: Temperature and Snow Depth Bivariate Time-Series Data with a Lagged Effect - Implications for Sledding



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Sweden Early 70's: Department of Statistics, Uppsala University

- Bengt's grad school term project related to time-series analysis:
  - Repeated measurements on respiratory problems of 7 dogs
  - Fortran program for ML estimation with autoregressive and heteroscedastic residuals

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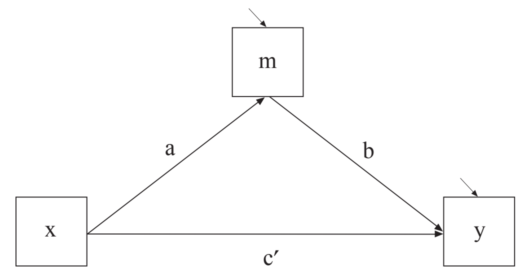
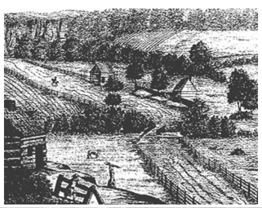
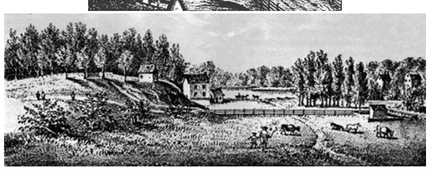
Mediation Analysis: When in Rome...



Swedish Harvest Data from 1750 - 1850





Sources:

- Thomas (1940). Social and Economic Aspects of Swedish Population Movements, 1790 - 1933
- McCleary & Hay (1980). Applied Time Series Analysis for the Social Sciences

Swedish Harvest Data from 1750 - 1850

3 yearly measurements:

- Harvest index: Swedish grain harvest rated on a nine-point scale. Total crop failure scored 0; superabundant crop scored 9
- Fertility: Births per 1,000 female population
- Population rate: Birth rate - death rate
  - Birth rate: the total number of live births per 1,000 of a population in a year
  - Death rate: the number of deaths per 1,000 of the population in a year

Time-Series Plots of Harvest, Fertility, and Population Rate

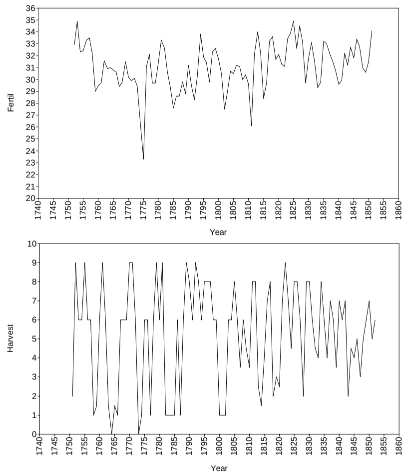


Figure : Harvest (bottom) and Fertility (top)

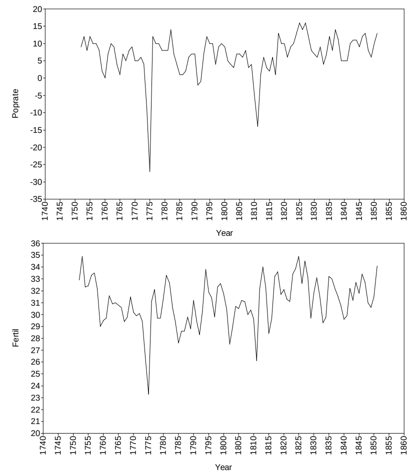


Figure : Fertility (bottom) and Population Rate (top)

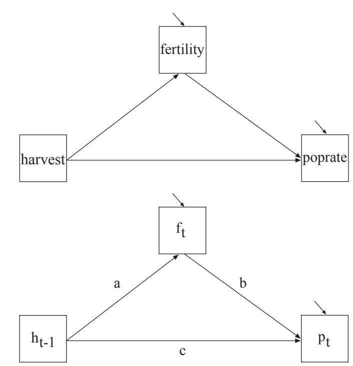
Demographer Sundbärg's Hypothesis: Harvest, Fertility, and Population Rate, 1750-1850

Irrespective of which party had gained control, or whether the King himself was on the throne, if the harvest was good, marriage and birth rates were high and death rates comparatively low, that is, the bulk of the of the population flourished.
On the contrary, when the harvest failed, marriage and birth rates declined and death devastated the land, bearing witness to need and privation and at times even to starvation. Whether the factories fared well or badly or whether the bank-rate rose or fell - all the things at this time, were scarcely more than ripples on the surface (Thomas, 1940: 82).

Theory for how Harvest Influences Fertility

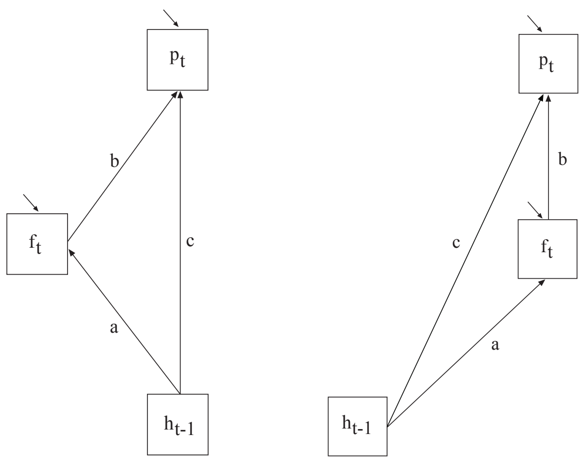
Thomas (1940) cites a number of plausible mechanisms for this relationship.
First, in years following crop failure, marriage rates (and hence, fertility rates) drop.
Second, and more importantly, in years following a crop failure, young women who might otherwise bear children in Sweden are likely to emigrate (primarily to Finland and the United States during this period).
As a result of emigration, the average age of the female population rises dramatically in years following a crop failure and fertility drops accordingly.

Mediation Model for Harvest Data: Note that $N = 1$

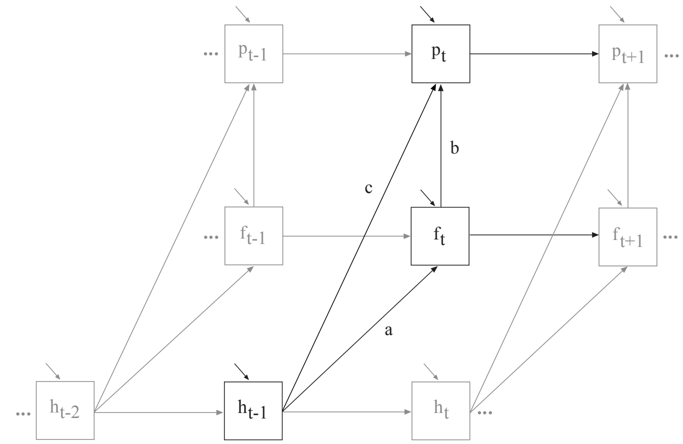


- How can you identify the a, b, c parameters from $N = 1$?

Rotating the Mediation Figure 90 Degrees Counter-Clock-Wise



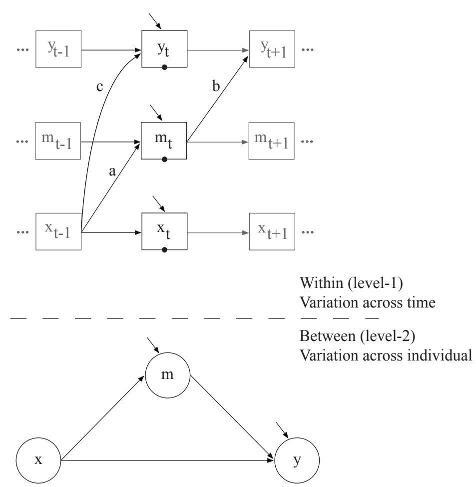
Time-Series Mediation Model ($N = 1$): Harvest, Fertility, and Population Rate, 1750 - 1850



Mplus Version 8 Time-Series Input for Swedish Harvest Data: $N = 1$, $T = 102$

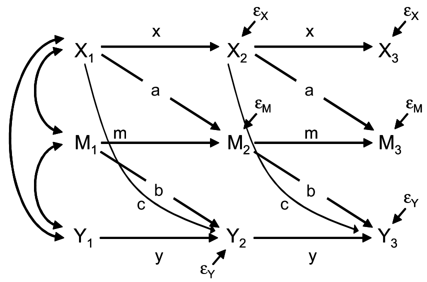
```
DATA:          FILE = swedish_harvest_data.txt;
VARIABLE:      NAME = year harvest fertil poprate;
               USEVARIABLES = harvest-poprate;
               MISSING = all (999);
               LAGVARIABLES = harvest(1) fertil(1) poprate(1);
DEFINE:        fertil = fertil/10;
ANALYSIS:      ESTIMATOR = BAYES;
               PROCESSORS = 2;
               BITERATIONS = (10000);
MODEL:         poprate ON fertil (b)
               harvest&1;
               fertil ON harvest&1 (a);
               ! auto-regressive part:
               poprate ON poprate&1;
               fertil ON fertil&1;
               harvest ON harvest&1;
MODEL CONSTRAINT:
               NEW(indirect);
               indirect = a*b;
```


$N > 1$, Two-Level Time-Series Mediation Analysis: Random Effects, Temporal Order, Causality



Longitudinal Mediation

- Maxwell et al. (2007; 2011): Cross-sectional mediation analysis does not capture indirect/direct effects of longitudinal mediation processes



- Special 2011 issue of Multivariate Behavioral Research (editor S. West; comments by Reichardt, Shrout, Imai et al.)
- What is missing? - Random effects: Variation across subjects in mean, variance, and auto-regression

Interventions and Time-Series Analysis

- $N = 1$: Implications for ABAB designs
  - Bulté & Onghena (2008). An R package for single-case randomization tests. *Behavior Research Methods*
- Susan Murphy: Just-In-Time Adaptive Interventions (JITAIs) in which real-time, passively or actively collected, information on the patient (e.g., Ecological Momentary Assessments: EMA) is used to inform the real-time delivery of intervention options (e.g., recommendations, information and prompts)
- ARIMA impact assessment: transfer functions

Causal Inference for Time-Series Models: Counterfactually-Defined Causal Effects (Robins, Pearl, VanderWeele, Imai, Vansteelandt)

- $N = 1$ case versus $N > 1$ case
- Time-varying treatments (exposure), time-varying confounding
- Marginal structural models and inverse probability weighting:
  - Robins et al. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology*
  - VanderWeele et al. (2011). A marginal structural model analysis for loneliness: Implications for intervention trials and clinical practice. *Journal of Consulting and Clinical Psychology*
  - Vandecandeleare et al. (2016). Time-varying treatments in observational studies: Marginal structural models of the effects of early grade retention on math achievement. *Multivariate Behavioral Research*
- Granger causality (cross-lagged modeling)

What About Other Methods for Intensive Longitudinal Data Part 2. TVEM: Time-Varying Effect Model

For individual i at the j^{th} observation,

$$y_{ij} = \beta_0(t_{ij}) + \beta_1(t_{ij})\, x_{ij} + \varepsilon_{ij},$$

where $\beta_0(t_{ij})$ and $\beta_1(t_{ij})$ are continuous functions of time using P-spline-based methods and varying the number of knots (Hastie & Tibshirani, 1990).

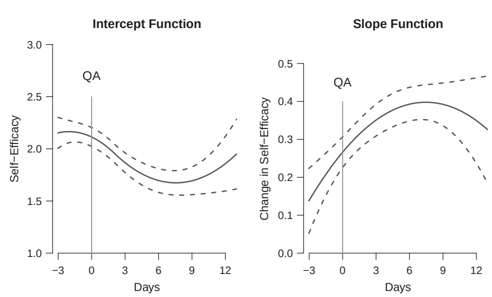
Based on the varying coefficient model of Hastie & Tibshirani (1993) in *Journal of the Royal Statistical Society, Series B*.

TVEM Example: Smoking Cessation Study

- Tan, Shiyko, Li, Li & Dierker (2012). A time varying effect model for intensive longitudinal data. *Psychological Methods*
  - RCT of a smoking cessation intervention
  - People asked to smoke on personal digital assistant (PDA) prompts - eliminating free will and increasing self-efficacy (confidence) for quitting
  - Analysis of the regression of smoking abstinence self-efficacy (y) on momentary positive affect (x)
  - Immediately prior to and following a quit attempt (QA)
  - $N = 66$, $T = 25$ $(1 - 117)$

Tan et al. (2012), Continued

- Analysis of the regression of smoking abstinence self-efficacy (y) on momentary positive affect (x) immediately prior to and following a quit attempt (QA)
- $N = 66$, $T = 25$ $(1 - 117)$
- Time-varying intercept and slope



What's Missing in Regular TVEM?

- A multilevel ($N > 1$) time-series is analyzed but no time-series modeling features are included (individually-varying auto-regression coefficient ϕ, mean, and variance)
- This is presumably difficult to do in combination with splines
- An alternative for $N = 1$ is presented in:
  - Bringmann et al. (2016). Changing dynamics: Time-varying autoregressive models using generalized additive modeling. Forthcoming in *Psychological Methods*

$$Time - varying - AR(1)\ \ model:\ y_t = \beta_{0,t} + \beta_{1,t}\, y_{t-1} + \varepsilon_t$$

- Bringman et al. (2016) discusses generalizations:
  - Multivariate - challenging
  - Multilevel - even more challenging

What's Missing in Regular TVEM? Dynamic Mediation Analysis

- Huang & Yuan (2016; online). Bayesian dynamic mediation analysis. *Psychological Methods*
  - Multilevel ($N > 1$) and multivariate
  - Time-varying coefficients in a mediation model
  - Nonparametric penalized spline approach
  - Autoregressive modeling
- What is missing here?

- Continuous-time modeling

Continuous-Time Modeling (CTM): Differential Equations Applied to Mediation Analysis

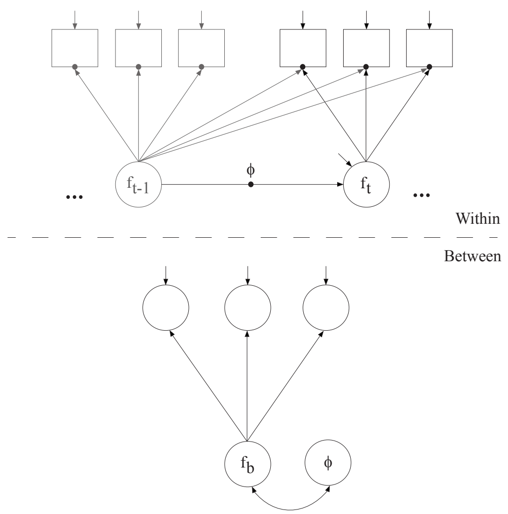
CTMs applied in a mediation context would allow researchers to gain insight into how key effects vary as a function of lag.

- Boker & Nesselroade (2002). A method for modeling the intrinsic dynamics of intraindividual variability. *Multivariate Behavioral Research*
- Voelkle & Oud (2013). Continuous-time modeling with individually-varying time intervals. *British Journal of Mathematical and Statistical Psychology*
- Voelkle & Oud (2015). Relating latent change score and continuous time models. *Structural Equation Modeling*
- Deboeck & Preacher (2015). No need to be discrete: A method for continuous time mediation analysis. *Structural Equation Modeling*

Time-Series Analysis with Latent Variables: Three Final Model Types

- Continuous latent variables:
  - Multilevel ($N > 1$) cross-lagged analysis with factors measured by multiple indicators
  - Cross-classified factor model (time crossed with subject)
- Categorical latent variables:
  - Transition modeling (Hidden Markov, regime switching, time-series LTA) with latent class variables

Multilevel Time-Series/Dynamic Factor Analysis



Time-Series Factor Analysis

- $N = 1$ methods (single-level modeling):
  - Molenaar (1985). A dynamic factor model for the analysis of multivariate time series. *Psychometrika*
  - Hamaker, Nesselroade, Molenaar (2007). The integrated trait-state model. *Journal of Research in Personality*
  - Zhang and Nesselroade (2007). Bayesian estimation of categorical dynamic factor models. *Multivariate Behavioral Research*
  - Zhang, Hamaker & Nesselroade (2008). Comparisons of four methods for estimating a dynamic factor model. *Structural Equation Modeling*
- $N > 1$ methods - two-level modeling with random effects: Mplus Version 8

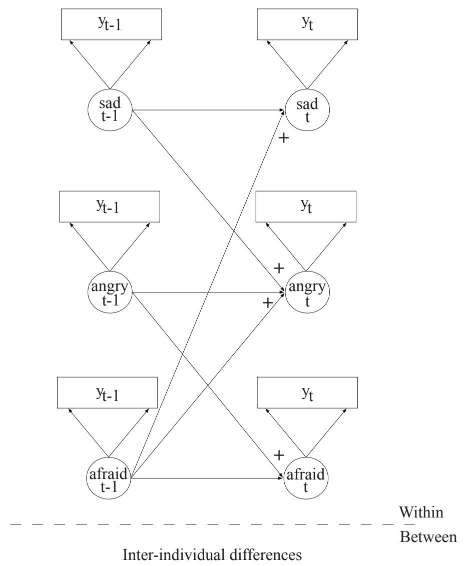
Example: Affective Instability In Ecological Momentary Assessment

- Jahng S., Wood, P. K.,& Trull, T. J., (2008). Analysis of Affective Instability in Ecological Momentary Assessment: Indices Using Successive Difference and Group Comparison via Multilevel Modeling. Psychological Methods, 13, 354-375
- An example of the growing amount of EMA data
- 84 outpatient subjects: 46 meeting borderline personality disorder (BPD) and 38 meeting MDD or DYS
- Each individual is measured several times a day for 4 weeks for total of about 100 assessments
- A mood factor for each individual is measured with 21 self-rated continuous items
- The research question is if the BPD group demonstrates more temporal negative mood instability than the MDD/DYS group

3-Factor EFA/CFA DAFS

- EFA suggests 3 factors (although time-series ESEM is needed):
  - Angry: Upset, Distressed, Angry, Irritable
  - Sad: Downhearted, Sad, Blue, Lonely
  - Afraid: Afraid, Frightened, Scared
- 3-factor EFA-within-CFA DAFS factor autocorrelation:
  - 0.536 (Angry), 0.578 (Sad), 0.623 (Afraid)
  - - To which you could add random effects for the factor autocorrelations to see if they have different variability across subjects

Multilevel Cross-Lagged Time-Series Modeling with Factors



- How to standardize the coefficients?
- Schuurman et al. (2106). How to compare cross-lagged associations in a multilevel autoregressive model. Forthcoming in *Psychological Methods*

Mplus Version 8 Input for Cross-Lagged Factor Model

```
ANALYSIS:   TYPE = TWOLEVEL RANDOM;
            ESTIMATOR = BAYES; PROCESSORS = 2; THIN = 5;
            BITERATIONS = (10000);
MODEL:      %WITHIN%
            f1 BY jittery-scornful*0 (&1);
            f2 BY jittery-scornful*0 (&1);
            f3 BY jittery-scornful*0 (&1);
            f1 BY downhearted*1 sad*1 blue*1 lonely*1;
            f1 BY angry@0 afraid@0;
            f2 BY angry*1 irritable*1 hostile*1 scornful*1;
            f2 BY downhearted@0 afraid@0;
            f3 BY afraid*1 frightened*1 scared*1;
            f3 BY downhearted@0 angry@0;
            f1-f3@1;
            s1 | f1 ON f1&1;
            s2 | f2 ON f2&1;
            s3 | f3 ON f3&1;
            f1 ON f2&1 f3&1;
            f2 ON f1&1 f3&1;
            f3 ON f1&1 f2&1;
            %BETWEEN%
            fb BY jittery-scornful*;
            fb s1-s3 ON group; fb@1;
```


Cross-Classified Time-Series Factor Analysis

Cross-classification of time and subject gives flexible modeling with random intercepts and factor loadings:

- Mplus Version 7: Asparouhov & Muthén (2015). General random effect latent variable modeling: Random subjects, items, contexts, and parameters. In Harring, Stapleton & Beretvas (Eds.) *Advances in multilevel modeling for educational research: Addressing practical issues found in real-world applications*. Charlotte, NC: Information Age Publishing, Inc.
- Mplus Version 8: Expanded to time-series version
  - Auto-regression for factor and factor indicators
  - Random factor loadings varying across subjects and random intercepts for measurement and factor intercepts varying across time
  - Can variation across time in random slopes be used to study trends?

Cross-Classified Analysis with Factor Variation Across Time: Finding a Trend by Estimating Time-Series Random Slope of *Y* on *X* Using Mplus Version 8 - TVEM-Like Feature

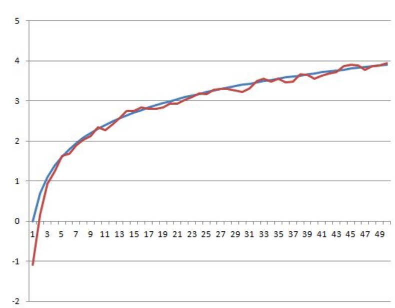


Figure : Intercept

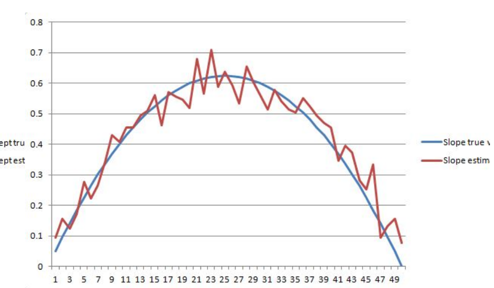
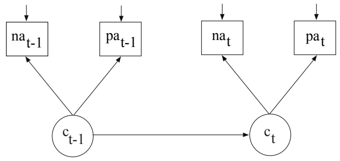


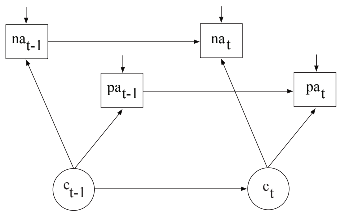
Figure : Slope

Time-Series Modeling with Latent Class Variables: $N = 1$

Latent Transition Analysis (LTA; Hidden Markov model; HMM):



LTA with autoregression (Markov switching autoreg. model; MSAR):



- Hamaker et al. (2016). Modeling BAS dysregulation in bipolar disorder: Illustrating the potential of time series analysis. *Assessment*

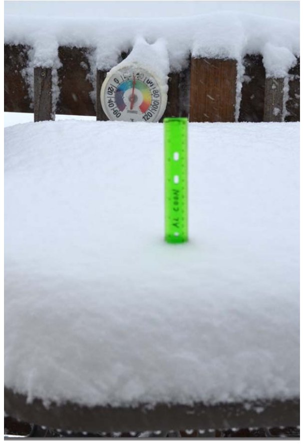
Epilogue: Which Methods Do We Need for Intensive Longitudinal Data?

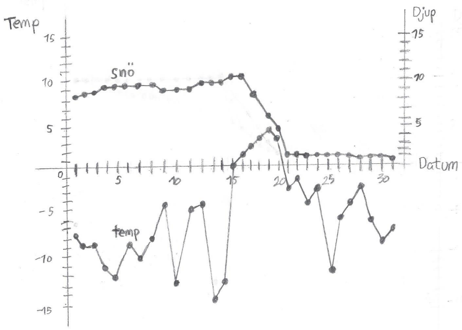
- What's the answer?
  - All the above and more
- For this we need the input from many researchers

To Learn More About Time-Series Analysis

- Classic but only $N = 1$:
  - Hard: Hamilton (1994), Chatfield (2003)
  - Less hard: Shumway & Stoffer (2011)
  - Quite accessible: Hamaker & Dolan (2009). *Idiographic data analysis*. Book chapter
- Accessible, applied writings with $N > 1$:
  - Chow et al. (2010). Equivalence and differences between SEM and state-space modeling. *Structural Equation Modeling*
  - Jongerling, Laurenceau & Hamaker (2015). A multilevel AR(1) model: Allowing for inter-individual differences in trait-scores, inertia, and innovation variance. *Multivariate Behavioral Research*
  - Wang, Hamaker & Bergeman (2012). Investigating inter-individual differences in short-term intra-individual variability. *Psychological Methods*
  - More in the pipeline

Epilogue: The Transitional Aspect of Snow: Temperature and Snow Depth - Implications for Sledding





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The Transitional Aspect of Snow (Foreshadowing)

“Foreshadowing or guessing ahead is a literary device by which an author hints what is to come. Foreshadowing is a dramatic device in which an important plot-point is mentioned early in the story and will return in a more significant way. It is used to avoid disappointment. It is also sometimes used to arouse the reader”.