Longitudinal Research: Present status and future prospects

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Examine our new book,
Applied Longitudinal Data Analysis (Oxford University Press, 2003) at:
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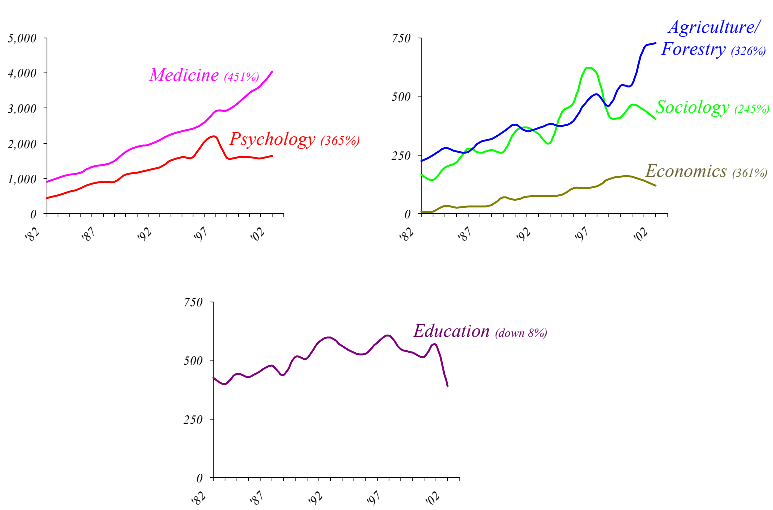
In the past 20 years, the number of longitudinal studies has increased rapidly

Annual searches for keyword 'longitudinal' in 6 OVID databases, between 1982 and 2002



What do these longitudinal studies actually look like?

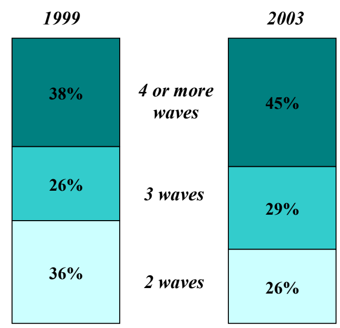
We (arbitrarily) selected psychology and (haphazardly) selected 10 journals from each of two recent years (1999 & 2003)

- ✓ *3 issues of Developmental Psychology*
- ✓ *3 issues of Journal of Personality and Social Psychology*
- ✓ *2 issues Journal of Applied Psychology*
- ✓ *2 issues of Journal of Consulting and Clinical Psychology*

Yielded > 150 papers/year, many of which are longitudinal

- ✓ *In 1999, 33%*
- ✓ *In 2003, 47%*

***First, the good news:* An increasing percentage of these longitudinal studies are truly longitudinal (i.e., more than 2 waves)**



Now, the bad news: Analytic methods lag VERY FAR behind

	'99	'03
Traditional methods	***91%***	***80%***
•Repeated measures ANOVA *(no parametric method for change)*	*40%*	*29%*
•Wave-to-wave regression *(e.g., regression of T_2 on T_1, T_3 on T_2)*	*38%*	*32%*
•Separate but parallel analyses *(ignoring replicate measures over time)*	*8%*	*17%*
•"Simplifying" analyses by….		
– *Setting aside waves*	*8%*	*7%*
– *Combining waves*	*6%*	*8%*
•Ignoring age-heterogeneity in sample *(even when measurement wave is surely not the best metric for time)*	*6%*	*9%*

	'99	'03
Modern methods	***9%***	***20%***
• Growth modeling	***7%***	***15%***
• Survival analysis	***2%***	***5%***

Since modern analytic methods are now easily implemented, why does empirical research lag so far behind?

Part of the problem may be reviewers' ignorance

Comments received this year from two reviewers of a paper that fit individual growth models to 3 waves of data on vocabulary size among young children:

Reviewer A:
"I do not understand the statistics used in this study deeply enough to evaluate their appropriateness. I imagine this is also true of 99% of the readers of *Developmental Psychology*. … Previous studies in this area have used simple correlation or regression which provide easily interpretable values for the relationships among variables. … In all, while the authors are to be applauded for a detailed longitudinal study, … the statistics are difficult. … I thus think *Developmental Psychology* is not really the place for this paper."

Reviewer B:
"The analyses fail to live up to the promise…of the clear and cogent introduction. I will note as a caveat that I entered the field before the advent of sophisticated growth-modeling techniques, and they have always aroused my suspicion to some extent. I have tried to keep up and to maintain an open mind, but parts of my review may be naïve, if not inaccurate."

What kinds of research questions require longitudinal methods?

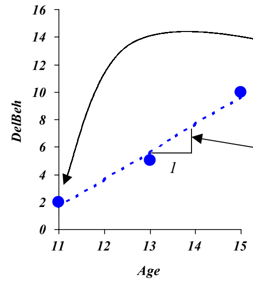
Questions about systematic change over time	*Questions about whether and when events occur*
• Espy et al. (2000) studied infant neuro-development. • 20 infants exposed to cocaine, 20 controls. • Each observed daily for 2 weeks. • Infants exposed to cocaine had lower rates of neuro-development.	• South (2001) studied marriage duration. • 3,523 couples. • Followed for 23 years, until divorce or until the study ended. • Couples in which the wife was employed tended to divorce earlier.
1. How does an infant's neuro-functioning change with time? *2 What's the rate of development?* *3 How does the rate of development vary by child characteristics?*	*1. Does each married couple eventually divorce?* *2. If so, when are couples most at risk of divorce?* *3. How does the risk of divorce vary by couple characteristics?*
Individual Growth Model/ Multilevel Model for Change	***Discrete- and Continuous-Time Survival Analysis***

Modeling change over time: An overview

Postulate statistical models at each of two levels in a natural hierarchy

At level-1: *Model the* ***individual change trajectory****, which describes how each person's status depends on time*

Example: ***Gender differences in delinquent behavior among teens***
(ID 994001 & 12 person sample from full sample of 124)



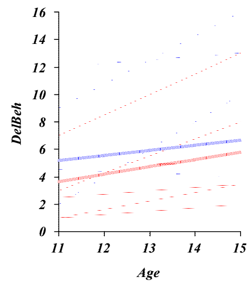
intercept for person i ("initial status")

$$Y_{ij} = \pi_{0i} + \pi_{1i}(AGE - 11)_{ij} + \varepsilon_{ij}$$

slope for person i ("growth rate")

residuals for person i, one for each occasion j

At level-2: *Model* ***inter-individual differences in change****, how features of the individual change trajectories (e.g., intercepts and slopes) vary across people*



Level-2 model for level-1 intercepts

$$\pi_{0i} = \gamma_{00} + \gamma_{01} MALE_i + \zeta_{0i}$$

Level-2 model for level-1 slopes

$$\pi_{1i} = \gamma_{10} + \gamma_{11} MALE_i + \zeta_{1i}$$

Modeling event occurrence over time: An overview

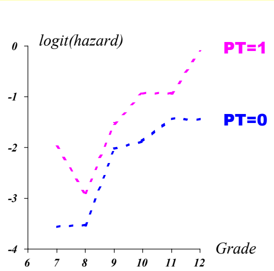
The Censoring Dilemma
What do you do with people who don't experience the event during data collection?
(Non-occurrence tells you a lot about event occurrence, but they don't have known event times.)

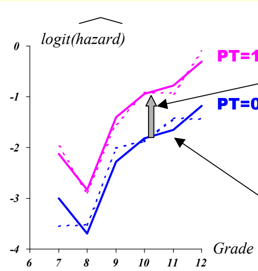
The Survival Analysis Solution
Model the ***hazard function****, the temporal profile of the conditional risk of event occurrence among those still "at risk"*
(those who haven't yet experienced the event)

Discrete-time*: Time is measured in intervals*
Hazard is a probability & we model its logit

Continuous-time: *Time is measured precisely*
Hazard is a rate & we model its logarithm

Example: ***Grade of first heterosexual intercourse*** *as a function of early parental transition status (PT)*





"shift in risk" corresponding to unit differences in PT

$$\text{logit } h(t_{ij}) = \alpha(t_j) + \beta_1 PT_i$$

"baseline" (logit) hazard function

Four important advantages of modern longitudinal methods

1. ***You have much more flexibility in research design***
   - ✓ *Not everyone needs the same rigid data collection schedule—cadence can be person specific*
   - ✓ *Not everyone needs the same number of waves—can use all cases, even those with just one wave!*
2. ***You can identify temporal patterns in the data***
   - ✓ *Does the outcome increase, decrease, or remain stable over time?*
   - ✓ *Is the general pattern linear or non-linear?*
   - ✓ *Are there abrupt shifts at substantively interesting moments?*
3. ***You can include time varying predictors*** *(those whose **values** vary over time)*
   - ✓ *Participation in an intervention*
   - ✓ *Family composition, employment*
   - ✓ *Stress, self-esteem*
4. ***You can include interactions with time*** *(to test whether a predictor's **effect** varies over time)*
   - ✓ *Some effects dissipate—they wear off*
   - ✓ *Some effects increase—they become more important*
   - ✓ *Some effects are especially pronounced at particular times.*

In the remainder of the talk,
we're going to illustrate these advantages using
data from several recently published studies

Including a time-varying predictor:

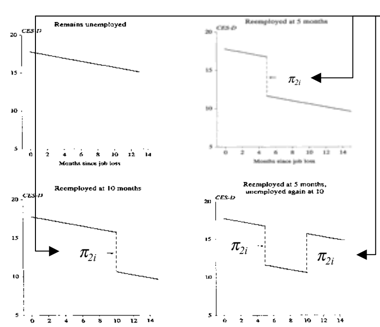
Trajectories of depressive symptoms among the unemployed

Ginexi, Howe & Caplan (2000)
- *254 interviews at unemployment offices (within 2 mos of job loss)*
- *2 other waves: @ 3-8 mos & @ 10-16 mos*
- *Assessed CES-D scores and unemployment status (UNEMP) at each wave*
- *RQ: **Does reemployment affect the depression trajectories and if so how?***

The person-period dataset

ID	MONTHS	CES-D	UNEMP	
7589	1.3142	36	1	Unemployed all 3 waves
7589	5.0924	40	1	
7589	11.7947	39	1	
65641	0.3285	32	1	Reemployed by wave 2
65641	4.1068	9	0	
65641	10.9405	10	0	
65441	1.0842	27	1	Reemployed by wave 3
65441	4.6982	15	1	
65441	11.2690	7	0	

Hypothesizing that the TV predictor's effect is constant over time:



Add the TV predictor to the level-1 model to register these shifts

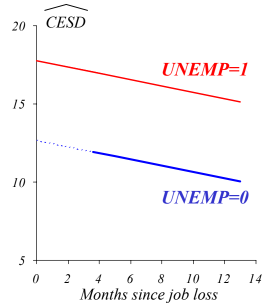
Level 1: $Y_{ij} = \pi_{0i} + \pi_{1i}TIME_{ij} + \pi_{2i}UNEMP_{ij} + \varepsilon_{ij}$

Level 2:
$$\pi_{0i} = \gamma_{00} + \zeta_{0i}$$
$$\pi_{1i} = \gamma_{10} + \zeta_{1i}$$
$$\pi_{2i} = \gamma_{20} + \zeta_{2i}$$

Determining if the time-varying predictor's effect is constant over time

3 sets of alternative prototypical CES-D trajectories

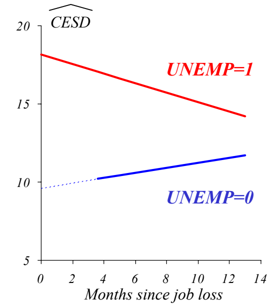
Assume its effect is constant



- Everyone starts on the declining UNEMP=1 line
- If you get a job you drop 5.11 pts to the UNEMP=0 line
- Lose that job and you rise back to the UNEMP=1 line

Must these lines be parallel?:
Might the effect of UNEMP vary over time?

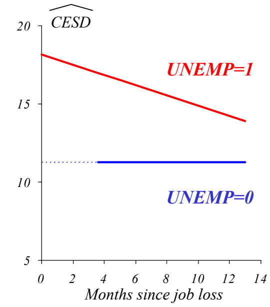
Allow its effect to vary over time



- When UNEMP=1, CES-D declines over time
- When UNEMP=0, CES-D increases over time???

Is this increase real?:
Might the line for the re-employed be flat?

Finalize the model



- Everyone starts on the declining UNEMP=1 line
- Get a job and you drop to the flat UNEMP=0 line
- Effect of UNEMP is 6.88 on layoff and declines over time (by 0.33/month)

This is the "best fitting" model of the set

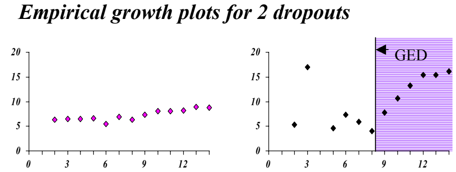
Is the individual growth trajectory discontinuous?

Wage trajectories of male HS dropouts

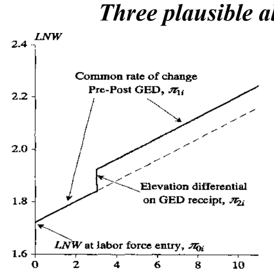
Murnane, Boudett & Willett (1999):

- Used NLSY data to track the wages of 888 HS dropouts
- Number and spacing of waves varies tremendously across people
- 40% earned a GED:
- RQ: **Does earning a GED affect the wage trajectory, and if so how?**

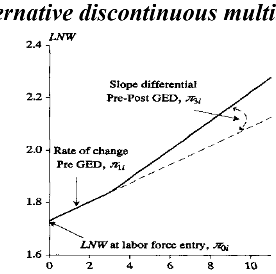
Empirical growth plots for 2 dropouts



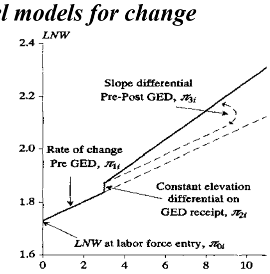
Three plausible alternative discontinuous multilevel models for change



$Y_{ij} = \pi_{0i} + \pi_{1i} EXPER_{ij} +$



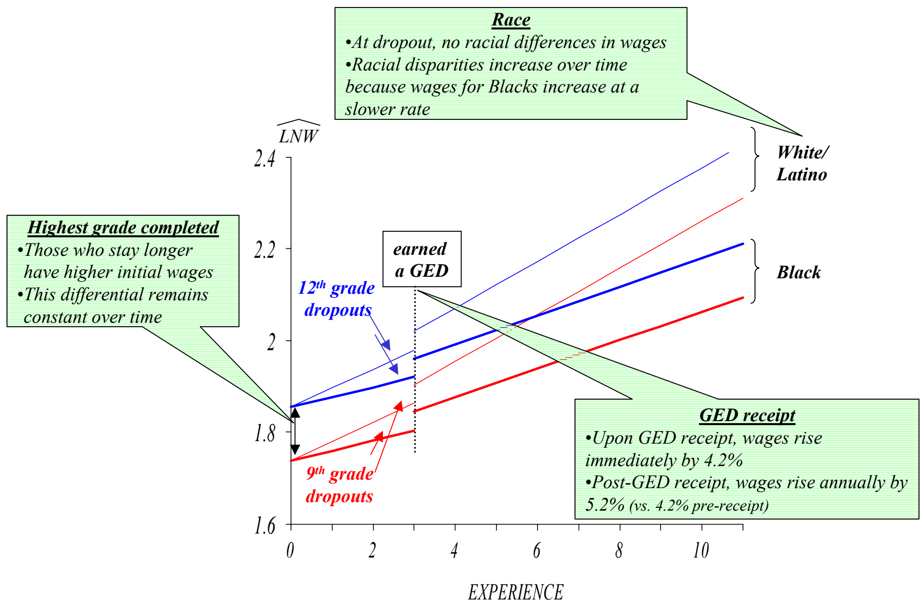
$Y_{ij} = \pi_{0i} + \pi_{1i} EXPER_{ij} +$



$Y_{ij} = \pi_{0i} + \pi_{1i} EXPER_{ij} +$

Displaying prototypical discontinuous trajectories

(Log Wages for HS dropouts pre- and post-GED attainment)



Using time-varying predictors to test competing hypotheses about a predictor's effect:

Risk of first depression onset: The effect of parental death

Wheaton, Roszell & Hall (1997)

- *Asked 1,393 Canadians whether (and when) each first had a depression episode*
- *27.8% had a first onset between 4 and 39*
- *RQ: **Is there an effect of PD, and if so, is it long-term or short-term?***

Parental death treated as a long-term effect

Odds of onset are 33% higher among people who parents have died

Postulating a discrete-time hazard model

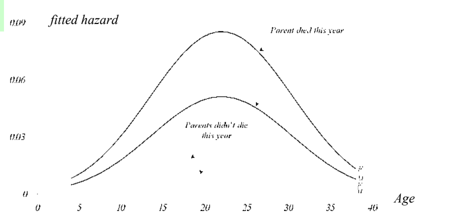
$$\textbf{logit}\, h(t_{ij}) = \alpha_0 + \alpha_1(AGE_{ij} - 18) + \alpha_2(AGE_{ij} - 18)^2 + \alpha_3(AGE_{ij} - 18)^3 + \beta_1 FEMALE_i + \beta_2 PD_{ij}$$

Well known gender effect

*Effect of PD coded as TV predictor, but in two different ways: **long-term** & **short-term***

Parental death treated as a short-term effect

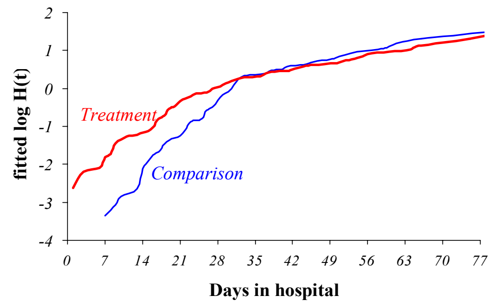
Odds of onset are 462% higher in the year a parent dies



Is a time-invariant predictor's effect constant over time?

Risk of discharge from an inpatient psychiatric hospital

Foster (2000):
- *Tracked hospital stay for 174 teens*
- *Half had traditional coverage*
- *Half had an innovative plan offering coordinating mental health services at no cost, regardless of setting (didn't need hospitalization to get services)*
- *RQ:* ***Does TREAT affect the risk of discharge (and therefore length of stay)?***



$$\log h(t_{ij}) = \alpha(t_j) + \beta_1 TREAT_i + \beta_2 TREAT_i \log(TIME_j)$$

Predictor	*Main effects model*	*Interaction with time model*
TREAT	***0.1457 (ns)***	***2.5335******
TREAT*(log Time)		***-0.5301*****

No statistically significant main effect of TREAT

There is an effect of TREAT, especially initially, but it declines over time

Is the individual growth trajectory non-linear?

Tracking cognitive development over time

Tivnan (1980)
- *Played up to 27 games of Fox 'n Geese with 17 1[st] and 2[nd] graders*
- *A strategy that guarantees victory exists, but it must be deduced over time*
- *NMOVES tracks the number of turns a child takes per game (range 1-20)*
- *RQ:* ***What trajectories do children follow when learning the game?***

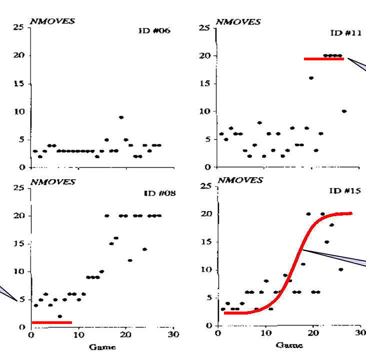
A level-1 logistic model

$$Y_{ij} = 1 + \frac{19}{1 + \pi_{0i} e^{-(\pi_{1i} TIME_{ij})}} + \varepsilon_{ij}$$

Familiar level-2 models

$$\pi_{0i} = \gamma_{00} + \gamma_{01}(READ_i - \overline{READ}_{\bullet}) + \zeta_{0i}$$
$$\pi_{1i} = \gamma_{10} + \gamma_{11}(READ_i - \overline{READ}_{\bullet}) + \zeta_{1i}$$

Three reasonable features of a hypothesized non-linear model



A lower asymptote*, because everyone makes at least 1 move and it takes a while to figure out what's going on*

An upper asymptote*, because a child can make only a finite # moves each game*

A smooth curve joining the asymptotes

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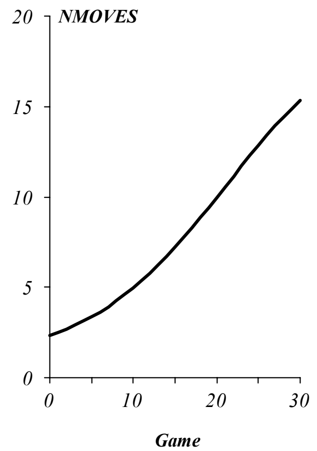
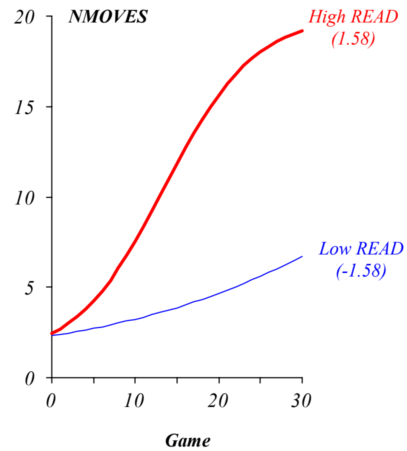
Prototypical fitted logistic growth trajectories

(Fox 'n Geese data)

Model A:
Fitted unconditional logistic growth trajectory

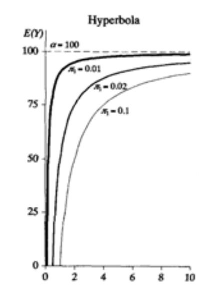


Model B:
Fitted logistic growth trajectories for children with low and high reading skills

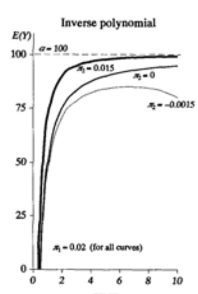


A limitless array of non-linear trajectories awaits…

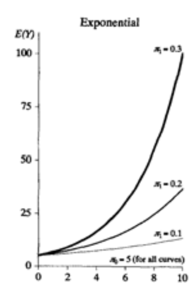
Four illustrative possibilities



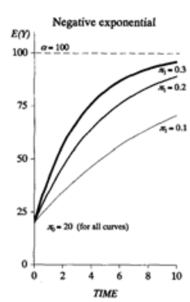
$$Y_{ij} = \alpha_i - \frac{1}{\pi_{1i} TIME_{ij}} + \varepsilon_{ij}$$



$$Y_{ij} = \alpha_i - \frac{1}{(\pi_{1i} TIME_{ij} + \pi_{2i} TIME_{ij}^2)} + \varepsilon_{ij}$$

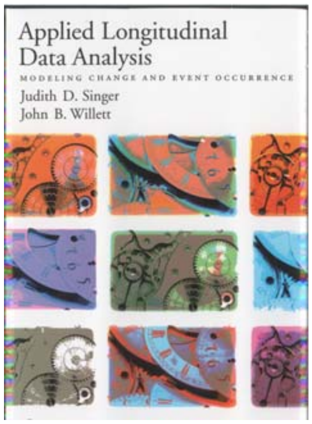


$$Y_{ij} = \pi_{0i} e^{\pi_{1i} TIME_{ij}} + \varepsilon_{ij}$$



$$Y_{ij} = \alpha_i - (\alpha_i - \pi_{0i}) e^{-\pi_{1i} TIME_{ij}} + \varepsilon_{ij}$$

Where to go to learn more



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www.ats.ucla.edu/stat/examples/alda

	Mplus	MLwiN	HLM	SAS	Stata	SPlus	SPSS	Chapter Title
Datasets	🗁	🗁	🗁	🗁	🗁	🗁	🗁	Table of contents
Ch 1								A framework for investigating change over time
Ch 2	🗁	🗁	🗁	🗁	🗁	🗁	🗁	Exploring longitudinal data on change
Ch 3		🗁	🗁	🗁	🗁	🗁	🗁	Introducing the multilevel model for change
Ch 4		🗁	🗁	🗁		🗁	🗁	Doing data analysis with the multilevel model for change
Ch 5	🗁	🗁	🗁	🗁		🗁	🗁	Treating time more flexibly
Ch 6	🗁	🗁	🗁	🗁		🗁	🗁	Modeling discontinuous and nonlinear change
Ch 7	🗁	🗁		🗁		🗁	🗁	Examining the multilevel model's error covariance structure
Ch 8	🗁			🗁				Modeling change using covariance structure analysis
Ch 9				🗁	🗁			A framework for investigating event occurrence
Ch 10				🗁	🗁		🗁	Describing discrete-time event occurrence data
Ch 11	🗁			🗁	🗁		🗁	Fitting basic discrete-time hazard models
Ch 12				🗁	🗁		🗁	Extending the discrete-time hazard model
Ch 13				🗁	🗁		🗁	Describing continuous-time event occurrence data
Ch 14				🗁	🗁		🗁	Fitting the Cox regression model
Ch 15				🗁	🗁		🗁	Extending the Cox regression model