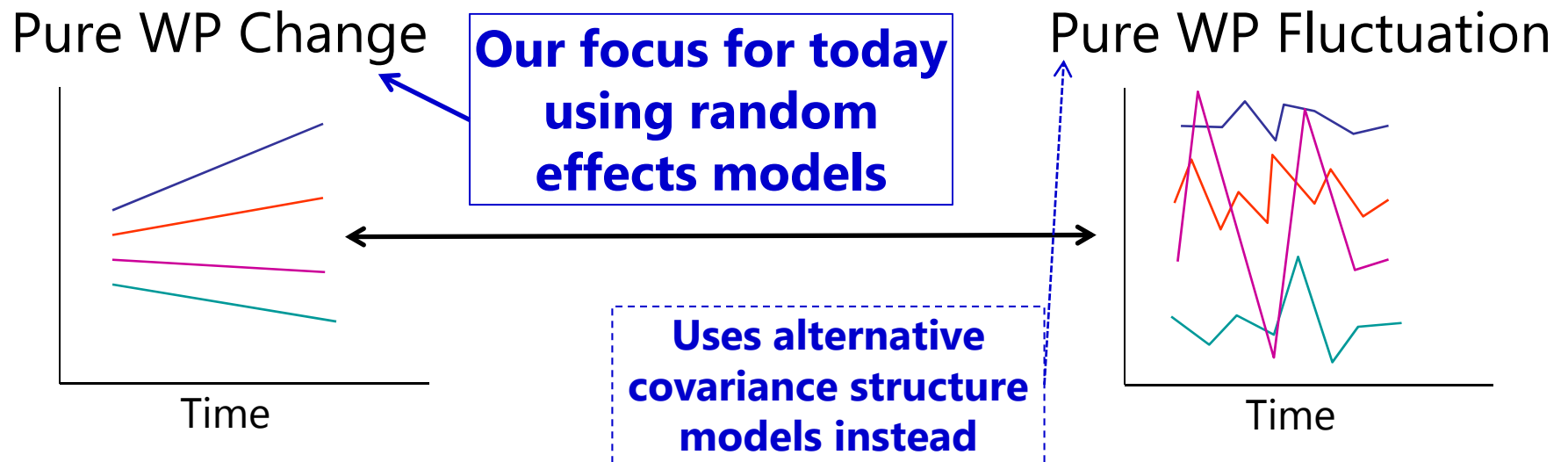


Describing Within-Person Change in Longitudinal Data

- Topics:
 - **Multilevel modeling notation and terminology**
 - Fixed and random effects of linear time
 - Predicted variances and covariances from random slopes
 - Dependency and effect size in random effects models
 - Describing nonlinear change: polynomial, piecewise models, and truly nonlinear models
 - Fun with likelihood estimation and model comparisons

Modeling Change vs. Fluctuation



Model for the Means:

- **WP Change** → describe pattern of *average* change (over “time”)
- WP Fluctuation → *may* not need anything (if no systematic change)

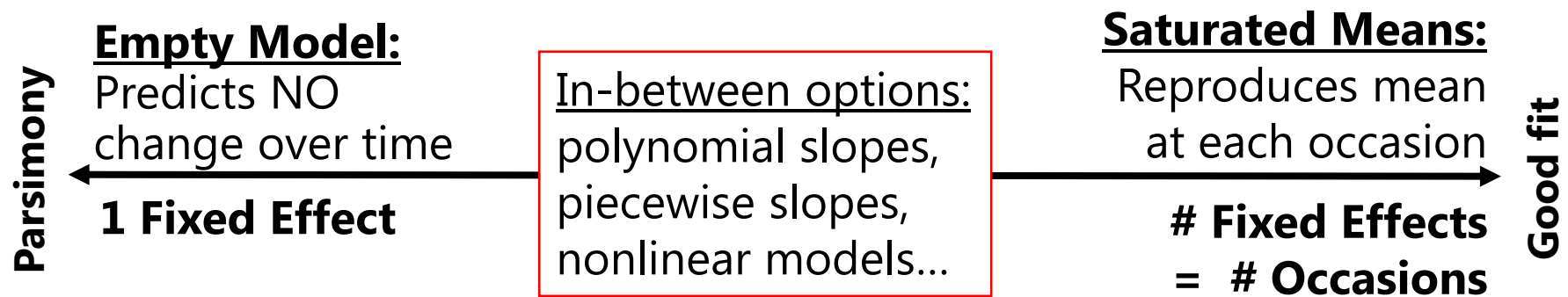
Model for the Variance:

- **WP Change** → describe *individual differences* in change (random effects)
→ this allows variances and covariances to differ over time
- WP Fluctuation → describe pattern of variances and covariances over time

The Big Picture of Longitudinal Data:

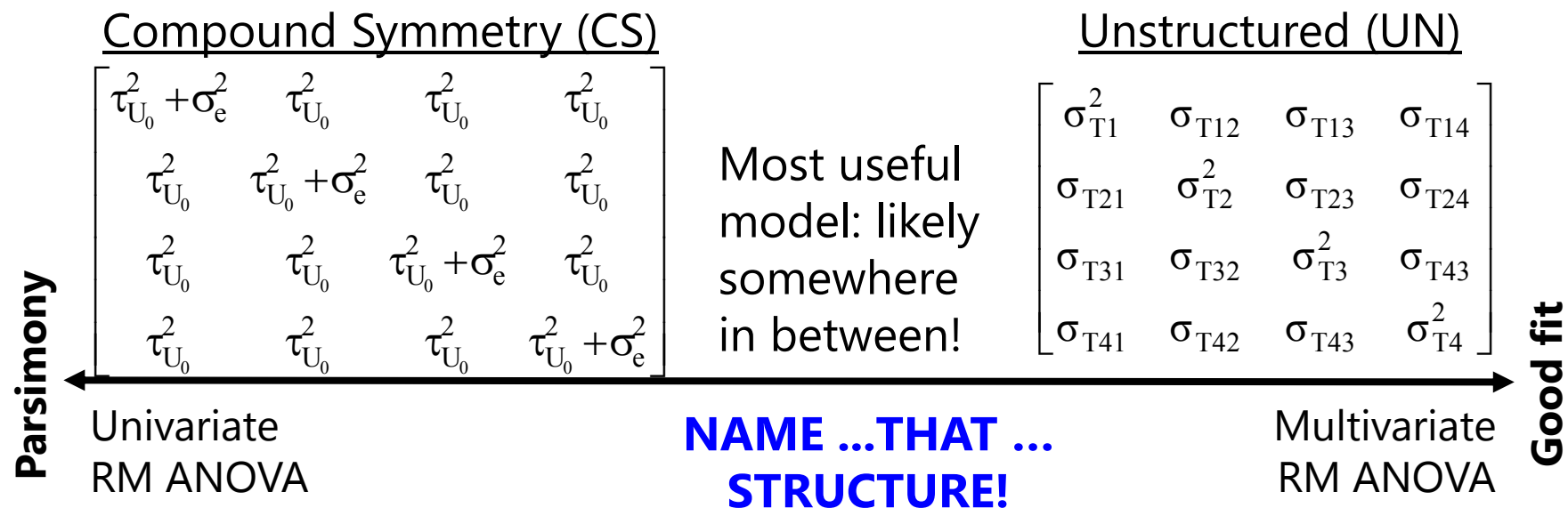
Models for the Means

- What kind of change occurs on average over “time”?
There are two baseline models to consider:
 - **“Empty”** → only a fixed intercept (predicts no change)
 - **“Saturated”** → all occasion mean differences from time 0
(ANOVA model that uses # fixed effects = n)
**** may not be possible in unbalanced data*



Name... that... Trajectory!

The Big Picture of Longitudinal Data: Models for the Variance

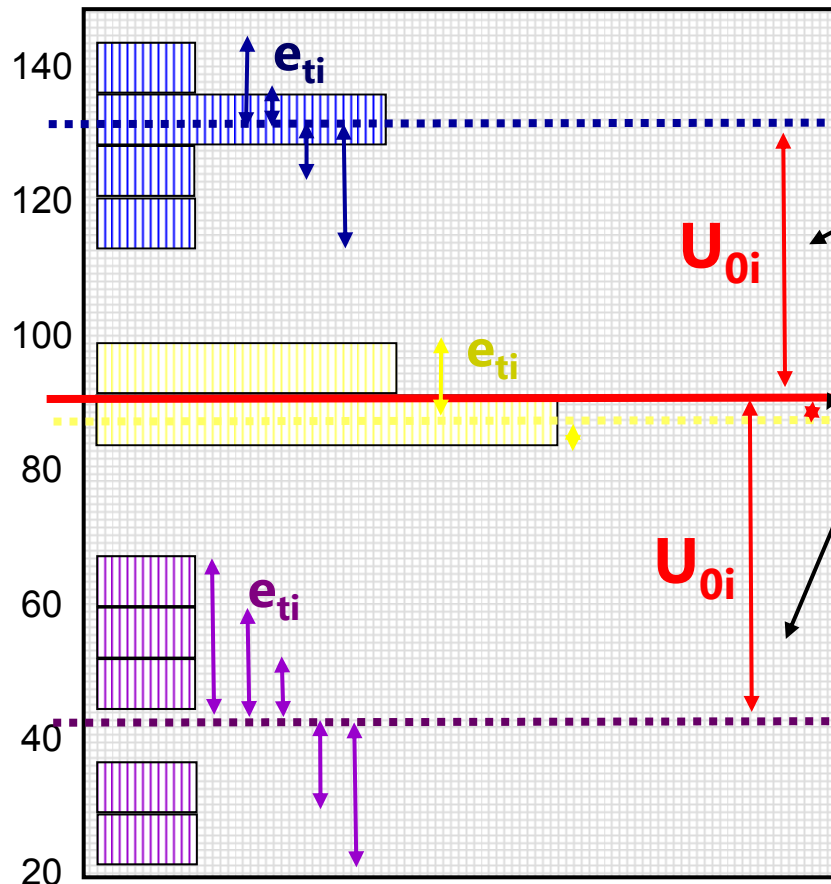


What is the pattern of variance and covariance over time?

CS and UN are just two of the many, many options available within MLM, including **random effects models** (for change) and **alternative covariance structure models** (for fluctuation).

Empty + Within-Person Model

Variance of Y \rightarrow 2 sources:



Level 2 Random Intercept Variance (of U_{0i} , as $\tau_{U_0}^2$):

- \rightarrow **Between**-Person Variance
- \rightarrow Differences from **GRAND** mean
- \rightarrow **INTER**-Individual Differences

Level 1 Residual Variance (of e_{ti} , as σ_e^2):

- \rightarrow **Within**-Person Variance
- \rightarrow Differences from **OWN** mean
- \rightarrow **INTRA**-Individual Differences

Empty Means, Random Intercept Model

GLM Empty Model:

- $y_i = \beta_0 + e_i$

MLM Empty Model:

- Level 1:

$$y_{ti} = \beta_{0i} + e_{ti}$$

- Level 2:

$$\beta_{0i} = \gamma_{00} + U_{0i}$$

Fixed Intercept
= grand mean
(because no
predictors yet)

Random Intercept
= individual-specific
deviation from
predicted intercept

Residual = time-specific deviation
from individual's predicted outcome

3 Total Parameters:

Model for the Means (1):

- Fixed Intercept γ_{00}

Model for the Variance (2):

- Level-1 Variance of $e_{ti} \rightarrow \sigma_e^2$
- Level-2 Variance of $U_{0i} \rightarrow \tau_{U_0}^2$

Composite equation:

$$y_{ti} = (\gamma_{00} + U_{0i}) + e_{ti}$$

Saturated Means, Random Intercept Model

- Although rarely shown this way, a saturated means, random intercept model would be represented as a multilevel model like this (for $n = 4$ here, in which the time predictors are dummy codes to distinguish each occasion from time 0):

- Level 1:

$$y_{ti} = \beta_{0i} + \beta_{1i}(\text{Time1}_{ti}) + \beta_{2i}(\text{Time2}_{ti}) + \beta_{3i}(\text{Time3}_{ti}) + e_{ti}$$

- Level 2:

$$\beta_{0i} = Y_{00} + U_{0i}$$

$$\beta_{1i} = Y_{10}$$

$$\beta_{2i} = Y_{20}$$

$$\beta_{3i} = Y_{30}$$

Composite equation (6 parameters):

$$y_{ti} = Y_{00} + Y_{10}(\text{Time1}_{ti}) + Y_{20}(\text{Time2}_{ti}) + Y_{30}(\text{Time3}_{ti}) + U_{0i} + e_{ti}$$

This model is also known as **univariate repeated measures ANOVA**. Although the means are perfectly predicted, the random intercept assumes parallel growth (and equal variance/covariance over time).

Describing Within-Person Change in Longitudinal Data

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Augmenting the empty means, random intercept model with *time*

- 2 questions about the possible effects of *time*:

1. **Is there an effect of time on average?**

- If the line describing the sample means not flat?
- Significant **FIXED** effect of time

2. **Does the average effect of time vary across individuals?**

- Does each individual need his or her own line?
- Significant **RANDOM** effect of time

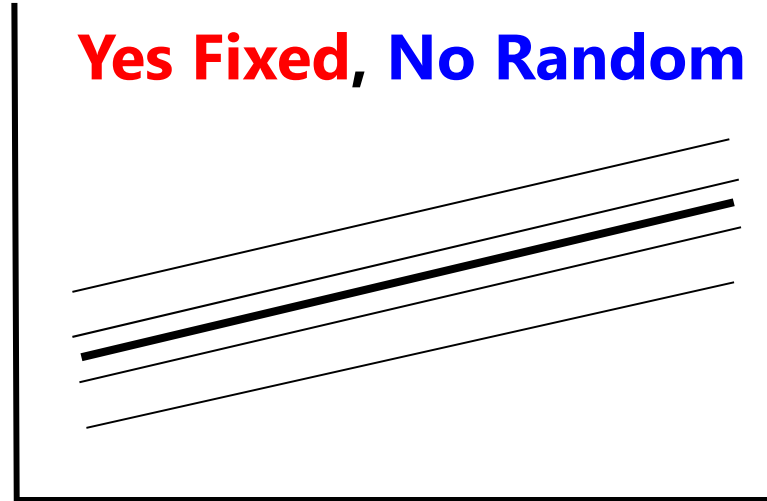
Fixed and Random Effects of Time

(Note: The intercept is random in every figure)

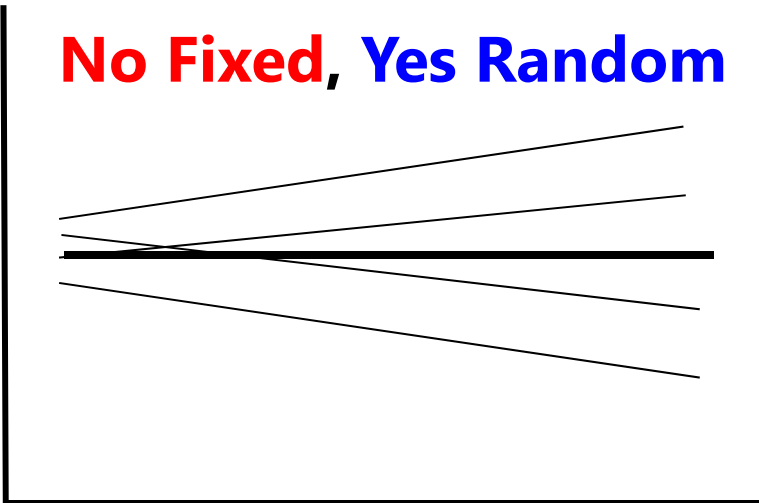
No Fixed, No Random



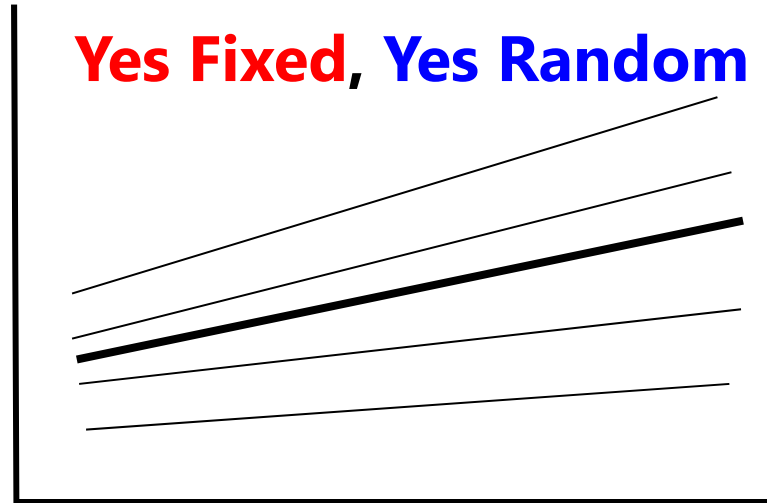
Yes Fixed, No Random



No Fixed, Yes Random



Yes Fixed, Yes Random



Fixed Linear Time, Random Intercept Model

(4 total parameters: effect of time is **FIXED** only)

Multilevel Model

Residual = time-specific deviation from individual's predicted outcome → estimated variance of σ_e^2

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}(\text{Time}_{ti}) + e_{ti}$

Fixed Intercept
= predicted mean
outcome at time 0

Fixed Linear Time Slope
= predicted mean rate
of change per unit time

Level 2: $\beta_{0i} = \gamma_{00} + u_{0i}$ $\beta_{1i} = \gamma_{10}$

Random Intercept = individual-specific deviation from fixed intercept → estimated variance of $\tau_{u_0}^2$

Composite Model

$$y_{ti} = (\underbrace{\gamma_{00} + u_{0i}}_{\beta_{0i}}) + (\underbrace{\gamma_{10}}_{\beta_{1i}})(\text{Time}_{ti}) + e_{ti}$$

Because the effect of time is **fixed**, everyone is predicted to change at exactly the same rate.

Random Intercept Models Imply...

- **People differ from each other systematically in only ONE way**—in intercept (U_{0i}), which implies **ONE kind of BP variance**, which translates to **ONE source of person dependency** (covariance or correlation in the outcomes from the same person)
- If so, after controlling for BP intercept differences (by estimating the variance of U_{0i} as $\tau_{U_0}^2$ in the **G** matrix), the **e_{ti} residuals** (whose variance and covariance are estimated in the **R** matrix) should be **uncorrelated with homogeneous variance across time**, as shown:

Level-2
G matrix:
RANDOM
TYPE=UN

$$\begin{bmatrix} \tau_{U_0}^2 \end{bmatrix}$$

Level-1 **R** matrix:
REPEATED TYPE=VC

$$\begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

G and **R** matrices combine to create a total **V** matrix with CS pattern

$$\begin{bmatrix} \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 \end{bmatrix}$$

Matrices in a Random Intercept Model

Total predicted data matrix is called **V matrix**, created from the **G [TYPE=UN]** and **R [TYPE=VC]** matrices as follows:

$$\mathbf{V} = \mathbf{Z} * \mathbf{G} * \mathbf{Z}^T + \mathbf{R} = \mathbf{V}$$

$$\mathbf{V} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} \tau_{U_0}^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} + \begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix} = \begin{bmatrix} \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 & \tau_{U_0}^2 \\ \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 & \tau_{U_0}^2 + \sigma_e^2 \end{bmatrix}$$

VCORR then provides the intraclass correlation, calculated as:

$$\text{ICC} = \tau_{U_0}^2 / (\tau_{U_0}^2 + \sigma_e^2)$$

$$\begin{bmatrix} 1 & \text{ICC} & \text{ICC} & \text{ICC} \\ \text{ICC} & 1 & \text{ICC} & \text{ICC} \\ \text{ICC} & \text{ICC} & 1 & \text{ICC} \\ \text{ICC} & \text{ICC} & \text{ICC} & 1 \end{bmatrix} \text{ assumes a constant correlation over time}$$

For any random effects model:

G matrix = BP variances/covariances

R matrix = WP variances/covariances

Z matrix = values of predictors with random effects (just intercept here), which can vary per person

V matrix = Total variance/covariance

Summary so far...

- Regardless of what kind of model for the means you have...
 - Empty means = 1 fixed intercept that predicts no change
 - Saturated means = 1 fixed intercept + $n-1$ fixed effects for mean differences that perfectly predict the means over time
 - Is a description, not a model, and may not be possible with unbalanced time
 - Fixed linear time = 1 fixed intercept, 1 fixed linear time slope that predicts linear average change across time
 - Is a model that works with balanced or unbalanced time
- A random intercept model...
 - Predicts constant total variance and covariance over time in **V** using **G**
 - Should be possible in balanced or unbalanced data
 - Still has residual variance (always there via default **R** matrix TYPE=VC)
- Now we'll see what happens when adding other kinds of random effects, such as a random linear effect of time...

Random Linear Time Model (6 total parameters)

Multilevel Model

Residual = time-specific deviation from individual's predicted outcome → estimated variance of σ_e^2

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}(\text{Time}_{ti}) + e_{ti}$

Fixed Intercept
= predicted mean outcome at time 0

Fixed Linear Time Slope
= predicted mean rate of change per unit time

Level 2: $\beta_{0i} = \gamma_{00} + U_{0i}$ $\beta_{1i} = \gamma_{10} + U_{1i}$

Random Intercept = individual-specific deviation from fixed intercept at time 0 → estimated variance of $\tau_{U_0}^2$

Random Linear Time Slope = individual-specific deviation from fixed linear time slope → estimated variance of $\tau_{U_1}^2$

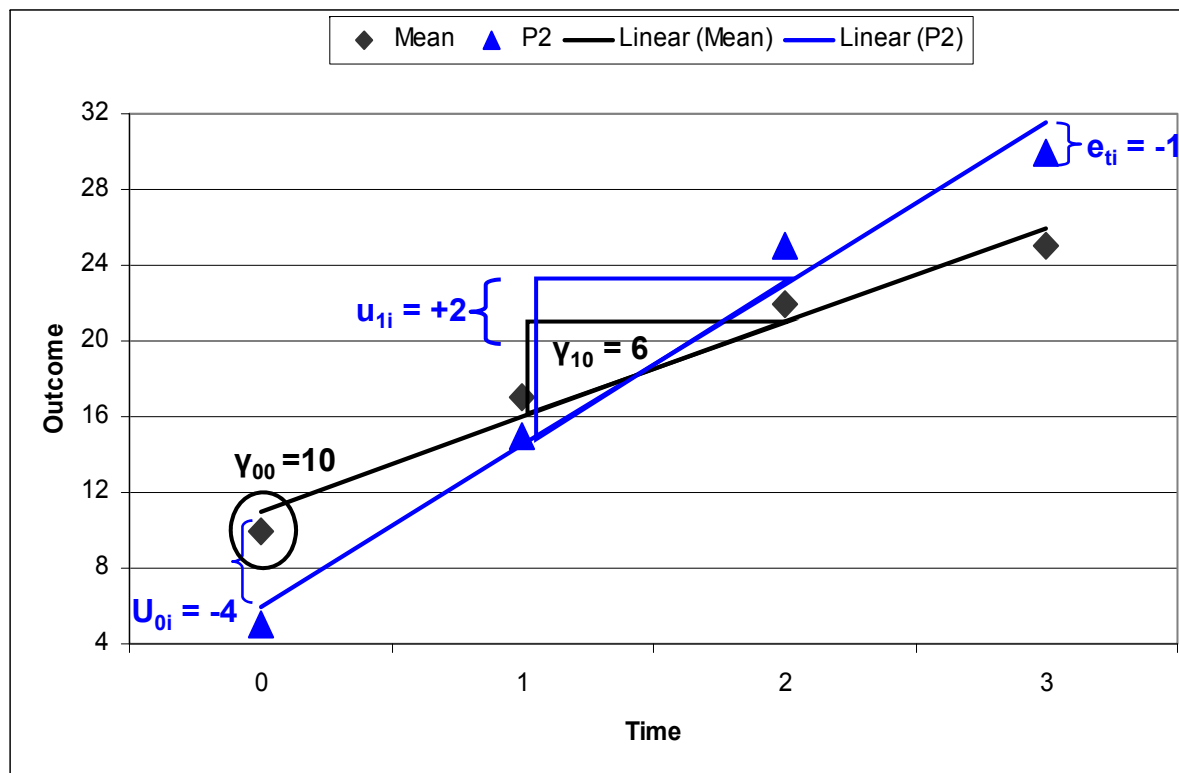
Also has an estimated covariance of random intercepts and slopes of $\tau_{U_{01}}$

Composite Model

$$y_{ti} = (\underbrace{\gamma_{00} + U_{0i}}_{\beta_{0i}}) + (\underbrace{\gamma_{10} + U_{1i}}_{\beta_{1i}})(\text{Time}_{ti}) + e_{ti}$$

Random Linear Time Model

$$y_{ti} = (\underbrace{Y_{00}}_{\text{Fixed Intercept}} + \underbrace{U_{0i}}_{\text{Random Intercept Deviation}}) + (\underbrace{Y_{10}}_{\text{Fixed Slope}} + \underbrace{U_{1i}}_{\text{Random Slope Deviation}})(\text{Time}_{ti}) + \underbrace{e_{ti}}_{\text{error for person } i \text{ at time } t}$$



6 Parameters:

2 Fixed Effects:

Y_{00} Intercept, Y_{10} Slope

2 Random Effects

Variances:

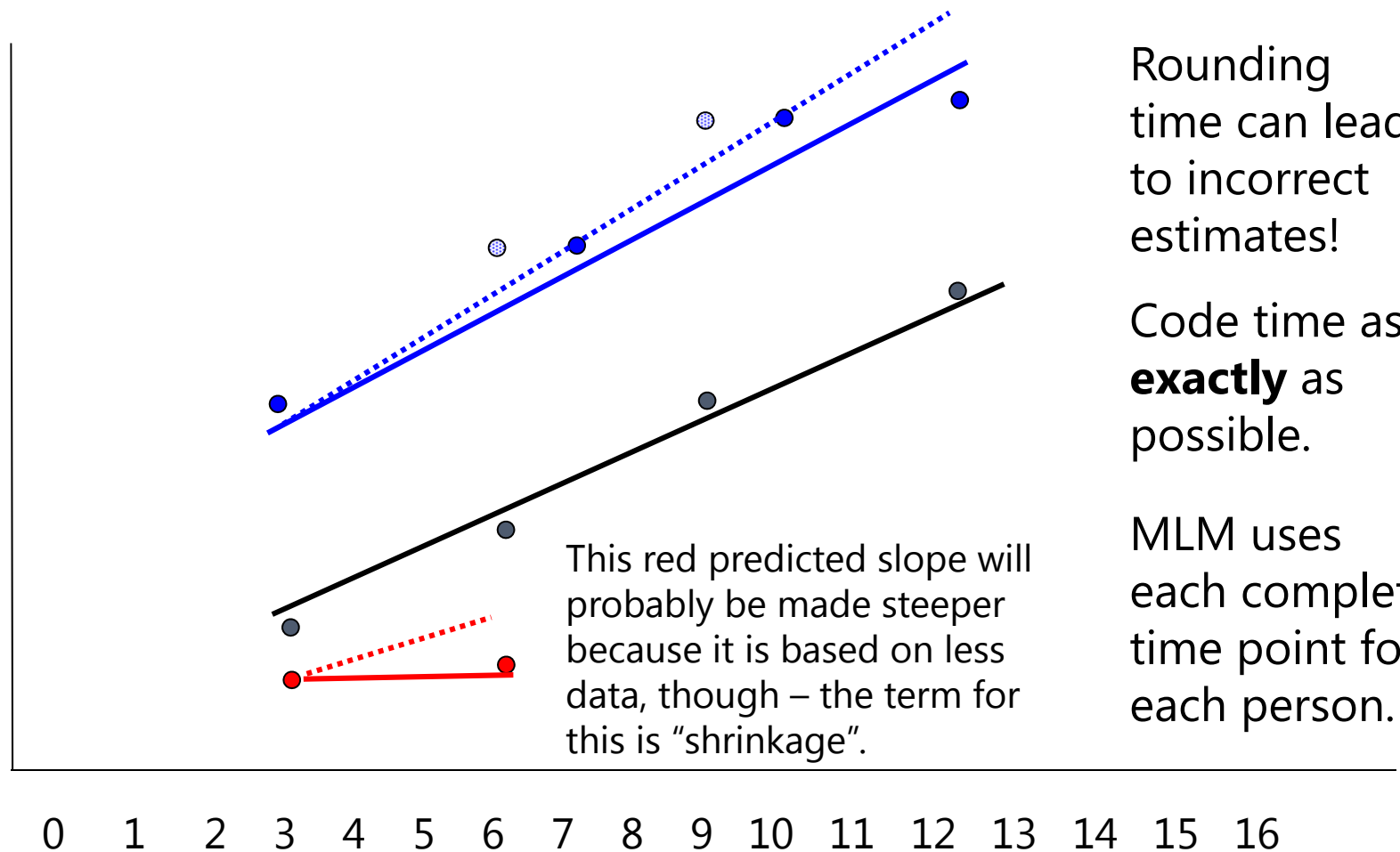
U_{0i} Intercept Variance
 $= \tau_{U0}^2$

U_{1i} Slope Variance
 $= \tau_{U1}^2$

Int-Slope Covariance
 $= \tau_{U01}$

1 e_{ti} Residual Variance
 $= \sigma_e^2$

Unbalanced Time → Different time occasions across persons? No problem!



Summary: Sequential Models for Effects of Time

Level 1: $y_{ti} = \beta_{0i} + e_{ti}$

Level 2: $\beta_{0i} = \gamma_{00} + u_{0i}$

Composite: $y_{ti} = \gamma_{00} + u_{0i} + e_{ti}$

Empty Means,
Random Intercept Model:
3 parms = γ_{00} , σ_e^2 , $\tau_{U_0}^2$

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}(\text{Time}_{ti}) + e_{ti}$

Level 2: $\beta_{0i} = \gamma_{00} + u_{0i}$
 $\beta_{1i} = \gamma_{10}$

Composite: $y_{ti} = (\gamma_{00} + u_{0i}) + \gamma_{10}(\text{Time}_{ti}) + e_{ti}$

Fixed Linear Time,
Random Intercept Model:
4 parms = γ_{00} , γ_{10} , σ_e^2 , $\tau_{U_0}^2$

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}(\text{Time}_{ti}) + e_{ti}$

Level 2: $\beta_{0i} = \gamma_{00} + u_{0i}$
 $\beta_{1i} = \gamma_{10} + u_{1i}$

Composite: $y_{ti} = (\gamma_{00} + u_{0i}) + (\gamma_{10} + u_{1i})(\text{Time}_{ti}) + e_{ti}$

Random Linear Time Model:
6 parms = γ_{00} , γ_{10} , σ_e^2 , $\tau_{U_0}^2$,
 $\tau_{U_1}^2$, $\tau_{U_{01}}$ (\rightarrow cov of U_{0i} and U_{1i})

Describing Within-Person Change in Longitudinal Data

- Topics:
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 - **Predicted variances and covariances from random slopes**
 - Dependency and effect size in random effects models
 - Describing nonlinear change: polynomial, piecewise models, and truly nonlinear models
 - Fun with likelihood estimation and model comparisons

Random Linear Time Models Imply:

- **People differ from each other systematically in TWO ways**—in intercept (U_{0i}) and slope (U_{1i}), which implies **TWO kinds of BP variance**, which translates to **TWO sources of person dependency** (covariance or correlation in the outcomes from the same person)
- If so, after controlling for both BP intercept and slope differences (by estimating the $\tau_{U_0}^2$ and $\tau_{U_1}^2$ variances in the **G** matrix), the **e_{ti} residuals** (whose variance and covariance are estimated in the **R** matrix) should be **uncorrelated with homogeneous variance across time**, as shown:

Level-2
G matrix:
RANDOM
TYPE=UN

$$\begin{bmatrix} \tau_{U_0}^2 & \tau_{U_{01}} \\ \tau_{U_{01}} & \tau_{U_1}^2 \end{bmatrix}$$

Level-1 **R** matrix:
REPEATED TYPE=VC

$$\begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

G and **R** combine to create a total **V** matrix whose per-person structure depends on the specific time occasions each person has (very flexible for unbalanced time)

Random Linear Time Model

(6 total parameters: effect of time is now **RANDOM**)

- How the model predicts each element of the **V** matrix:

Level 1: $\mathbf{y}_{ti} = \boldsymbol{\beta}_{0i} + \boldsymbol{\beta}_{1i}(\text{Time}_{ti}) + \mathbf{e}_{ti}$

Level 2: $\boldsymbol{\beta}_{0i} = \boldsymbol{\gamma}_{00} + \mathbf{U}_{0i}$

$$\boldsymbol{\beta}_{1i} = \boldsymbol{\gamma}_{10} + \mathbf{U}_{0i}$$

Composite Model: $\mathbf{y}_{ti} = (\boldsymbol{\gamma}_{00} + \mathbf{U}_{0i}) + (\boldsymbol{\gamma}_{10} + \mathbf{U}_{0i})(\text{Time}_{ti}) + \mathbf{e}_{ti}$

Predicted *Time-Specific* Variance:

$$\begin{aligned}\text{Var}[y_{ti}] &= \text{Var}[(\gamma_{00} + U_{0i}) + (\gamma_{10} + U_{1i})(\text{Time}_i) + e_{ti}] \\ &= \text{Var}[(U_{0i}) + (U_{1i} * \text{Time}_i) + e_{ti}] \\ &= \{\text{Var}(U_{0i})\} + \{\text{Var}(U_{1i} * \text{Time}_i)\} + \{2 * \text{Cov}(U_{0i}, U_{1i} * \text{Time}_i)\} + \{\text{Var}(e_{ti})\} \\ &= \{\text{Var}(U_{0i})\} + \{\text{Time}_i^2 * \text{Var}(U_{1i})\} + \{2 * \text{Time}_i * \text{Cov}(U_{0i}, U_{1i})\} + \{\text{Var}(e_{ti})\} \\ &= \{\tau_{U_0}^2\} + \{\text{Time}_i^2 * \tau_{U_1}^2\} + \{2 * \text{Time}_i * \tau_{U_{01}}\} + \{\sigma_e^2\}\end{aligned}$$

Random Linear Time Model

(6 total parameters: effect of time is now **RANDOM**)

- How the model predicts each element of the **V** matrix:

Level 1: $\mathbf{y}_{ti} = \boldsymbol{\beta}_{0i} + \boldsymbol{\beta}_{1i}(\text{Time}_{ti}) + \mathbf{e}_{ti}$

Level 2: $\boldsymbol{\beta}_{0i} = \boldsymbol{\gamma}_{00} + \mathbf{U}_{0i}$

$$\boldsymbol{\beta}_{1i} = \boldsymbol{\gamma}_{10} + \mathbf{U}_{0i}$$

Composite Model: $\mathbf{y}_{ti} = (\boldsymbol{\gamma}_{00} + \mathbf{U}_{0i}) + (\boldsymbol{\gamma}_{10} + \mathbf{U}_{0i})(\text{Time}_{ti}) + \mathbf{e}_{ti}$

Predicted *Time-Specific* Covariances (Time A with Time B):

$$\begin{aligned}\text{Cov}[y_{Ai}, y_{Bi}] &= \text{Cov}\left[\{(\gamma_{00} + U_{0i}) + (\gamma_{10} + U_{1i})(A_i) + e_{Ai}\}, \{(\gamma_{00} + U_{0i}) + (\gamma_{10} + U_{1i})(B_i) + e_{Bi}\}\right] \\ &= \text{Cov}\left[\{U_{0i} + (U_{1i}A_i)\}, \{U_{0i} + (U_{1i}B_i)\}\right] \\ &= \text{Cov}[U_{0i}, U_{0i}] + \text{Cov}[U_{0i}, U_{1i}B_i] + \text{Cov}[U_{0i}, U_{1i}A_i] + \text{Cov}[U_{1i}A_i, U_{1i}B_i] \\ &= \{\text{Var}(U_{0i})\} + \{(A_i + B_i) * \text{Cov}(U_{0i}, U_{1i})\} + \{(A_i B_i) \text{Var}(U_{1i})\} \\ &= \{\tau_{U_0}^2\} + \boxed{\{(A_i + B_i)\tau_{U_{01}}\} + \{(A_i B_i)\tau_{U_1}^2\}}\end{aligned}$$

Random Linear Time Model

(6 total parameters: effect of time is now **RANDOM**)

- Scalar “mixed” model equation per person:

$$\mathbf{Y}_i = \mathbf{X}_i * \boldsymbol{\gamma} + \mathbf{Z}_i * \mathbf{U}_i + \mathbf{E}_i$$

$$\begin{bmatrix} y_{0i} \\ y_{1i} \\ y_{2i} \\ y_{3i} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} \gamma_{00} \\ \gamma_{10} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} U_{0i} \\ U_{1i} \end{bmatrix} + \begin{bmatrix} e_{0i} \\ e_{1i} \\ e_{2i} \\ e_{3i} \end{bmatrix}$$

$$\begin{bmatrix} y_{0i} \\ y_{1i} \\ y_{2i} \\ y_{3i} \end{bmatrix} = \begin{bmatrix} \gamma_{00} + \gamma_{10}(0) \\ \gamma_{00} + \gamma_{10}(1) \\ \gamma_{00} + \gamma_{10}(2) \\ \gamma_{00} + \gamma_{10}(3) \end{bmatrix} + \begin{bmatrix} U_{0i} + U_{1i}(0) \\ U_{0i} + U_{1i}(1) \\ U_{0i} + U_{1i}(2) \\ U_{0i} + U_{1i}(3) \end{bmatrix} + \begin{bmatrix} e_{0i} \\ e_{1i} \\ e_{2i} \\ e_{3i} \end{bmatrix}$$

$$\begin{bmatrix} y_{0i} \\ y_{1i} \\ y_{2i} \\ y_{3i} \end{bmatrix} = \begin{bmatrix} \gamma_{00} + \gamma_{10}(0) + U_{0i} + U_{1i}(0) + e_{0i} \\ \gamma_{00} + \gamma_{10}(1) + U_{0i} + U_{1i}(1) + e_{1i} \\ \gamma_{00} + \gamma_{10}(2) + U_{0i} + U_{1i}(2) + e_{2i} \\ \gamma_{00} + \gamma_{10}(3) + U_{0i} + U_{1i}(3) + e_{3i} \end{bmatrix}$$

$\mathbf{X}_i = n \times k$ values of **predictors with fixed effects**, so can differ per person
($k = 2$: intercept, linear time)

$\boldsymbol{\gamma} = k \times 1$ estimated **fixed effects**,
so will be the same for all persons
(γ_{00} = intercept, γ_{10} = linear time)

$\mathbf{Z}_i = n \times u$ values of **predictors with random effects**, so can differ per person
($u = 2$: intercept, linear time)

$\mathbf{U}_i = u \times 2$ estimated individual **random effects**, so can differ per person

$\mathbf{E}_i = n \times n$ time-specific residuals,
so can differ per person

Random Linear Time Model

(6 total parameters: effect of time is now **RANDOM**)

- Predicted total variances and covariances per person:

$$\mathbf{V}_i = \mathbf{Z}_i * \mathbf{G}_i * \mathbf{Z}_i^T + \mathbf{R}_i$$

$$\mathbf{V}_i = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} \tau_{U_0}^2 & \tau_{U_{01}} \\ \tau_{U_{01}} & \tau_{U_1}^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \end{bmatrix} + \begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

\mathbf{V}_i matrix: Variance $[y_{\text{time}}]$

$$= \tau_{U_0}^2 + \left[(\text{time})^2 \tau_{U_1}^2 \right] + \left[2(\text{time}) \tau_{U_{01}} \right] + \sigma_e^2$$

\mathbf{V}_i matrix: Covariance $[y_A, y_B]$

$$= \tau_{U_0}^2 + \left[(A + B) \tau_{U_{01}} \right] + \left[(AB) \tau_{U_1}^2 \right]$$

\mathbf{V}_i matrix =
complicated ☺

$\mathbf{Z}_i = n \times u$ values of **predictors with random effects**, so can differ per person ($u = 2$: int., time slope)

$\mathbf{Z}_i^T = u \times n$ values of predictors with random effects (just \mathbf{Z}_i transposed)

$\mathbf{G}_i = u \times u$ estimated **random effects variances and covariances**, so will be the same for all persons ($\tau_{U_0}^2 = \text{int. var.}$, $\tau_{U_1}^2 = \text{slope var.}$)

$\mathbf{R}_i = n \times n$ **time-specific residual variances and covariances**, so will be same for all persons (here, just diagonal σ_e^2)

Building **V** across persons: Random Linear Time Model

- **V** for two persons with **unbalanced time** observations:

$$\mathbf{V} = \mathbf{Z} * \mathbf{G} * \mathbf{Z}^T + \mathbf{R}$$

$$\mathbf{V} = \begin{bmatrix} 1 & 0.0 & 0 & 0 \\ 1 & 1.0 & 0 & 0 \\ 1 & 2.0 & 0 & 0 \\ 1 & 3.0 & 0 & 0 \\ 0 & 0 & 1 & 0.2 \\ 0 & 0 & 1 & 1.4 \\ 0 & 0 & 1 & 2.3 \\ 0 & 0 & 1 & 3.5 \end{bmatrix} \begin{bmatrix} \tau_{U_0}^2 & \tau_{U_{01}} & 0 & 0 \\ \tau_{U_{01}} & \tau_{U_1}^2 & 0 & 0 \\ 0 & 0 & \tau_{U_0}^2 & \tau_{U_{01}} \\ 0 & 0 & \tau_{U_{01}} & \tau_{U_1}^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0.0 & 1.0 & 2.0 & 3.0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0.2 & 1.4 & 2.3 & 3.5 \end{bmatrix} + \begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_e^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_e^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

- The giant combined **V** matrix across persons is how the multilevel or mixed model is actually estimated
- Known as "**block diagonal**" structure → predictions are given for each person, but 0's are given for the elements that describe relationships between persons (because persons are supposed to be independent here!)

Building **V** across persons: Random Linear Time Model

- **V** for two persons also with **different n** per person:

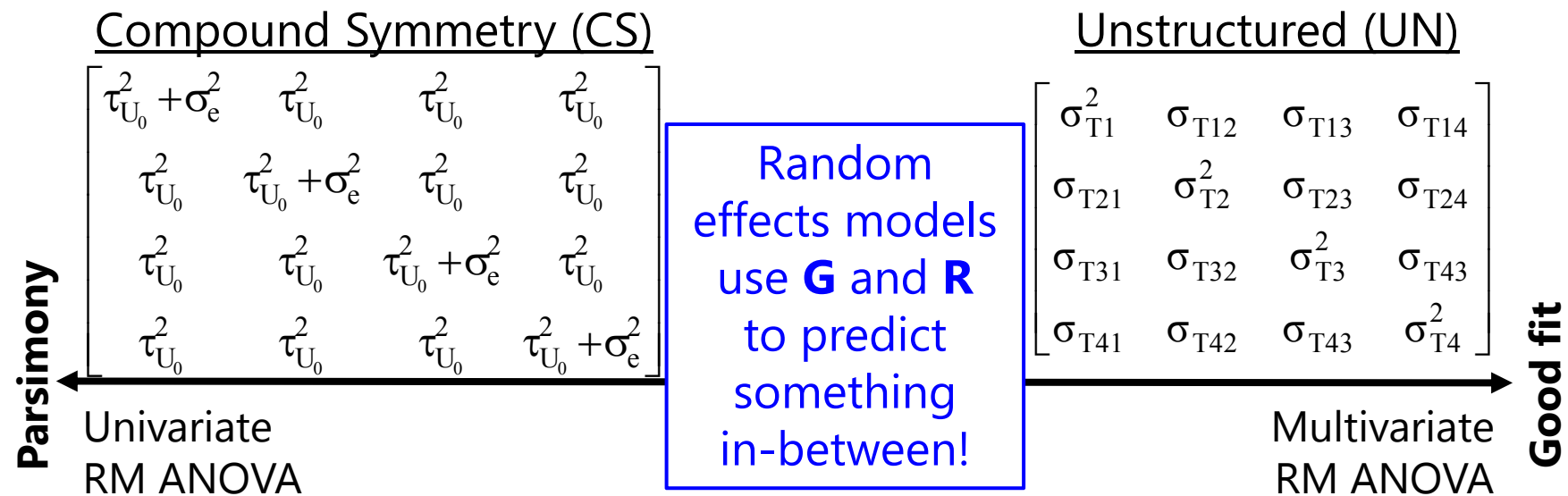
$$\mathbf{V} = \mathbf{Z} * \mathbf{G} * \mathbf{Z}^T + \mathbf{R}$$

$$\mathbf{V} = \begin{bmatrix} 1 & 0.0 & 0 & 0 \\ 1 & 1.0 & 0 & 0 \\ 1 & 2.0 & 0 & 0 \\ 1 & 3.0 & 0 & 0 \\ 0 & 0 & 1 & 0.2 \\ 0 & 0 & 1 & 1.4 \\ 0 & 0 & 1 & 3.5 \end{bmatrix} \begin{bmatrix} \tau_{U_0}^2 & \tau_{U_{01}} & 0 & 0 \\ \tau_{U_{01}} & \tau_{U_1}^2 & 0 & 0 \\ 0 & 0 & \tau_{U_0}^2 & \tau_{U_{01}} \\ 0 & 0 & \tau_{U_{01}} & \tau_{U_1}^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0.0 & 1.0 & 2.0 & 3.0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0.2 & 1.4 & 3.5 \end{bmatrix} + \begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_e^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_e^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_e^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_e^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_e^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$$

- The “block diagonal” does not need to be the same size or contain the same time observations per person...
- **R** matrix can also include non-0 covariance or differential residual variance across time (as in ACS models), although the models based on the idea of a “lag” won’t work for unbalanced or unequal-interval time

G, R, and V: The Take-Home Point

- The partitioning of variance into piles...
 - **Level 2 = BP** → **G** matrix of random effects variances/covariances
 - **Level 1 = WP** → **R** matrix of residual variances/covariances
 - **G** and **R** combine via **Z** to create **V** matrix of total variances/covariances
 - Many flexible options that allows the variances and covariances to vary in a time-dependent way that better matches the actual data
 - Can allow variance and covariance due to other predictors, too



Describing Within-Person Change in Longitudinal Data

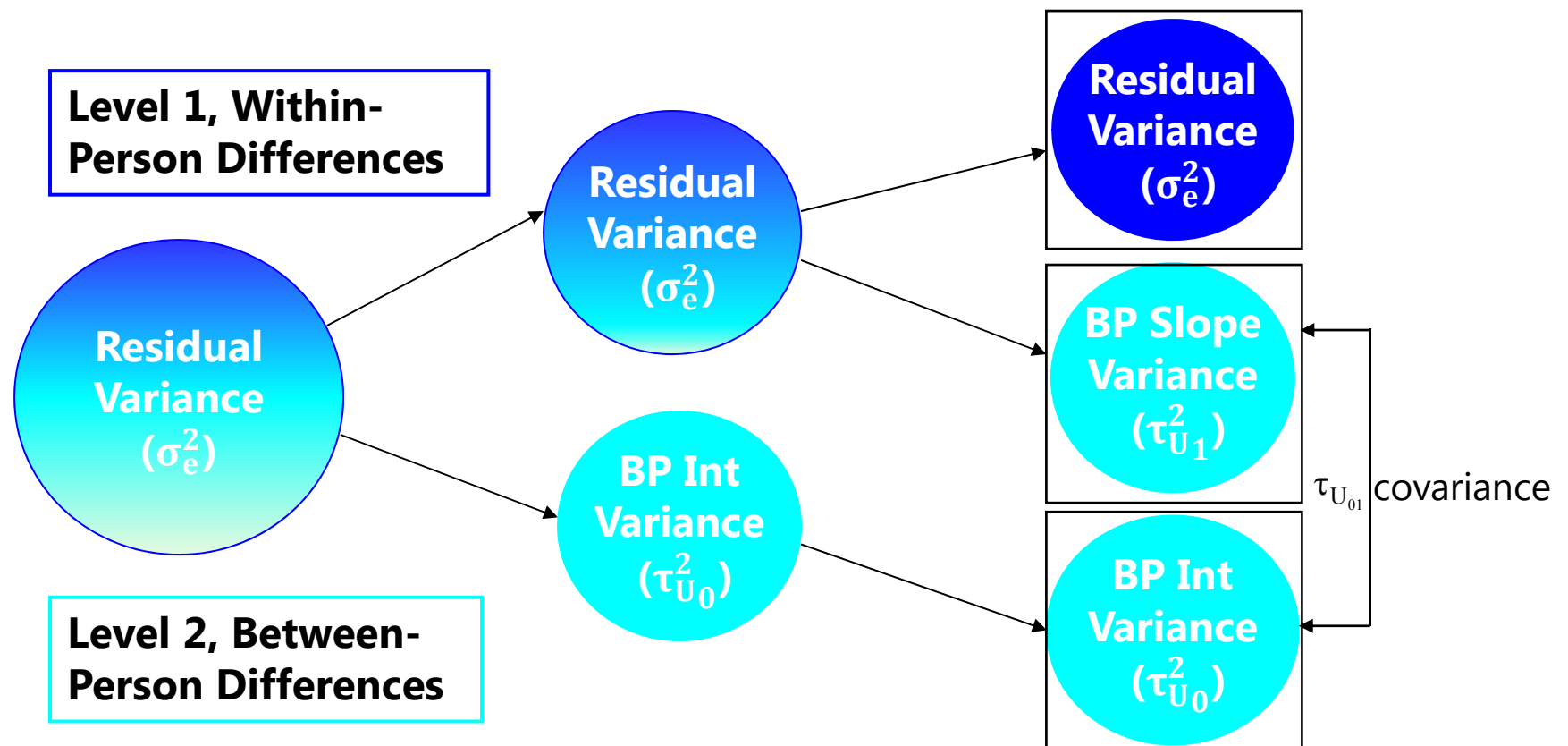
- Topics:
 - Multilevel modeling notation and terminology
 - Fixed and random effects of linear time
 - Predicted variances and covariances from random slopes
 - **Dependency and effect size in random effects models**
 - Describing nonlinear change: polynomial, piecewise models, and truly nonlinear models
 - Fun with likelihood estimation and model comparisons

How MLM “Handles” Dependency

- Common description of the purpose of MLM is that it “addresses” or “handles” correlated (dependent) data...
- But where does this correlation come from?
3 places (here, an example with health as an outcome):
 1. *Mean differences across persons*
 - Some people are just healthier than others (at every time point)
 - This is what a random intercept is for
 2. *Differences in effects of predictors across persons*
 - Does *time* (or *stress*) affect health more in some persons than others?
 - This is what random slopes are for
 3. Non-constant within-person correlation for unknown reasons
 - Occasions closer together may just be more related
 - This is what ACS models are for

MLM “Handles” Dependency

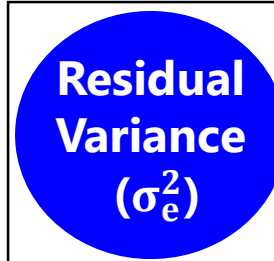
- Where does each kind of person dependency go? Into a new random effects variance component (or “pile” of variance):



Piles of Variance

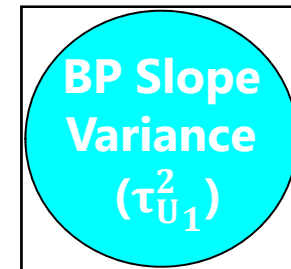
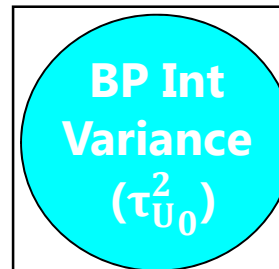
- By adding a random slope, we **carve up** our total variance into 3 piles:
 - BP (error) variance around intercept
 - BP (error) variance around slope
 - WP (error) residual variance
- These 2 piles are 1 pile of "error variance" in Univ. RM ANOVA
- But making piles does NOT make error variance go away...**

Level 1 (one source of)
Within-Person Variation:
 gets accounted for by
 time-level predictors



FIXED effects make variance go away (explain variance).
RANDOM effects just make a new pile of variance.

Level 2 (two sources of)
Between-Person Variation:
 gets accounted for by
 person-level predictors



τ_{U01} covariance

Fixed vs. Random Effects of Persons

- Person dependency: via **fixed effects in the model for the means** or via **random effects in the model for the variance**?
 - Individual intercept differences can be included as:
 - **N-1 person dummy code fixed main effects** OR **1 random U_{0i}**
 - Individual time slope differences can be included as:
 - **N-1*time person dummy code interactions** OR **1 random $U_{1i} \cdot \text{time}_{ti}$**
 - Either approach would appropriately control for dependency (fixed effects are used in some programs that 'control' SEs for sampling)
- Two important advantages of **random effects**:
 - Quantification: Direct measure of how much of the outcome variance is due to person differences (in intercept or in effects of predictors)
 - Prediction: Person differences (main effects and effects of time) then become predictable quantities – this can't happen using fixed effects
 - **Summary: Random effects give you *predictable* control of dependency**

Explained Variance from Fixed Linear Time

- Most common measure of effect size in MLM is Pseudo- R^2
 - Is supposed to be variance accounted for by predictors
 - Multiple piles of variance mean multiple possible values of pseudo R^2 (can be calculated per variance component or per model level)
 - A fixed linear effect of time will reduce level-1 residual variance σ_e^2 in **R**
 - By how much is the residual variance σ_e^2 reduced?

$$\text{Pseudo } R_e^2 = \frac{\text{residual variance}_{\text{fewer}} - \text{residual variance}_{\text{more}}}{\text{residual variance}_{\text{fewer}}}$$

- If time varies between persons, then level-2 random intercept variance $\tau_{U_0}^2$ in **G** may also be reduced:

$$\text{Pseudo } R_{U_0}^2 = \frac{\text{random intercept variance}_{\text{fewer}} - \text{random intercept variance}_{\text{more}}}{\text{random intercept variance}_{\text{fewer}}}$$

- But you are likely to see a (net) INCREASE in $\tau_{U_0}^2$ instead.... Here's why:

Increases in Random Intercept Variance

- Level-2 random intercept variance $\tau_{U_0}^2$ will often increase as a consequence of reducing level-1 residual variance σ_e^2
- Observed level-2 $\tau_{U_0}^2$ is NOT just between-person variance
 - Also has a small part of within-person variance (level-1 σ_e^2), or:
Observed $\tau_{U_0}^2 = \text{True } \tau_{U_0}^2 + (\sigma_e^2/n)$
 - As n occasions increases, bias of level-1 σ_e^2 is minimized
 - Likelihood-based estimates of "true" $\tau_{U_0}^2$ use (σ_e^2/n) as correction factor:
True $\tau_{U_0}^2 = \text{Observed } \tau_{U_0}^2 - (\sigma_e^2/n)$
- For example: observed level-2 $\tau_{U_0}^2=4.65$, level-1 $\sigma_e^2=7.06$, $n=4$
 - True $\tau_{U_0}^2 = 4.65 - (7.60/4) = 2.88$ in empty means model
 - Add fixed linear time slope \rightarrow reduce σ_e^2 from 7.06 to 2.17 ($R^2 = .69$)
 - But now True $\tau_{U_0}^2 = 4.65 - (2.17/4) = 4.10$ in fixed linear time model

Quantification of Random Effects Variances

- We can test if a random effect variance is significant, but the variance estimates are not likely to have inherent meaning
 - e.g., “I have a significant fixed linear time effect of $\gamma_{10} = 1.72$, so people increase by 1.72/time on average. I also have a significant random linear time slope variance of $\tau_{U_1}^2 = 0.91$, so people need their own slopes (people change differently). But how much is a variance of 0.91 , really?”
- **95% Random Effects Confidence Intervals** can tell you
 - Can be calculated for each effect that is random in your model
 - Provide range around the fixed effect within which 95% of your sample is predicted to fall, based on your random effect variance:
$$\text{Random Effect 95\% CI} = \text{fixed effect} \pm (1.96 * \sqrt{\text{Random Variance}})$$
$$\text{Linear Time Slope 95\% CI} = \gamma_{10} \pm (1.96 * \sqrt{\tau_{U_1}^2}) \rightarrow 1.72 \pm (1.96 * \sqrt{0.91}) = -0.15 \text{ to } 3.59$$
 - So although people improve on average, individual slopes are predicted to range from -0.15 to 3.59 (so some people may actually decline)

Describing Within-Person Change in Longitudinal Data

- Topics:
 - Multilevel modeling notation and terminology
 - Fixed and random effects of linear time
 - Predicted variances and covariances from random slopes
 - Dependency and effect size in random effects models
 - **Describing nonlinear change: polynomial, piecewise models, and truly nonlinear models**
 - Fun with likelihood estimation and model comparisons

Summary: Modeling **Means** and **Variances**

- We have two tasks in describing within-person change:
- **Choose a Model for the Means**
 - What kind of change in the outcome do we have **on average**?
 - What kind and how many **fixed effects** do we need to predict that mean change as parsimoniously but accurately as possible?
- **Choose a Model for the Variances**
 - What pattern do the variances and covariances of the outcome show over time because of **individual differences** in change?
 - What kind and how many **random effects** do we need to predict that pattern as parsimoniously but accurately as possible?

Name that trajectory... Polynomial?

- Predict **mean change** with **polynomial fixed effects of time**:
 - Linear → *constant* amount of change (up or down)
 - Quadratic → *change* in linear rate of change (acceleration/deceleration)
 - Cubic → *change* in acceleration/deceleration of linear rate of change (known in physics as jerk, surge, or jolt)
 - Terms work together to describe curved trajectories
 - **Can have polynomial fixed time slopes UP TO: $n - 1$ ***
 - 3 occasions = 2nd order (time²) = Fixed Quadratic Time or less
 - 4 occasions = 3rd order (time³) = Fixed Cubic Time or less
 - Interpretable polynomials past cubic are rarely seen in practice
- * $n-1$ rule can be broken in unbalanced data (but cautiously)

Interpreting Quadratic Fixed Effects

A Quadratic time effect is a two-way interaction: time*time

- Fixed quadratic time = “**half the rate of acceleration/deceleration**”
- So to interpret it as how the linear time effect changes per unit time, **you must multiply the quadratic coefficient by 2**
- If fixed linear time slope = 4 at time 0, with quadratic slope = 0.3?
 - Instantaneous linear rate of Δ at time 0 = 4.0, at time 1 = 4.6...
- The “twice” part comes from taking the derivatives of the function:

Intercept (Position) at Time T:	$\hat{y}_T = 50.0 + 4.0T + 0.3T^2$
First Derivative (Velocity) at Time T:	$\frac{d\hat{y}_T}{d(T)} = 4.0 + 0.6T$
Second Derivative (Acceleration) at Time T:	$\frac{d^2\hat{y}_T}{d(T)} = 0.6$

Interpreting Quadratic Fixed Effects

A Quadratic time effect is a two-way interaction: time*time

- Fixed quadratic time = “**half the rate of acceleration/deceleration**”
- So to interpret it as how the linear time effect changes per unit time, **you must multiply the quadratic coefficient by 2**
- If fixed linear time slope = 4 at time 0, with quadratic slope = 0.3?
 - Instantaneous linear rate of Δ at time 0 = 4.0, at time 1 = 4.6...

- The “twice” part also comes from what you remember about the role of interactions with respect to their constituent main effects:

$$\hat{y} = \beta_0 + \beta_1 X + \beta_2 Z + \beta_3 XZ$$

$$\text{Effect of } X = \beta_1 + \beta_3 Z$$

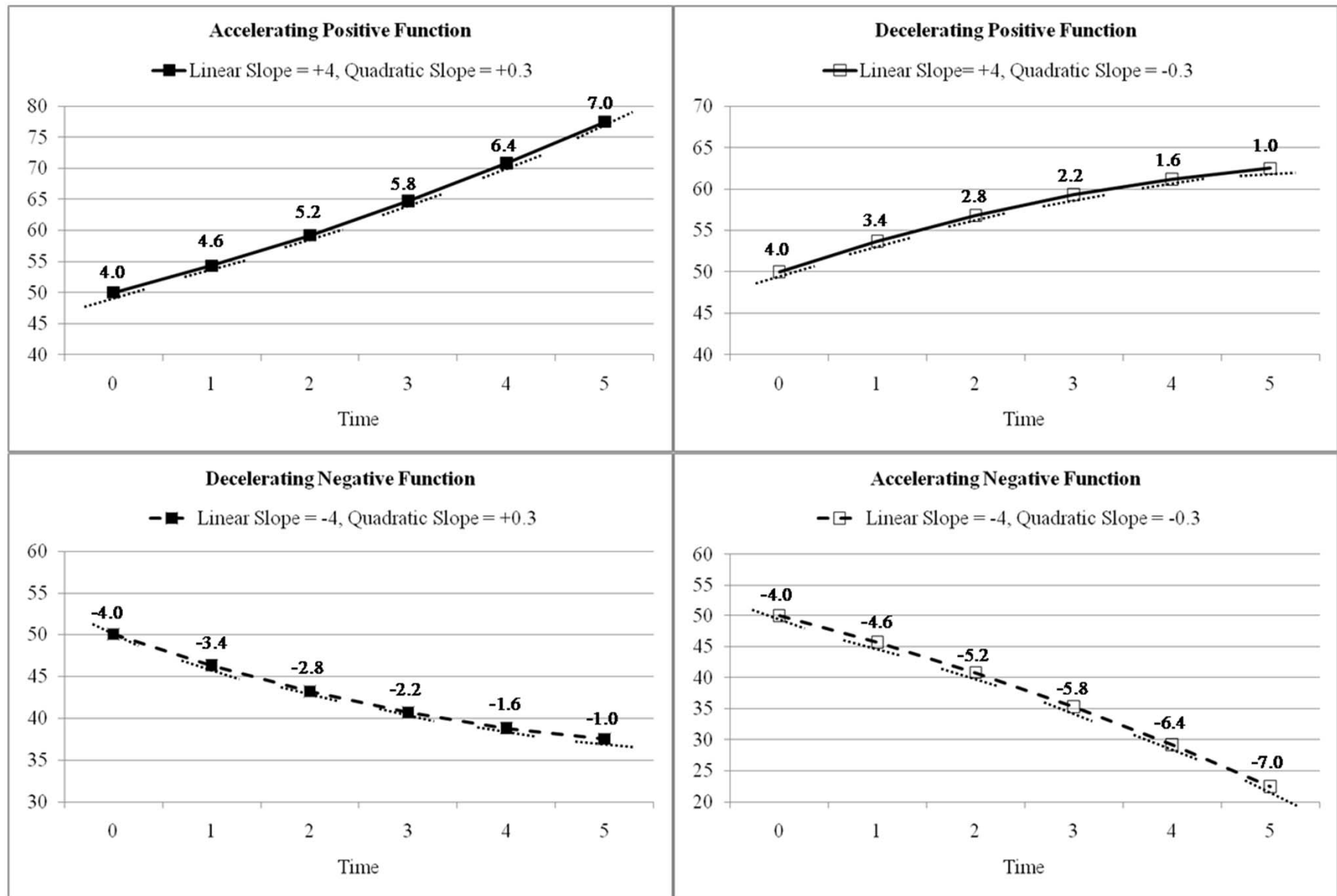
$$\text{Effect of } Z = \beta_2 + \beta_3 X$$

$$\hat{y}_T = \beta_0 + \beta_1 \text{Time}_T + \text{_____} + \beta_3 \text{Time}_T^2$$

$$\text{Effect of Time}_T = \beta_1 + 2\beta_3 \text{Time}_T$$

- Because time is interacting with itself, there is no second main effect in the model for the interaction to modify as usual. So the quadratic time effect gets applied twice to the one (main) linear effect of time.

Examples of Fixed Quadratic Time Effects



Conditionality of Polynomial **Fixed Time Effects**

- We've seen how main effects become conditional simple effects once they are part of an interaction
- The same is true for polynomial **fixed effects of time**:
 - **Fixed Intercept Only?**
 - Fixed Intercept = predicted mean of Y *for any occasion* (= grand mean)
 - **Add Fixed Linear Time?**
 - Fixed Intercept = **now** predicted mean of Y from linear time *at time=0* (would be different if time was centered elsewhere)
 - Fixed Linear Time = mean linear rate of change *across all occasions* (would be the same if time was centered elsewhere)
 - **Add Fixed Quadratic Time?**
 - Fixed Intercept = still predicted mean of Y *at time=0* (but from quadratic model) (would be different if time was centered elsewhere)
 - Fixed Linear Time = **now** mean linear rate of change *at time=0* (would be different if time was centered elsewhere)
 - Fixed Quadratic Time = half the mean rate of acceleration or deceleration of change *across all occasions* (i.e., the linear slope changes the same over time)

Polynomial **Fixed** vs. **Random** Time Effects

- **Polynomial fixed effects** combine to describe mean trajectory over time (can have fixed slopes up to **$n - 1$**):
 - Fixed Intercept = Predicted mean level (at time 0)
 - Fixed Linear Time = Mean linear rate of change (at time 0)
 - Fixed Quadratic Time = Half of mean acceleration/deceleration in linear rate of change (2*quad is how the linear time slope changes per unit time if quadratic is highest order fixed effect of time)
- **Polynomial random effects** (individual deviations from the fixed effect) describe individual differences in those change parameters (can have random slopes up to **$n - 2$**):
 - Random Intercept = BP variance in level (at time 0)
 - Random Linear Time = BP variance in linear time slope (at time 0)
 - Random Quadratic Time = BP variance in half the rate of acceleration/deceleration of linear time slope (across all time if quadratic is highest-order random effect of time)

Random Quadratic Time Model

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}\text{Time}_{ti} + \beta_{2i}\text{Time}_{ti}^2 + e_{ti}$

Level 2 Equations (one per β):

$$\beta_{0i} = Y_{00} + U_{0i}$$

Intercept for person i Fixed (mean) Intercept Random (Deviation) Intercept

Fixed Effect Subscripts:

1st = which Level 1 term

2nd = which Level 2 term

$$\beta_{1i} = Y_{10} + U_{1i}$$

Linear Slope for person i Fixed (mean) Linear Slope Random (Deviation) Linear Slope

Number of Possible Slopes by Number of Occasions (n):

Fixed slopes = $n - 1$

Random slopes = $n - 2$

Need $n = 4$ occasions to fit random quadratic time model

$$\beta_{2i} = Y_{20} + U_{2i}$$

Quad Slope for person i Fixed (mean) Quad Slope Random (Deviation) Quad Slope

Conditionality of Polynomial **Random Effects**

- We saw previously that lower-order fixed effects of time are conditional on higher-order polynomial fixed effects of time
- The same is true for polynomial **random effects of time**:
 - **Random Intercept Only?**
 - Random Intercept = BP variance *for any occasion* in predicted mean Y
(= variance in grand mean because individual lines are parallel)
 - **Add Random Linear Time?**
 - Random Intercept = **now** BP variance *at time=0* in predicted mean Y
(*would be different if time was centered elsewhere*)
 - Random Linear Time = BP variance *across all occasions* in linear rate of change
(*would be the same if time was centered elsewhere*)
 - **Add Random Quadratic Time?**
 - Random Intercept = still BP variance *at time=0* in predicted mean Y
 - Random Linear Time = **now** BP variance *at time=0* in linear rate of change
(*would be different if time was centered elsewhere*)
 - Random Quadratic Time = BP variance *across all occasions* in half of accel/decel of change
(*would be the same if time was centered elsewhere*)

Random Effects Allowed by #Occasions

	<u>Data</u>	<u>G Matrix</u>	<u>R Matrix</u>	<u>Variance Model # Parameters</u>
<u>$n=2$ occasions</u> 3 unique pieces of information	$\begin{bmatrix} \sigma_1^2 & & \\ \sigma_{21} & \sigma_2^2 & \\ & & \end{bmatrix}$	$\begin{bmatrix} \tau_{U_0}^2 & & \\ & & \\ \text{Random Intercept only} & & \end{bmatrix}$	$\begin{bmatrix} \sigma_e^2 & 0 \\ 0 & \sigma_e^2 \end{bmatrix}$	2
<u>$n=3$ occasions</u> 6 unique pieces of information	$\begin{bmatrix} \sigma_1^2 & & & \\ \sigma_{21} & \sigma_2^2 & & \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \\ & & & \end{bmatrix}$	$\begin{bmatrix} \tau_{U_0}^2 & & & \\ & \tau_{U_1}^2 & & \\ \tau_{U_{01}} & \tau_{U_1}^2 & & \\ \text{Up to 1 Random slope} & & & \end{bmatrix}$	$\begin{bmatrix} \sigma_e^2 & 0 & 0 & \\ 0 & \sigma_e^2 & 0 & \\ 0 & 0 & \sigma_e^2 & \\ 0 & 0 & 0 & \sigma_e^2 \end{bmatrix}$	4
<u>$n=4$ occasions</u> 10 unique pieces of information	$\begin{bmatrix} \sigma_1^2 & & & & \\ \sigma_{21} & \sigma_2^2 & & & \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & & \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_4^2 & \end{bmatrix}$	$\begin{bmatrix} \tau_{U_0}^2 & & & & \\ & \tau_{U_1}^2 & & & \\ \tau_{U_{01}} & \tau_{U_1}^2 & & & \\ \tau_{U_{02}} & \tau_{U_{12}} & \tau_{U_2}^2 & & \\ \text{Up to 2 Random slopes} & & & & \end{bmatrix}$	$\begin{bmatrix} \sigma_e^2 & 0 & 0 & 0 & \\ 0 & \sigma_e^2 & 0 & 0 & \\ 0 & 0 & \sigma_e^2 & 0 & \\ 0 & 0 & 0 & \sigma_e^2 & \end{bmatrix}$	7

Predicted **V** Matrix from Polynomial Random Effects Models

- **Random linear model?** Variance has a **quadratic** dependence on time

- Variance will be at a minimum when time = $-\text{Cov}(U_0, U_1)/\text{Var}(U_1)$, and will increase parabolically and symmetrically over time
- **Predicted variance** at each occasion and covariance between A and B:

$$\text{Var}(y_{\text{time}}) = \text{Var}(e_t) + \text{Var}(U_0) + 2\text{Cov}(U_0, U_1)(\text{time}_t) + \text{Var}(U_1)(\text{time}_t^2)$$

$$\text{Cov}(y_A, y_B) = \text{Var}(U_0) + \text{Cov}(U_0, U_1)(A + B) + \text{Var}(U_1)(AB)$$

- **Random quadratic model?** Variance has a **quartic** dependence on time

$$\begin{aligned} \text{Var}(y_{\text{time}}) = & \text{Var}(e_t) + \text{Var}(U_0) + 2\text{Cov}(U_0, U_1)(\text{time}_t) + \text{Var}(U_1)(\text{time}_t^2) + \\ & 2\text{Cov}(U_0, U_2)(\text{time}_t^2) + 2\text{Cov}(U_1, U_2)(\text{time}_t^3) + \text{Var}(U_2)(\text{time}_t^4) \end{aligned}$$

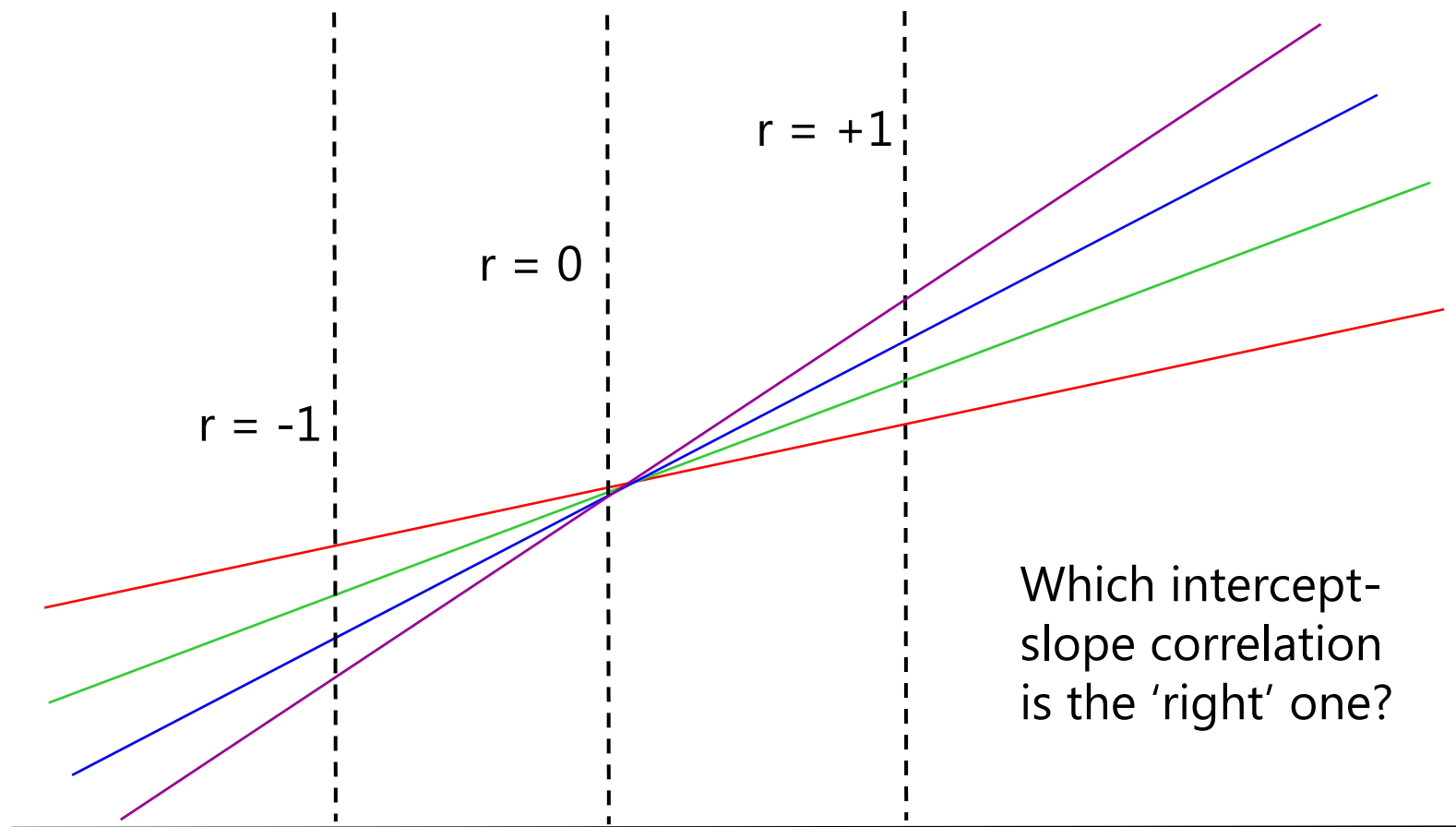
$$\begin{aligned} \text{Cov}(y_A, y_B) = & \text{Var}(U_0) + \text{Cov}(U_0, U_1)(A + B) + \text{Var}(U_1)(AB) + \text{Cov}(U_0, U_2)(A^2 + B^2) + \\ & \text{Cov}(U_1, U_2)[(AB^2) + (A^2B)] + \text{Var}(U_2)(A^2B^2) \end{aligned}$$

- *The point of the story: random effects of time are a way of allowing the variances and covariances to differ over time in specific, time-dependent patterns (that result from differential individual change over time).*

Rules for Polynomial Models (and in general for fixed and random effects)

- On the same side of the model (means or variances side), lower-order effects stay in EVEN IF NONSIGNIFICANT (for correct interpretation)
 - e.g., Significant *fixed* quadratic? Keep the *fixed* linear
 - e.g., Significant *random* quadratic? Keep the *random* linear
- Also remember—you can have a significant random effect EVEN IF the corresponding fixed effect is not significant (keep it anyway):
 - e.g., Fixed linear not significant, but random linear is significant?
→ No linear change *on average*, but significant individual differences in change
- Language: A random effect supersedes a fixed effect:
 - If Fixed = intercept, linear, quad; Random = intercept, linear, quad?
 - Call it a “Random quadratic model” (implies everything beneath those terms)
 - If Fixed = intercept, linear, quad; Random = intercept, linear?
 - Call it a “Fixed quadratic, random linear model” (distinguishes no random quad)
- Intercept-slope correlation depends largely on centering of time...

Correlation between Random Intercept and Random Linear Slope depends on time 0



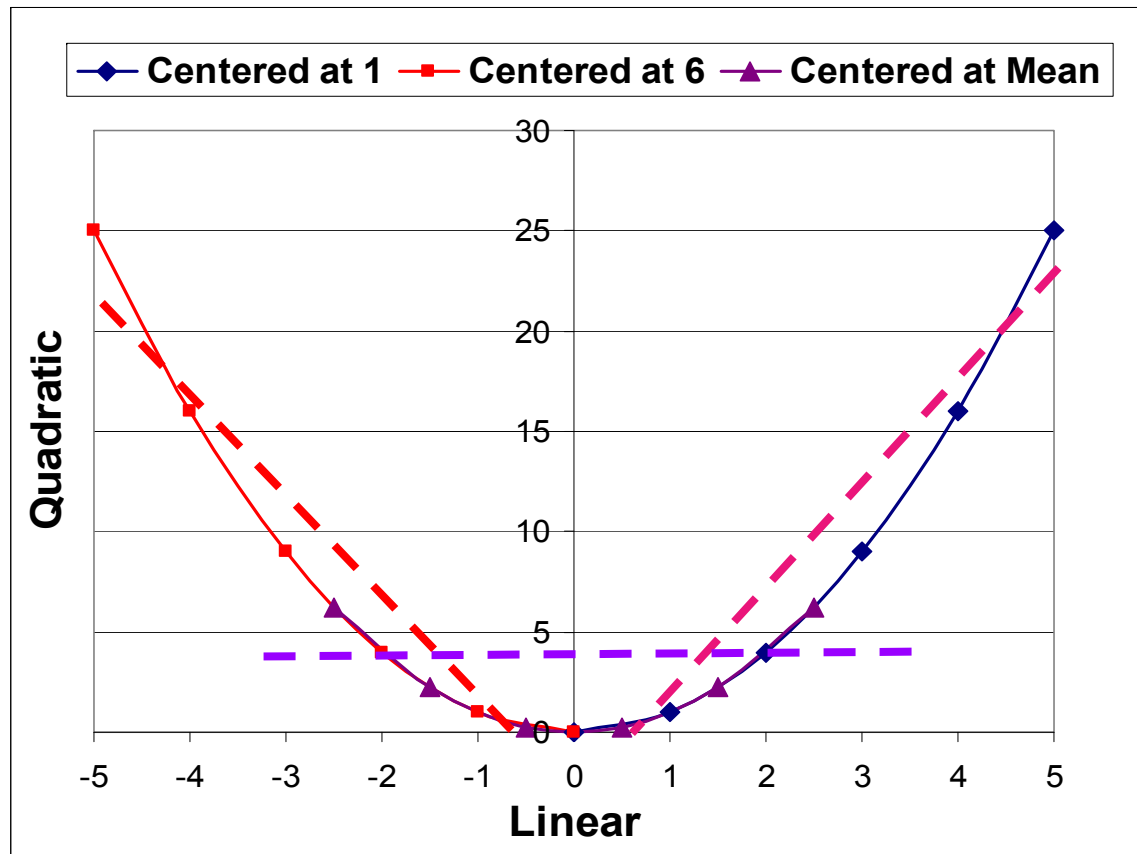
!! Nonparallel lines will eventually cross.

Correlations among polynomial slopes

Session Centered at 1:		
Session	Linear	Quadratic
1	0	0
2	1	1
3	2	4
4	3	9
5	4	16
6	5	25

Session Centered at 6:		
Session	Linear	Quadratic
1	-5	25
2	-4	16
3	-3	9
4	-2	4
5	-1	1
6	0	0

Session Centered at Mean:		
Session	Linear	Quadratic
1	-2.5	6.25
2	-1.5	2.25
3	-0.5	0.25
4	0.5	0.25
5	1.5	2.25
6	2.5	6.25

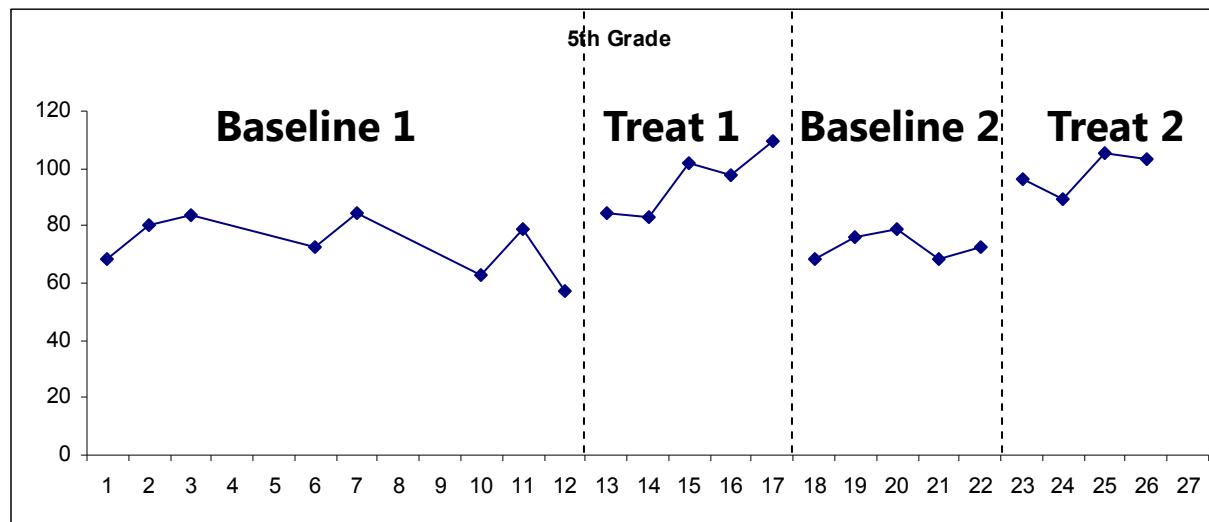


Correlations among polynomial effects of time can be induced by centering time near the start or near the end.

Therefore, these correlations will be *most* interpretable when centering time at its mean instead.

Other Random Effects Models of Change

- **Piecewise models:** Discrete slopes for discrete phases of time
 - Separate terms describe sections of overall trajectories
 - Useful for examining change in intercepts and slopes before/after discrete events (changes in policy, interventions)
 - **Must know where the break point is ahead of time!**



Piecewise Model:

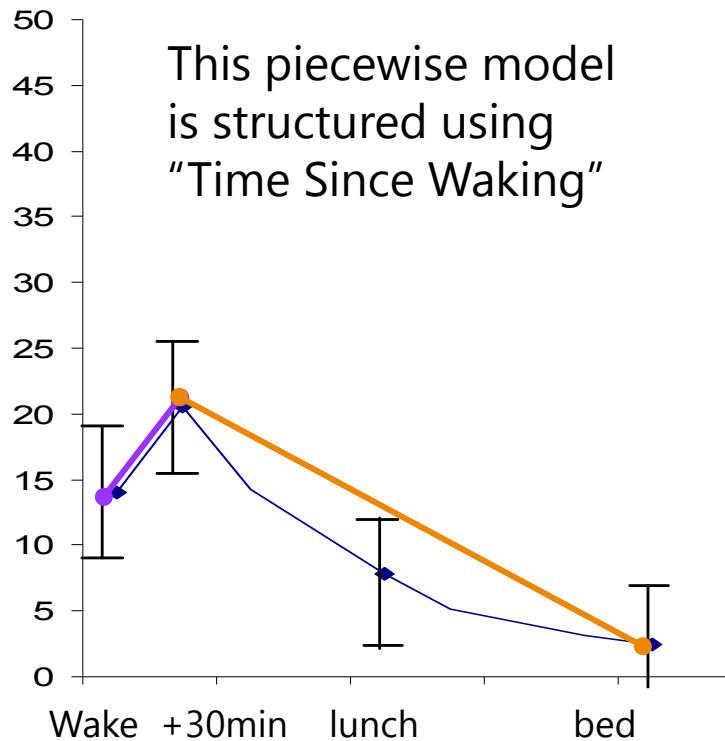
4 slopes
(one per phase)

3 "jumps"
(shift in intercept
between phases)

Example of Daily Cortisol Fluctuation: Morning Rise and Afternoon Decline

Average Trajectories

This piecewise model is structured using "Time Since Waking"



SAS Code to create two piecewise slopes from continuous time of day in stacked data:

```
IF occasion=1 THEN DO;
```

```
    P1=0;                P2=0; END;
```

```
IF occasion=2 THEN DO;
```

```
    P1= time2-time1; P2=0; END;
```

```
IF occasion=3 THEN DO;
```

```
    P1= time2-time1; P2=time3-time2; END;
```

```
IF occasion=4 THEN DO;
```

```
    P1= time2-time1; P2=time4-time2; END;
```

Note that a quadratic slope may be necessary for the afternoon decline slope!

Random Two-Slope Piecewise Model

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i}\text{Slope1}_{ti} + \beta_{2i}\text{Slope2}_{ti} + e_{ti}$

Level 2 Equations (one per β):

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

Intercept
for person i

Fixed (mean)
Intercept

Random
(Deviation)
Intercept

Fixed Effect Subscripts:

1st = which Level 1 term

2nd = which Level 2 term

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

Slope1
for person i

Fixed (mean)
Slope1

Random
(Deviation)
Slope1

**Number of Possible Slopes
by Number of Occasions (n):**

Fixed slopes = $n - 1$

Random slopes = $n - 2$

$$\beta_{2i} = \gamma_{20} + u_{2i}$$

Slope2
for person i

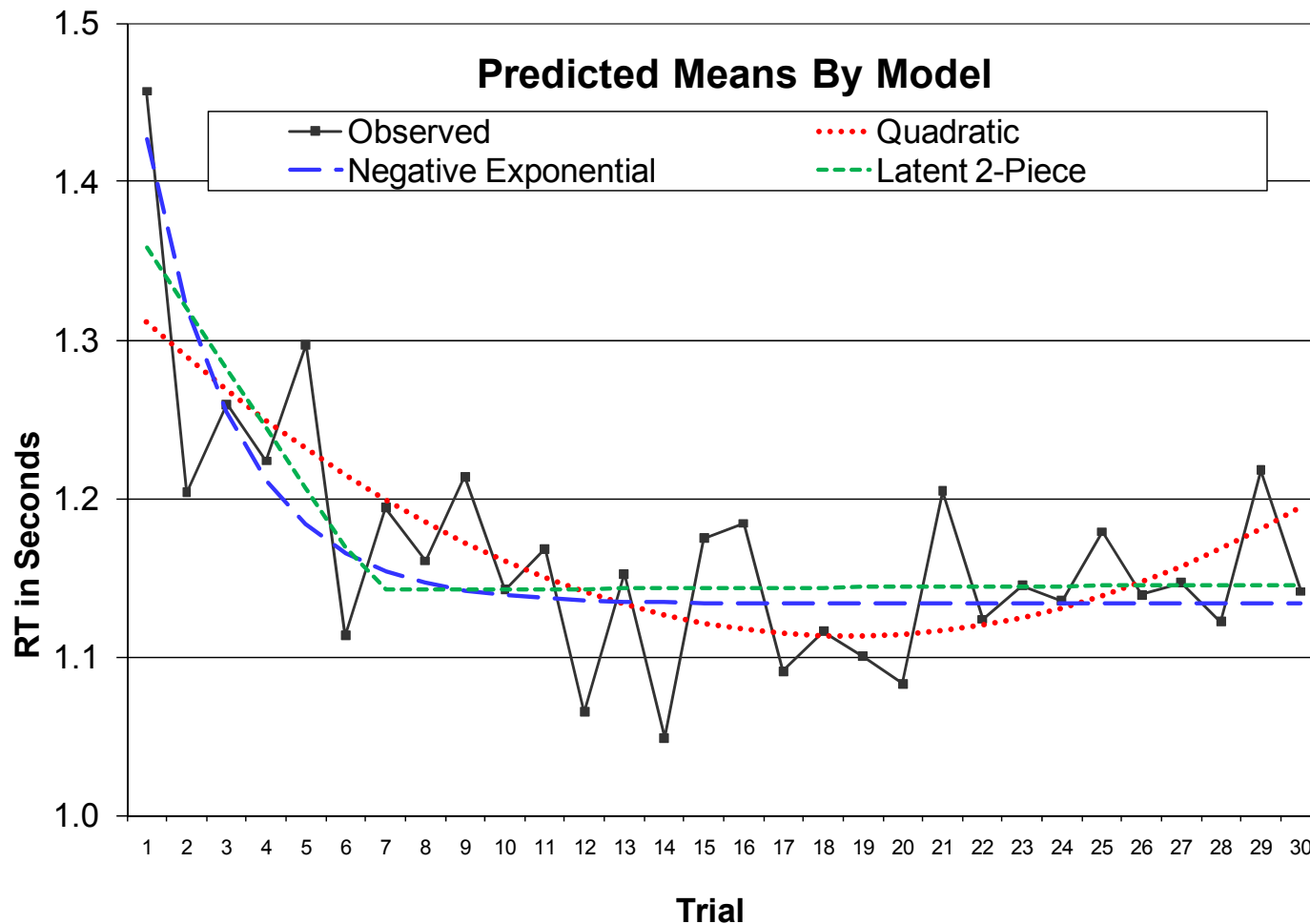
Fixed (mean)
Slope2

Random
(Deviation)
Slope2

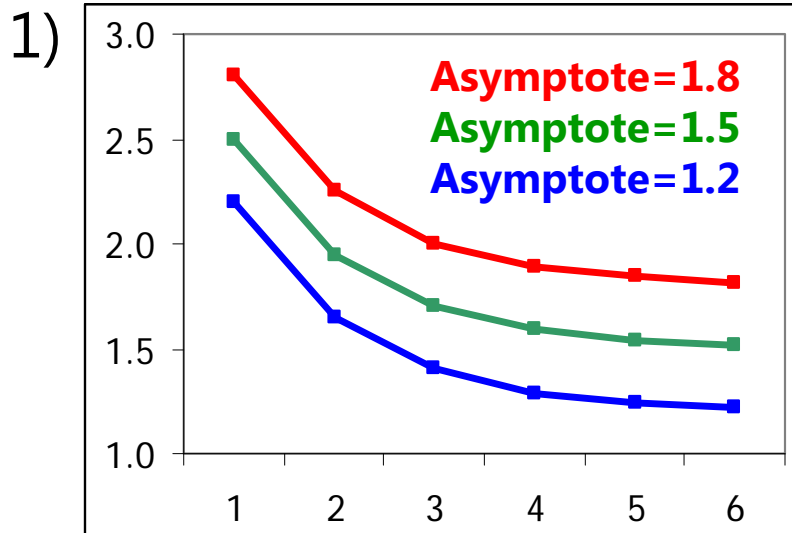
Need $n = 4$ occasions to fit
random two-slope model

Other Random Effects for Change

- **Truly nonlinear models:** Non-additive terms to describe change
 - Models can include **asymptotes** (so change can “shut off” as needed)
 - Include **power** and **exponential** functions (see chapter 6 for references)



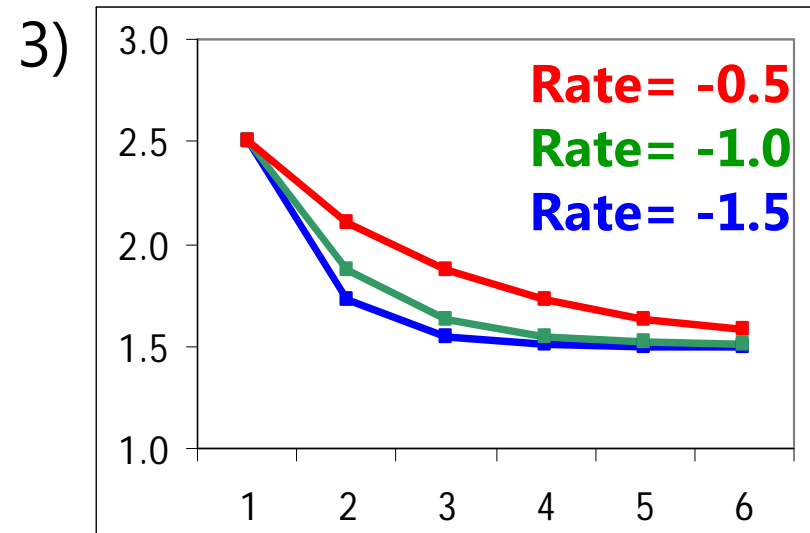
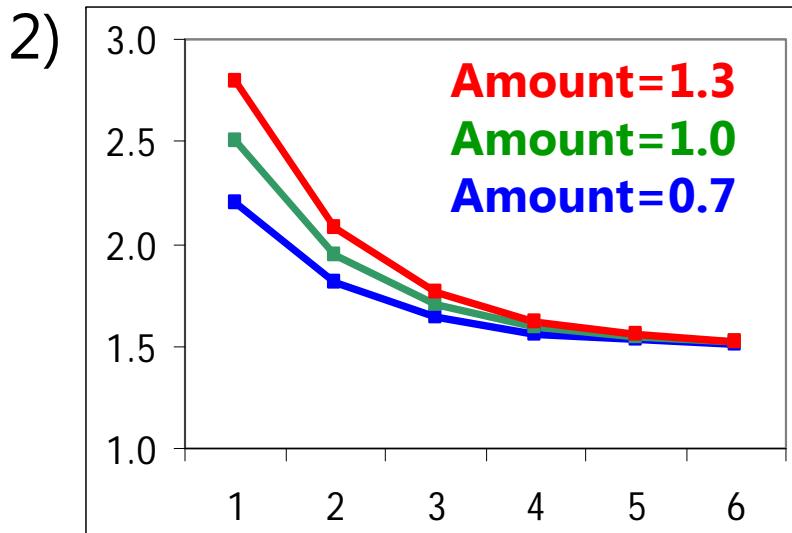
(Negative) Exponential Model Parameters



1) Different **Asymptotes**, same amount and rate

2) Different **Amounts**, same asymptote and rate

3) Different **Rates**, same asymptote and amount



Exponential Model (3 Random Effects)

Level 1: $y_{ti} = \beta_{0i} + \beta_{1i} \cdot \exp(\beta_{2i} \cdot \text{Time}_{ti}) + e_{ti}$

Level 2 Equations (one per β):

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

β_{0i} ↑ Asymptote for person i
 γ_{00} ↑ Fixed (mean) Asymptote
 u_{0i} ↑ Random (Deviation) Asymptote

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

β_{1i} ↑ Amount for person i
 γ_{10} ↑ Fixed (mean) Amount
 u_{1i} ↑ Random (Deviation) Amount

$$\beta_{2i} = \gamma_{20} + u_{2i}$$

β_{2i} ↑ Rate for person i
 γ_{20} ↑ Fixed (mean) Rate
 u_{2i} ↑ Random (Deviation) Rate

Fixed Effect Subscripts:

1st = which Level 1 term

2nd = which Level 2 term

Number of Possible Slopes by Number of Occasions (n):

Fixed slopes = $n - 1$

Random slopes = $n - 2$

Also need 4 occasions to fit random exponential model

(Likely need way more occasions to find U_{2i} , though)

Describing Within-Person Change in Longitudinal Data

- Topics:
 - Multilevel modeling notation and terminology
 - Fixed and random effects of linear time
 - Predicted variances and covariances from random slopes
 - Dependency and effect size in random effects models
 - Describing nonlinear change: polynomial, piecewise models, and truly nonlinear models
 - **Fun with likelihood estimation and model comparisons**

3 Decision Points for Model Comparisons

1. Are the models **nested** or **non-nested**?

- Nested: have to add OR subtract effects to go from one to other
 - Can conduct significance tests for improvement in fit
- Non-nested: have to add AND subtract effects
 - No significance tests available for these comparisons

2. Differ in model for the **means**, **variances**, or **both**?

- Means? Can only use ML $-2\Delta LL$ tests (or p -value of each fixed effect)
- Variances? Can use ML (or preferably REML) $-2\Delta LL$ tests, no p -values
- Both sides? Can only use ML $-2\Delta LL$ tests

3. Models estimated using **ML** or **REML**?

- ML: All model comparisons are ok
- REML: Model comparisons are ok for the variance parameters only

Likelihood-Based Model Comparisons

- Relative model fit is indexed by a “**deviance**” statistic → **-2LL**
 - Log of likelihood (**LL = total data height**) of observing the data given model parameters, $-2*LL$ so that the differences between model LL values follow $\sim\chi^2$
 - **-2LL is a measure of BADNESS of fit, so smaller values = better models**
 - Models are compared using their deviance values (significance tests)
 - Two estimation flavors (labeled as $-2 \log$ likelihood in SAS, SPSS, but given as LL instead in STATA): Maximum Likelihood (**ML**) or Restricted (Residual) ML (**REML**)
- Fit is also indexed by **Information Criteria** that reflect **-2LL** deviance AND # parameters used and/or sample size
 - **AIC** = Akaike IC = $-2LL + 2 * (\#parameters)$
 - **BIC** = Bayesian IC = $-2LL + \log(N) * (\#parameters)$ → penalty for complexity
 - In ML → #parameters = all parameters (means and variances models)
 - In REML → #parameters = variance model parameters only (except in STATA!)
 - No significance tests or critical values, just “smaller is better”

– $2\Delta LL$ (i.e., LRT, Deviance) Tests: (models must use the same estimator & N)

1. Calculate $-2\Delta LL$: $(-2LL_{\text{fewer}}) - (-2LL_{\text{more}})$
 2. Calculate Δdf : $(\# \text{Parms}_{\text{more}}) - (\# \text{Parms}_{\text{fewer}})$
 3. Compare $-2\Delta LL$ to χ^2 distribution with $df = \Delta df$
CHIDIST function in excel will give exact p-values for the difference test; so will STATA
1. & 2. must be positive values!
- Fixed effects $p < .05$: $-2\Delta LL(1) > 3.84$, $-2\Delta LL(2) > 5.99$, $-2\Delta LL(3) > 7.82$
 - Some controversy about $-2\Delta LL$ tests when testing random effects variances that cannot be negative (i.e., the “boundary problem”)
 - χ^2 is not distributed as usual (mean=df) \rightarrow is actually a mixture χ^2 with df and df–1, so using the critical χ^2 for actual df results in conservative model comparison test
 - e.g., $-2\Delta LL(df=2) > 5.99$, whereas $-2\Delta LL(df=\text{mixture of } 1,2) > 5.14$
 - Two proposed solutions when testing random effects variances:
 - For random intercepts, can use a 1-tailed test (χ^2 for $p < .10$): $-2\Delta LL(1) > 2.71$
 - Use mixture p -value = $0.5 \cdot \text{prob}(\chi^2_{df-1} > -2\Delta LL) + 0.5 \cdot \text{prob}(\chi^2_{df} > -2\Delta LL)$
 - In practice these assume no relationship among how well variance parameters are estimated, which is suspect \rightarrow I tend to just use the conservative test and call it good

Critical Values for 50:50 χ^2 Mixtures

df (q)	Significance Level				
	0.10	0.05	0.025	0.01	0.005
0 vs. 1	1.64	2.71	3.84	5.41	6.63
1 vs. 2	3.81	5.14	6.48	8.27	9.63
2 vs. 3	5.53	7.05	8.54	10.50	11.97
3 vs. 4	7.09	8.76	10.38	12.48	14.04
4 vs. 5	8.57	10.37	12.10	14.32	15.97
5 vs. 6	10.00	11.91	13.74	16.07	17.79
6 vs. 7	11.38	13.40	15.32	17.76	19.54
7 vs. 8	12.74	14.85	16.86	19.38	21.23
8 vs. 9	14.07	16.27	18.35	20.97	22.88
9 vs. 10	15.38	17.67	19.82	22.52	24.49
10 vs. 11	16.67	19.04	21.27	24.05	26.07

This may work ok if only one new parameter is bounded ... for example:

+ Random Intercept
df=1: 2.71 vs. 3.84

+ Random Linear
df=2: 5.14 vs. 5.99

+ Random Quad
df=3: 7.05 vs. 7.82

Critical values such that the right-hand tail probability =
 $0.5 \times \Pr(\chi^2_q > c) + 0.5 \times \Pr(\chi^2_{q+1} > c)$

Source: Appendix C (p. 484) from Fitzmaurice, Laird, & Ware (2004).
Applied Longitudinal Analysis. Hoboken, NJ: Wiley

ML vs. REML

Remember “population” vs. “sample” formulas for calculating variance?

Population: $\sigma_e^2 = \frac{\sum_{i=1}^N (y_i - \mu)^2}{N}$

Sample: $\sigma_e^2 = \frac{\sum_{i=1}^N (y_i - \bar{y})^2}{N-1}$

All comparisons must have same N!!!	ML	REML
To select, type...	METHOD=ML (-2 log likelihood)	METHOD=REML <i>default</i> (-2 res log likelihood)
In estimating variances, it treats fixed effects as...	Known (df for having to also estimate fixed effects is not factored in)	Unknown (df for having to estimate fixed effects is factored in)
So, in small samples, L2 variances will be...	Too small (less difference after N=30-50 or so)	Unbiased (correct)
But because it indexes the fit of the...	Entire model (means + variances)	Variances model only
You can compare models differing in...	Fixed and/or random effects (either/both)	Random effects only (same fixed effects)

Rules for Comparing Multilevel Models

All observations must be the same across models!

Compare Models Differing In:

Type of Comparison:	Means Model (Fixed) Only	Variance Model (Random) Only	Both Means and Variance Model (Fixed and Random)
<u>Nested?</u> YES, can do significance tests via...	Fixed effect p -values from ML or REML -- OR -- ML $-2\Delta LL$ only (NO REML $-2\Delta LL$)	NO p -values REML $-2\Delta LL$ (ML $-2\Delta LL$ is ok if big N)	ML $-2\Delta LL$ only (NO REML $-2\Delta LL$)
<u>Non-Nested?</u> NO signif. tests, instead see...	ML AIC, BIC (NO REML AIC, BIC)	REML AIC, BIC (ML ok if big N)	ML AIC, BIC only (NO REML AIC, BIC)

Nested = one model is a direct subset of the other

Non-Nested = one model is not a direct subset of the other

Summary: Model Comparisons

- Significance of **fixed effects** can be tested with EITHER their ***p*-values** OR **ML $-2\Delta LL$** (LRT, deviance difference) tests
 - *p*-value → Is EACH of these effects significant? (fine under ML or REML)
 - ML $-2\Delta LL$ test → Does this SET of predictors make my model better?
 - *REML $-2\Delta LL$ tests are WRONG for comparing models differing in fixed effects*
- Significance of **random effects** can only be tested with **$-2\Delta LL$ tests** (preferably using REML; here ML is not wrong, but results in too small variance components and fixed effect SEs in smaller samples)
 - Can get *p*-values as part of output but *shouldn't* use them
 - #parms added (df) should always include the random effect covariances
- My recommended approach to building models:
 - Stay in REML (for best estimates), test new fixed effects with their *p*-values
 - THEN add new random effects, testing $-2\Delta LL$ against previous model

Example Sequence for Testing Fixed and Random Polynomial Effects of Time

Build up fixed and random effects simultaneously:

1. Empty Means, Random Intercept → to calculate ICC
2. Fixed Linear, Random Intercept → check fixed linear p -value
3. Random Linear → check $-2\Delta LL(df \approx 2)$ for random linear variance
4. Fixed Quadratic, Random Linear → check fixed quadratic p -value
5. Random Quadratic → check $-2\Delta LL(df \approx 3)$ for random quadratic variance
6.

*** In general: Can use **REML** for all models, so long as you:

- Test significance of new **fixed** effects by their **p -values**
- Test significance of new **random** effects in separate step by **$-2\Delta LL$**
- Also see if AIC and BIC are smaller when adding random effects