

# From CLRM to Multilevel Model

$$e_{ij} = \beta_j^0 + \beta_j^{lr} \text{lftrt}_{ij} + \dots + \varepsilon_{ij}$$

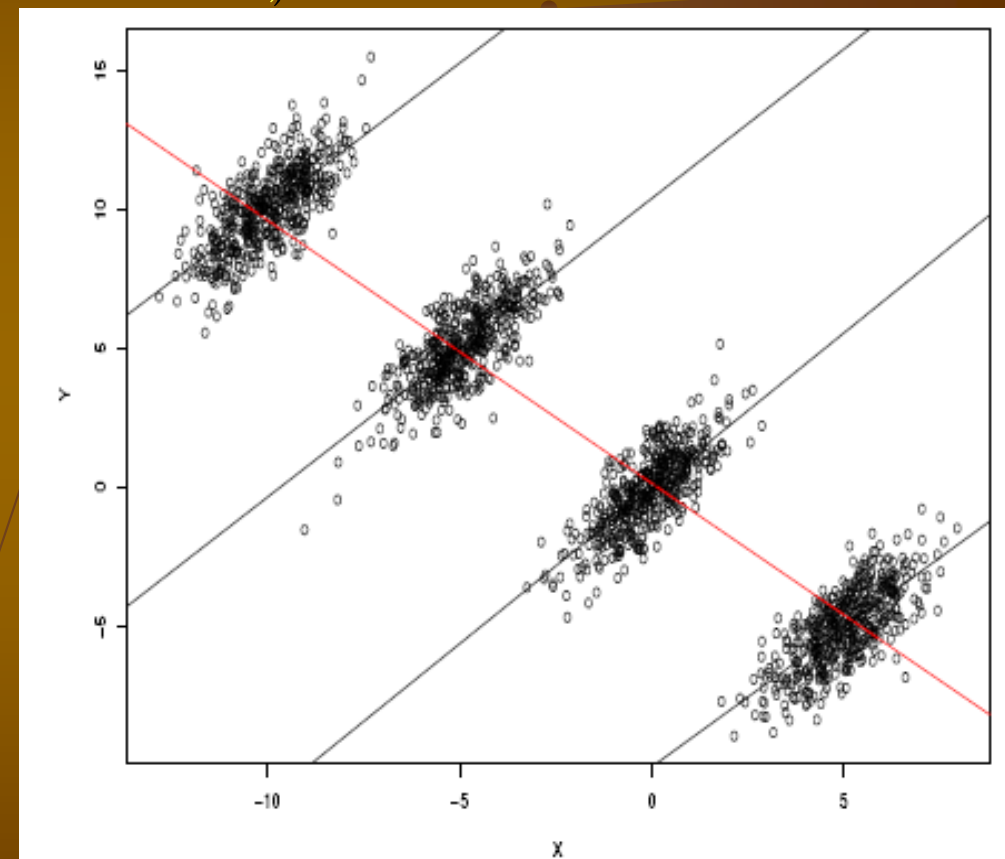
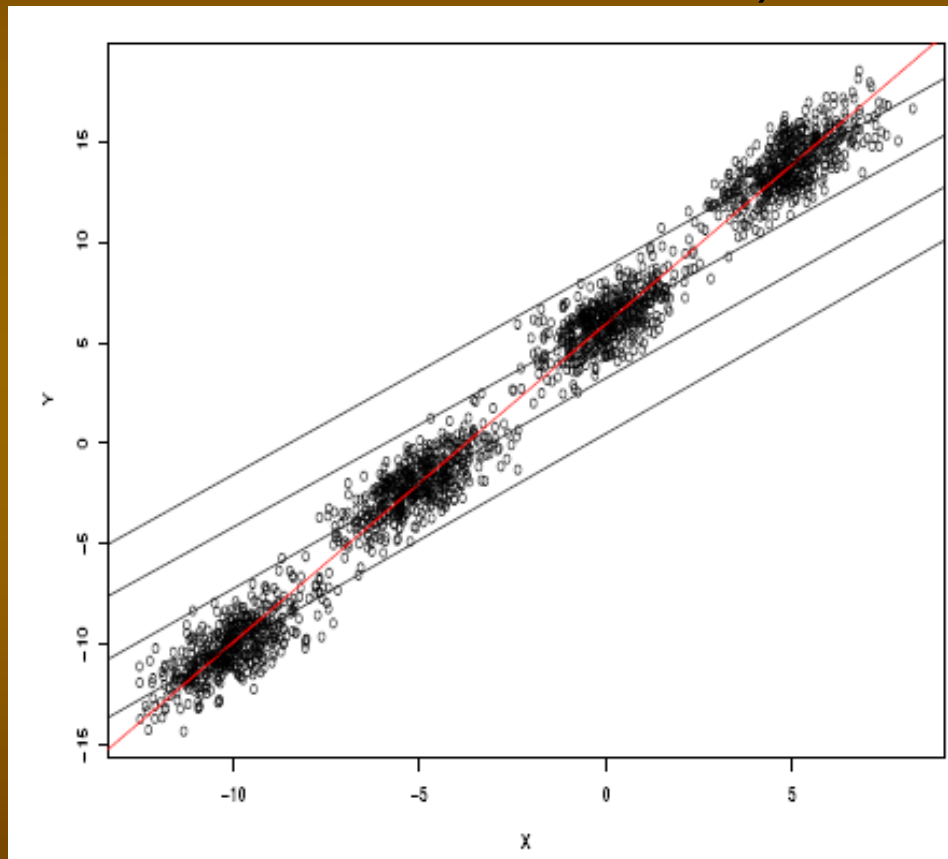
$$\beta_j^0 = \alpha_0 + \alpha_1 \text{GSPEND}_j + u_j^0$$

$$\beta_j^{lr} = \gamma_0 + \gamma_1 \text{GSPEND}_j + u_j^1$$

- If CLRM assumptions apply, then OLS unbiased, consistent, and efficient.
  - Two main issues of concern:
    - Parameter heterogeneity: (see pictures)
      - systematic &/or stochastic (fixed v. rndm intrcpt/coeff)
      - can cause bias if pattern unmodeled hetero relates to X,
    - Non-spherical error cov-mat: an efficiency & proper s.e.'s issue, not a bias/consistency one
      - But “mere inefficiency” can be serious.
      - And accurate std err's very important.

# From the CLRM to HLM

- Examples of parameter heterogeneity that covaries w/  $X$  values, so bias:



- Note: FE v. RE both theoretically could cause bias if cov w/  $X$ , but latter i.d.'d off orthog

# From the CLRM to RE Model

- Std. R.E. Model: Odd that std. lin-interact model:

- Assumes know  $y=f(X)+error$ :  $y_i = \beta_0 + \beta_x x_i + \beta_z z_i + \beta_{xz} x_i z_i + \varepsilon_i$

- But  $dy/dx=f(z)$  w/o error!:  $\frac{\partial y}{\partial x} = \beta_x + \beta_{xz} xz$

- So, try:  $y = \beta_0 + \beta_1 x + \beta_2 z + \varepsilon^0$

$$\frac{\partial y}{\partial x} \equiv \beta_1 = \alpha_0 + \alpha_1 z + \varepsilon^1$$

$$\frac{\partial y}{\partial z} \equiv \beta_2 = \gamma_0 + \gamma_1 x + \varepsilon^2$$

$$\Rightarrow y = \beta_0 + (\alpha_0 + \alpha_1 z + \varepsilon^1) x + (\gamma_0 + \gamma_1 x + \varepsilon^2) z + \varepsilon^0$$

$$= \beta_0 + \alpha_0 x + \gamma_0 z + (\alpha_1 + \gamma_1) xz + (\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z)$$

- => std. lin-interact...except compound error-term...

- Std. HLM: Same model, except  $x_{ij}$  &  $z_j$ , &

- So std lin-interact, but w/ diff compound-error struct.

$$\varepsilon^* = \varepsilon_{ij}^0 + \varepsilon_j^1 x_{ij} + \varepsilon_{ij}^2 z_j$$

# From CLRM to Hierarchical Model

- Std. HLM: Same model, except  $x_{ij}$  &  $z_j$ , &
  - So a std. lin-interact too, but with different compound-error stochastic properties.

$$\text{eusup}_{ij} = \beta_j^0 + \beta_j^{lr} \text{lfrt}_{ij} + \dots + \varepsilon_{ij}$$

$$\beta_j^0 = \alpha_0 + \alpha_1 \text{GSPEND}_j + u_j^0$$

$$\beta_j^{lr} = \gamma_0 + \gamma_1 \text{GSPEND}_j + u_j^1$$

$$\Rightarrow \text{eusup}_{ij} = \alpha_0 + \alpha_1 \text{GSPEND}_j + u_j^0 + \gamma_0 \text{lfrt}_{ij} \\ + \gamma_1 \text{lfrt}_{ij} \times \text{GSPEND}_j + \text{lfrt}_{ij} u_j^1 + \dots + \varepsilon_{ij}$$

gathering terms :

$$\text{eusup}_{ij} = \alpha_0 + \dots + \alpha_1 \text{GSPEND}_j + \gamma_0 \text{lfrt}_{ij} \\ + \gamma_1 \text{lfrt}_{ij} \times \text{GSPEND}_j + \dots + (u_j^0 + \text{lfrt}_{ij} u_j^1 + \varepsilon_{ij})$$

$$\Rightarrow \frac{\partial \text{eusup}}{\partial \text{lfrt}} = b_{\text{lfrt}} + b_{lrGS} \text{GS} + u_j^1 \quad \& \quad \frac{\partial \text{eusup}}{\partial \text{GS}} = b_{GS} + b_{lrGS} \text{edu}$$

$$E\left(\frac{\partial \text{eusup}}{\partial \text{lfrt}}\right) = b_{\text{lfrt}} + b_{lrGS} \text{GS}$$

# Properties of OLS under HLM Conditions

- Properties of OLS Estimates of Lin-Interact Model if truly RE/HLM:

$$y = \beta_0 + \beta_x x + \beta_z z + \beta_{xz} xz + (\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z) = \mathbf{X}\boldsymbol{\beta} + (\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z)$$

- So, OLS coeff. est's still differ from truth by  $\Lambda\varepsilon^*$ :

$$\begin{aligned}\hat{\boldsymbol{\beta}}_{LS} &= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'y = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'[\mathbf{X}\boldsymbol{\beta} + (\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z)] \\ &= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{X}\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'(\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z) = \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\varepsilon^*\end{aligned}$$

- So, OLS coeff. est's unbiased & consistent:

$$\begin{aligned}E(\hat{\boldsymbol{\beta}}_{LS}) &= E[\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\varepsilon^*] = E[\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'(\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z)] \\ &= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'E(\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z) = \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'[E(\varepsilon^0) + E(\varepsilon^1)x + E(\varepsilon^2)z] \\ &= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'[0 + E(\varepsilon^1)x + E(\varepsilon^2)z] = \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'[0 + 0 + 0] = \boldsymbol{\beta}. \quad Q.E.D.\end{aligned}$$

- Note: only works for models w/ additively separable stochastic component; not nec'ly for others (log/prob)

# Properties of OLS under HLM Conditions

- But, OLS s.e.'s will be wrong; not  $s^2(\mathbf{X}'\mathbf{X})^{-1}$ , but:

$$\begin{aligned}V(\hat{\boldsymbol{\beta}}_{LS}) &= V\left[\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}^*\right] \\&= V[\boldsymbol{\beta}] + V\left[(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}^*\right] + 2C\left[\boldsymbol{\beta}, (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}^*\right] \\&= 0 + V\left[(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}^*\right] + 0 \\&= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'V(\boldsymbol{\varepsilon}^*)\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\&= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\left[V(\boldsymbol{\varepsilon}^0 + \boldsymbol{\varepsilon}^1\mathbf{x} + \boldsymbol{\varepsilon}^2\mathbf{z})\right]\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\&= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\left[V(\boldsymbol{\varepsilon}^0) + V(\boldsymbol{\varepsilon}^1\mathbf{x}) + V(\boldsymbol{\varepsilon}^2\mathbf{z})\right]\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\&\quad \text{(the covariance terms are assumed zero)}\end{aligned}$$

# Sandwich Estimators

$$V(\hat{\beta}_{LS}) = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' [V(\varepsilon^0) + V(\varepsilon^1 \mathbf{x}) + V(\varepsilon^2 \mathbf{z})] \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1}$$

- Not  $\sigma^2 I$  (even if each  $\varepsilon^*$  is), so whole thing doesn't reduce to  $\sigma^2 (\mathbf{X}'\mathbf{X})^{-1}$ , so OLS s.e.'s wrong?
- Be OK on avg (unbiased) & in limit (consistent) if that term varied in way “orthogonal to  $\mathbf{X}\mathbf{X}'$ ”
  - But def'ly not b/c  $[\cdot]$  includes  $\mathbf{x}$  &  $\mathbf{z}$ , which part of  $\mathbf{X}$ !
  - =brilliant insight of ‘robust’ (i.e., consistent) s.e. est's:
    - Only need s.e. formula that accounts relation  $V(\varepsilon^*)$  to “ $\mathbf{X}'\mathbf{X}$ ”, i.e., regressors, squares, & cross-prod's involved in  $\mathbf{X}'[\cdot]\mathbf{X}$ ”
- $\Rightarrow$  “, robust” & “, cluster” can work (for RE & HLM, resp'ly)
  - $\hat{V}(\hat{\beta})_{RE} = \sigma^2 (\mathbf{I} + \mathbf{xx}' + \mathbf{zz}')$  so track  $e^2$  rel  $\mathbf{xx}'$  &  $\mathbf{zz}' \Rightarrow [\cdot] = \frac{1}{n} \sum_{i=1}^n e_i^2 \mathbf{X}_i \mathbf{X}_i'$
  - $\hat{V}(\hat{\beta})_{HM} = \sigma_0^2 \mathbf{I} + \sigma_1^2 \mathbf{xx}' + \sigma_2^2 \mathbf{zz}'$  sim + grpng  $\Rightarrow h [\cdot] = \sum_{j=1}^J \left\{ \left( \sum_{i=1}^{n_j} e_{ij} \mathbf{X}_{ij} \right)' \left( \sum_{i=1}^{n_j} e_{ij} \mathbf{X}_{ij} \right) \right\}$

# From the CLRM to HLM

$$y = \beta_0 + \alpha_0 x + \gamma_0 z + (\alpha_1 + \gamma_1) xz + (\varepsilon^0 + \varepsilon^1 x + \varepsilon^2 z)$$

$$V(\hat{\beta}_{LS}) = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' [V(\varepsilon^0) + V(\varepsilon^1 x) + V(\varepsilon^2 z)] \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1}$$

- $\Rightarrow$  appropriate “, robust” & “, cluster” can work
  - I.e., asymptotically std errs right...BUT need large  $n_j$
  - I.e., coefficients still inefficient.
    - Want/need efficiency, or  $n_j$  low? HLM/RE or FGLS/FWLS.
    - Note: similarity RE/RC and HLM, RE & FWLS. As suggests, RE only helps efficiency and only rightly does so if that's all it does. (I.e., if the RE's orthogonal to X.)
  - I.e., “work” thusly for models with additively-separable stochastic components
    - As w/ all such “sandwich” estimators, logical disconnect in applying them to models w/o such separability.



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- So, OLS coeff. est's sill differ from truth by  $\mathbf{A}\boldsymbol{\varepsilon}^*$ :

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- So, OLS coeff. est's unbiased & consistent (*iff*...):

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- Note: only works for models with additively separable stochastic component; not nec'y others (e.g., logit/probit)

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*(note: the covariance terms are assumed zero)*

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- $\hat{V}(\hat{\beta})_{RE} = \sigma^2 (\mathbf{I} + \mathbf{x}\mathbf{x}' + \mathbf{z}\mathbf{z}')$  so track  $e^2$  rel  $\mathbf{x}\mathbf{x}'$  &  $\mathbf{z}\mathbf{z}' \Rightarrow$  *heterosked.*:

$$[\cdot] = \frac{1}{n} \sum_{i=1}^n e_i^2 \mathbf{X}_i \mathbf{X}_i'$$

- $\hat{V}(\hat{\beta})_{HM} = \sigma_0^2 \mathbf{I} + \sigma_1^2 \mathbf{x}\mathbf{x}' + \sigma_2^2 \mathbf{z}\mathbf{z}'$  sim+grpng  $\Rightarrow$  *cluster*:

$$[\cdot] = \sum_{j=1}^J \left\{ \left( \sum_{i=1}^{n_j} e_{ij} \mathbf{X}_{ij} \right)' \left( \sum_{i=1}^{n_j} e_{ij} \mathbf{X}_{ij} \right) \right\}$$

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$$V(\hat{\beta}_{LS}) = (X'X)^{-1} X' [V(\varepsilon^0) + V(\varepsilon^1 x) + V(\varepsilon^2 z)] X (X'X)^{-1}$$

- $\Rightarrow$  appropriate “, robust” & “, cluster” can work
  - I.e., asymptotically s.e.’s right... BUT need large  $n_j$  &  $N-k$ 
    - Specifically, from small-sample corrections, seems need small:  
$$\left[ n_j / (n_j - 1) \right] \left[ (N - 1) / (N - k) \right]$$
  - I.e., coefficients still inefficient.
    - Want/need efficiency, or  $n_j$  or  $N-k$  low? HLM/RE or FGLS/FWLS.
    - Note: similarity RE/RC and HLM, RE & FWLS. As that sim suggests, RE/RC only helps efficiency and only rightly does so if that’s all it does. (I.e., if the RE/RC’s orthogonal to  $X$ .)
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    - As w/ all such “sandwich” estimators, a sort of logical disconnect in applying them to models w/o such separability...