

Stochastic-Term Heterogeneity in Panel/TSCS

I. Recall Implications of *Model 2!*TM Strategy; first, call all RHS: $\mathbf{X}\boldsymbol{\beta}$, and suppose it's rightly specified.

$$\hat{\boldsymbol{\beta}}_{OLS} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'(\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon})$$

A.

$$= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{X}\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}$$

$$= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon} \Rightarrow E(\hat{\boldsymbol{\beta}}) = \boldsymbol{\beta} \text{ if } E(\mathbf{X}'\boldsymbol{\varepsilon}) = 0 \text{ (as usual)}$$

$$V(\hat{\boldsymbol{\beta}}_{OLS}) = V\left[(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}\right] = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'V(\boldsymbol{\varepsilon})\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$$

B.

$$= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\sigma^2\mathbf{I}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$$

$$= \sigma^2 (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$$

$$= \sigma^2 (\mathbf{X}'\mathbf{X})^{-1} \text{ if } V(\boldsymbol{\varepsilon}) = \sigma^2\mathbf{I}, \text{ (as usual)}$$

C. OLS=BLUE if model right^(*temporal, **spatial) ...

1. * Even if right RHS time-dynamic model, LDV covaries conditional mean, α_i , proportionally to $1/T = \text{Nickell-Hurwicz bias of } O(1/T)$. Small- T sample bias; still consistent in T .

2. ** Even if right RHS spatial-dynamic model, spatial lag covaries with residual because classic endogeneity: $y_i \Rightarrow y_j$ but also $y_j \Rightarrow y_i$.

D. If model not rt., or insuff., some decent properties may still hold

1. Argument of Franzese *PA* (2005): From theory-eval. perspective, worry about unmodeled heterogeneity only insofar as failure to model adequately biases or otherwise worsens estimates of what can model/understand, or certainty-estimates thereof.

2. Demonstrated there that hierarchical structure of error components *per se* does not bias OLS estimates of cross-level interactive models, as follows. Does bias OLS v-cov(**b**) estimates, however.

a) *Note*: demonstration is for linear model (separable error-components); may not apply for nonlinear (nonseparable stochastic components is real issue).

E. For example, suppose use just linear-interaction, when truth is linear-interaction w/ error (=random coefficients):

$$\text{Truth: } y_{it} = x_{it} (\gamma_0 + \gamma_1 z_{it} + \phi_i) + \varepsilon_{it}$$

$$\text{Model: } y_{it} = x_{it} (\gamma_0^* + \gamma_1^* z_{it}) + \varepsilon_{it}^*$$

$$\begin{aligned} \Rightarrow \hat{\boldsymbol{\beta}}_{OLS} &= \left(\begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' \mathbf{y} \\ &= \left(\begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' [\gamma_0 \mathbf{X} + \gamma_1 \mathbf{X} \cdot \mathbf{Z} + \boldsymbol{\phi} \cdot \mathbf{X} + \boldsymbol{\varepsilon}] \end{aligned}$$

$$1. \quad = \begin{bmatrix} \gamma_0 \\ \gamma_1 \end{bmatrix} + \left(\begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{X} & \mathbf{XZ} \end{bmatrix}' [\boldsymbol{\phi} \cdot \mathbf{X} + \boldsymbol{\varepsilon}]$$

$$\Rightarrow E(\hat{\boldsymbol{\beta}}) = \boldsymbol{\beta} \text{ if } E(\boldsymbol{\phi} \cdot \mathbf{X}) = \mathbf{0}, E(\mathbf{X}'\boldsymbol{\varepsilon}) = 0$$

$$\mathbf{V}(\hat{\boldsymbol{\beta}}_{OLS}) = \mathbf{V} \left[(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y} \right] = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' \mathbf{V}(\mathbf{x} \cdot \boldsymbol{\phi} + \boldsymbol{\varepsilon}) \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1}$$

$$2. \quad = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' \sigma^2 \boldsymbol{\Omega} \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1}$$

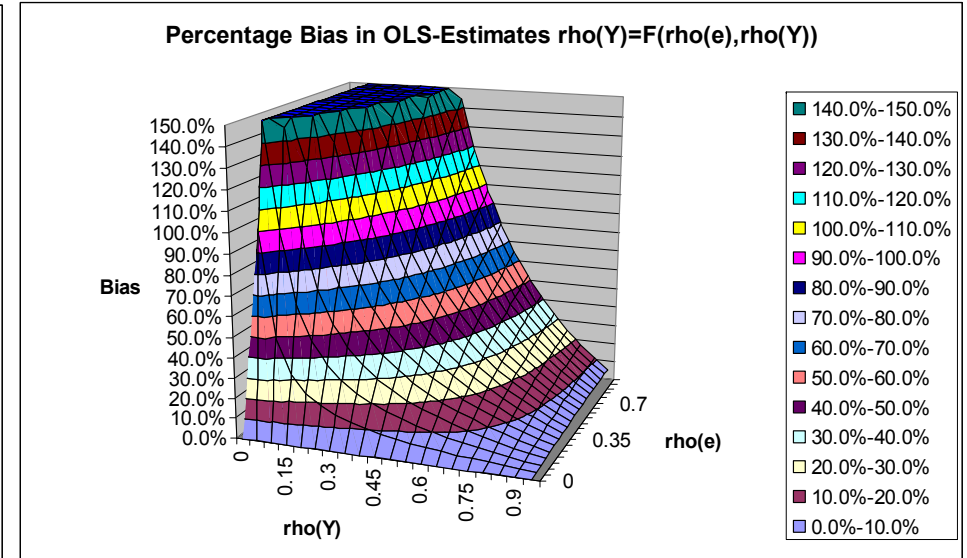
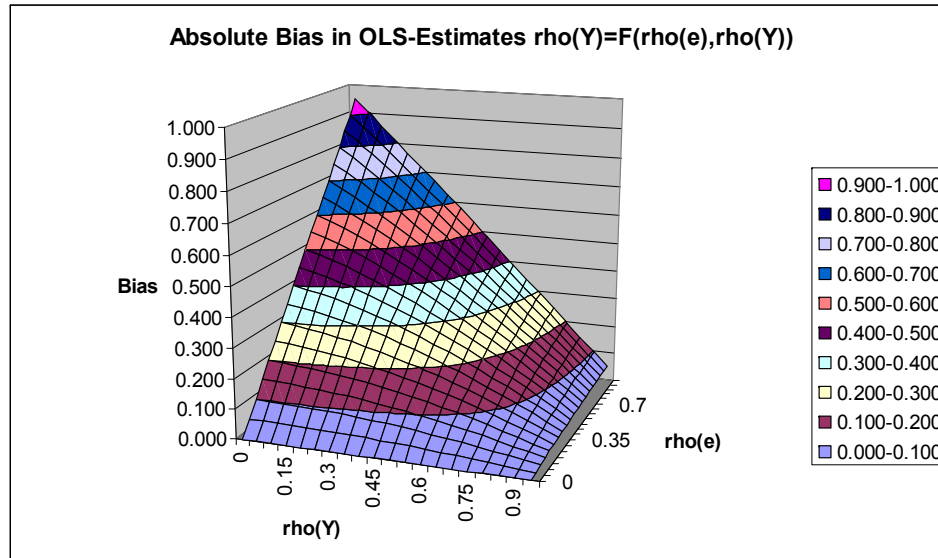
3. OLS=unbiased, but inefficient \mathbf{b} ; wrong v-cov(\mathbf{b}); some easy redresses

F. (Time-)Serial Dependence:

1. If temporal dynamics specified in systematic component sufficiently (no residual/stoch.-component corr. remains, which testable), OLS \rightarrow^A BLUE.
2. If insufficient, OLS inconsistent, but still:

a) Magnitude of the problem: $E(\hat{\rho}_y) = \rho_y + \rho_\varepsilon (1 - \rho_y^2) / (1 + \rho_\varepsilon \rho_y)$

b) And can (partially) address s.e. part of problem (as shall see...)



G. Spatial Dependence:

1. If all in stochastic component, & $\text{Cov}(\mathbf{X}, \boldsymbol{\varepsilon}) = \mathbf{0}$, then remains unbiased-but-inefficient coefficient-estimation, wrong s.e.
2. Recall that, if in systematic component, simultaneity bias even if rt RHS.

H. Limited & Qualitative Dep-Vars:

1. All these situations are more complicated...

2. Recall: issue is nonseparable stochastic component, not or more than nonlinearity or limited nature *per se*.

a) For instance, can't do likelihood NT obs as NT conditionally independent binary outcomes, so likelihood not just product of NT unidimensional distributions, but one NT-dimensional multivariate distribution.

I. Implications *Model 2t!*TM Strategy (read as flow-chart, left-to-right)

<i>Model 2t!</i> TM Adequacy	Second-Moment & Inadequacy Variance-Covariance Structure		Implications for OLS Properties
Model E(y) Sufficient	V(e) Spherical		OLS is BLUE
	V(e) Nonspherical	Nonsphericity Unrelated \mathbf{xx}'	OLS \mathbf{b} unbiased, inefficient; OLS V(\mathbf{b}) unbiased, inefficient
		Nonsphericity Related \mathbf{xx}'	OLS \mathbf{b} unbiased, inefficient; OLS V(\mathbf{b}) biased, inefficient
Model E(y) Insufficient	Unmodeled \mathbf{b} het unrelated \mathbf{X}	V(e) Will be Nonspherical & Related \mathbf{xx}'	OLS \mathbf{b} unbiased, inefficient; OLS V(\mathbf{b}) biased, inefficient
	Unmodeled \mathbf{b} het related to \mathbf{X}	V(e) Will be Nonspherical & Related \mathbf{xx}'	OLS \mathbf{b} biased, inefficient; OLS V(\mathbf{b}) biased, inefficient

II. Some Tests for Various Forms Non-Sphericity

A. White's General Test:

c. White test if form of Heteroskedasticity is unknown:

$$H_0: V[\varepsilon_i | x_i] = \sigma^2$$

$$H_a: V[\varepsilon_i | x_i] = \sigma_i^2$$

Estimate the model under H_0

Compute squared residuals: e_i^2

Use squared residuals as dependent variable of auxiliary regression: RHS: all regressors, their quadratic forms and interaction terms:

$$e_i^2 = \delta_0 + \delta_1 x_{i2} + \dots + \delta_{k-1} x_{ik} + \delta_{k-1} x_{i2}^2 + \delta_{k+1} x_{i2} x_{i3} + \dots + \delta_q x_{ik}^2 + \xi_i$$

Compute White statistic from R^2 of auxiliary regression: $n * R^2 \xrightarrow{a} \chi_{(q)}^2$

Use one-sided test and check if $n * R^2$ is larger than 95% quantile of χ^2

1. Can also do Wald or loss-of-fit F-test on RHS (asym. normality); Results intuitive, constructive, and directly relate to “more pernicious” form het

B. Many, Many Heteroskedasticity-Test Strategies:

help regress postestimation (estat [command])

1. Szroeter's class of tests:

$$S = \frac{\sum_{i=1}^{NT} h(x_i) e_i^2}{\sum_{i=1}^{NT} e_i^2} \text{ where } h(x_i) \text{ is some weight increasing in } x_i$$

a) King (1982) (another King, not Gary) suggests $h(x) = \text{rank}(x)$.

b) estat szroeter gives a Q-statistic transformation of S such that, under homoscedasticity, Q is approximately $N(0,1)$ distributed (Judge 1985:452).

2. Goldfeld-Quandt: sort e_i by some var. Take high & low sets, \mathbf{e}_1 & \mathbf{e}_2 , (some evidence more power discard middle set), & stat:

$$\frac{\mathbf{e}'_1 \mathbf{e}_1 / (n_1 - k)}{\mathbf{e}'_2 \mathbf{e}_2 / (n_2 - k)} = F \sim F_{n_1 - k, n_2 - k}$$

3. Glesjer's: Wald or $NT \times R^2$ test coefficients: $\ln e_i^2 = \delta_0 + \delta_1 z_{1i} + \dots + \delta_{kz} z_{ki} + v_i$;
can think White's important special case Glesjer's.

4. **Breusch-Pagan** LM test for known form: groupwise (i.e., panel) het.

$$LM = \frac{T}{2} \sum_{i=1}^n \left(\frac{s_i^2}{s^2} - 1 \right)^2$$

s_i^2 = sum of group-specific squared residuals

s^2 = OLS residuals

H0: homoskedasticity \sim Chi² with n-1 degrees of freedom

LM-test assumes normality of residuals, not appropriate if assumption not

5. **Likelihood Ratio Test**: $-2\Delta \ln(L) \sim^A \chi_{\Delta k}^2$, for any pair estimable models. For panel(groupwise)-heteroskedasticity, test is:

$$-2 \ln(\lambda) = (NT) \ln(\sigma^2) - \sum (T \ln(\sigma_i^2)) \sim \chi^2 (dF = n - 1)$$

C. **LM ARCH-Tests** (test-statistic $T \times R^2 \sim \chi^2_{(s)}$). For example:

$$e_t^2 = \delta_0 + \delta_1 x_{1t} + \dots + \delta_k x_{kt} + \sum_{s=1}^S \lambda_s e_{t-s}^2$$

D. Spatial LM tests: (elab Thursday)

- “Testing” (measuring) Spatial Association:

$$\text{Moran's I: } I = \frac{N}{S} \frac{\boldsymbol{\varepsilon}' \mathbf{W} \boldsymbol{\varepsilon}}{\boldsymbol{\varepsilon}' \boldsymbol{\varepsilon}}, \text{ where } S = \sum_{i=1}^N \sum_{j=1}^N w_{ij}, \text{ if row-nrmlzd: } I = \frac{\boldsymbol{\varepsilon}' \mathbf{W} \boldsymbol{\varepsilon}}{\boldsymbol{\varepsilon}' \boldsymbol{\varepsilon}}$$

- See also Anselin’s LISA...

- LM’s appropriate for LS residu (F&H OxfHndbk):

$$LM_{\rho} = \frac{\hat{\sigma}_{\varepsilon}^2 (\hat{\boldsymbol{\varepsilon}}' \mathbf{W} \mathbf{y} / \hat{\sigma}_{\varepsilon}^2)^2}{G + T \hat{\sigma}_{\varepsilon}^2}, \text{ and } LM_{\lambda} = \frac{(\hat{\boldsymbol{\varepsilon}}' \mathbf{W} \hat{\boldsymbol{\varepsilon}} / \hat{\sigma}_{\varepsilon}^2)^2}{T}$$

- But these test v. *iid*, & over-reject...

- Robust LM tests appropriate for SAR v. SAE:

$$LM_{\rho}^* = G^{-1} \hat{\sigma}_{\varepsilon}^2 (\hat{\boldsymbol{\varepsilon}}' \mathbf{W} \mathbf{y} / \hat{\sigma}_{\varepsilon}^2 - \hat{\boldsymbol{\varepsilon}}' \mathbf{W} \hat{\boldsymbol{\varepsilon}} / \hat{\sigma}_{\varepsilon}^2)^2, \text{ and } LM_{\lambda}^* = \frac{\left(\hat{\boldsymbol{\varepsilon}}' \mathbf{W} \hat{\boldsymbol{\varepsilon}} / \hat{\sigma}_{\varepsilon}^2 - \left[T \hat{\sigma}_{\varepsilon}^2 (G + T \hat{\sigma}_{\varepsilon}^2)^{-1} \right] \hat{\boldsymbol{\varepsilon}}' \mathbf{W} \mathbf{y} / \hat{\sigma}_{\varepsilon}^2 \right)^2}{T \left[1 - \frac{T \hat{\sigma}_{\varepsilon}^2}{G + T \hat{\sigma}_{\varepsilon}^2} \right]}$$

- Robust Joint Test: $LM_{\rho\lambda} = LM_{\lambda} + LM_{\rho}^* = LM_{\rho} + LM_{\lambda}^*$

E. Tests of Temporal Correlation (ELAB THURSDAY...)

1. Many, many of these also.

2. My favorite...

LM (Time-)Serial-Correlation Tests (test-statistic $T \times R^2 \sim \chi^2_{(s)}$):

$$e_t = \delta_0 + \delta_1 x_{1t} + \dots + \delta_k x_{kt} + \sum_{s=1}^S \lambda_s e_{t-s}$$

3. (a.k.a., Breusch-Godfrey).....for same reasons Glesjer's/White's favorite among hetttests:

a) Uses familiar, intuitive strategy. Constructive. Powerful.

b) **Plus:** valid following LDV model (include among x in auxiliary regression) unlike, e.g., DW; flexible (works either MA or AR).

III. Redresses, some partial &/or imperfect, of non-spherical $V(\mathbf{e})$ deficiencies in implementation of the *Model Qt!*TM strategy:

A. “Robust” or “Sandwich” Variance-Covariance Estimators

1. **Key Insight:** Ω has $\frac{1}{2}n(n+1) > n$ parameters; however, for consistent v-cov est: need consistent est only of $\mathbf{X}'\Omega\mathbf{X}$, which only $\frac{1}{2}k(k+1)$ elements total.

2. Proper $v(\hat{\beta}_{LS}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\Omega\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}$ differs from OLS $v(\hat{\beta}_{OLS}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}$, only insofar as $\mathbf{X}'\Omega\mathbf{X}$ differs from $\mathbf{X}'\mathbf{X}$, which is only insofar as elements of Ω covary with elements of \mathbf{xx}' , i.e. ω_{ij} w/ x 's, x^2 's, &/or cross-products of x 's.

3. Visualizing the matrix multiplication, we see that v-cov estimates using LS formula are off by factor of: $\sum_{i,j,s,t} e_{it}e_{js}(\mathbf{x}_{it}\mathbf{x}'_{js}) - \sum_{i,t} e_{it}^2\mathbf{I}_k$.

4. \therefore , we can *fix* our v-cov estimates, i.e. render them *robust*, i.e., consistent, to presence of certain pattern nonsphericity by replacing $\mathbf{X}'\Omega\mathbf{X}$ in formula w/ some $\sum_{i,j,s,t} e_{it}e_{js}(\mathbf{x}_{it}\mathbf{x}'_{js})$ configured to reflect that nonsphericity pattern.

$$\hat{V}_s(\hat{\beta}) = (\mathbf{X}'\mathbf{X})^{-1}\widehat{\mathbf{X}'\Omega\mathbf{X}}(\mathbf{X}'\mathbf{X})^{-1} \equiv (\mathbf{X}'\mathbf{X})^{-1}\hat{\mathbf{Q}}(\mathbf{X}'\mathbf{X})^{-1}$$

B. Cases of (Robust/Sandwich) Consistent V-Cov(**b**) Estimators:

1. Pure Heteroskedasticity (White's):
$$\hat{\mathbf{Q}} = \sum_i \sum_t e_{it}^2 (\mathbf{x}_{it} \mathbf{x}'_{it})$$

2. Pure Het. & (Time) Auto-Correlation (HAC) (Newey-West):

$$\hat{\mathbf{Q}} = \sum_i \sum_t e_{it}^2 (\mathbf{x}_{it} \mathbf{x}'_{it}) + \sum_i \sum_t \left(\sum_{s=1}^L w_s e_{it} e_{i,t-s} (\mathbf{x}_{it} \mathbf{x}'_{i,t-s} + \mathbf{x}_{i,t-s} \mathbf{x}'_{it}) \right)$$

where $L = \max$ lag-length considered appreciable & $w_t = 1 - \frac{t}{L-1}$

3. Panel Heteroskedasticity: i.e., constant variance within unit, but differing across units: could write, but would be subsumed by White's

4. Panel Het. & (Time) Auto-Correlation: panel heteroskedasticity + unit-specific temporal correlation: could write, but Newey-West would subsume.

5. Panel Het. & Contemporaneous (Spatial) Corr. (Beck-Katz PCSE):

$$\hat{\mathbf{Q}} = \mathbf{X}' \left(\frac{\mathbf{E}'\mathbf{E}}{T} \otimes \mathbf{I}_T \right) \mathbf{X} , \text{ where } \mathbf{E} = \text{the } T \times N \text{ matrix estimated residuals}$$

6. Many others possible. Several “cluster” types, e.g., designed for various multilevel/hierarchical data structures (i.e., panel ‘random-effect’ structure):

$$\hat{V}(\hat{\boldsymbol{\beta}}) = \frac{1}{N-k} (\mathbf{X}'\mathbf{X})^{-1} \left(\sum_{j=1}^{n_c} \left\{ \begin{bmatrix} \sum_{i=1}^{n_j} e_i \mathbf{x}_i \\ \sum_{i=1}^{n_j} e_i \mathbf{x}_i \end{bmatrix}' \right\} \right) (\mathbf{X}'\mathbf{X})^{-1}$$

where $n_j = \#$ obs. i in macro-level (cluster) j , & $n_c = \#$ clusters

7. Note: excepting Newey-West, asymptotics for these tend to be in N or in some function of N & T , not in T . Many may not work well in TSCS.

8. Some not assuredly “well-behaved” in estimation, so various *kludges*.

9. Small-sample adjusts been suggested for each; may be key in TSCS...

a) E.g., “[For White’s,] Davidson & MacKinnon (1993: 554) strongly suggest a finite-sample correction of replacing e_i^2 by $e_i^2 / (1 - \mathbf{x}_i(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i)$, which scales estimated squared residuals by their variance, or multiplying by $N/(N-k)$, which inflates estimates by factor reflecting the number of regressors as a percentage of degrees freedom. Accumulating simulation work favors their suggestion.”

b) E.g., for clustered: “As with [White’s], a finite-sample (degrees-of-freedom) correction, $[n_c/(n_c-1)][(N-1)/(N-k)]$, is suggested. This inflates standard errors as there, but now multiplicatively further, by a declining function of J . Again, simulations strongly support using such adjustments.”

c) Need note (using `help vcetype`, manuals) which of these adjustments Stata applies as defaults or options.

d) From many MC’s I’ve seen on Cluster, PCSE, etc., more attention to these small-sample adjustments would be a good thing, in TSCS esp.

IV. FGLS: Feasible Generalized-Least-Squares

A. Consistent V-Cov ests only address inconsistency of s.e.'s, not bias or efficiency coefficient estimates (although require consistent coefficient-estimates for formal properties); nor address s.e. unbiasedness, efficiency.

B. To improve efficiency coeff (& s.e.) estimates—still not directly or formally redress any bias concerns arising from other problems, OVB e.g., and still reliant on ‘first-stage’ consistency—can parameterize and estimate $\hat{\Omega}$, use it to transform the data to such that C(N)LRM applies.

C. Example: *Parks-Kmenta FGLS* for TSCS:

1. Panel-specific AR(1) in residuals $\Rightarrow N$ parameters

2. Panel-specific $\sigma_i^2 \Rightarrow N$ parameters

3. Dyad-specific $\sigma_{ij} \Rightarrow N(N-1)$ parameters (n.b., symmetric)

4. $\Rightarrow N(N+1)$ pars \Rightarrow unless $T \gg 2N$, inadvisable (Beck-Katz ‘95)

5. Note: Could offer more theoretically structured (& thereby parametrically reduced) structure non-sphericity pattern \Rightarrow greater efficiency & better small-sample properties. E.g., just contemp corr. $\Rightarrow N(N-1)$ parameters needs $T \gg N$.

D. FGLS: **properties:** (assuming consistent 1st-stage) consistent & asymptotically efficient. **Estimation:**

FGLS: given consistent est $\hat{\Omega}$, let $\mathbf{P} \equiv \hat{\Omega}^{-\frac{1}{2}}$, then:

$$\mathbf{P}\mathbf{y} = \mathbf{P}\mathbf{X}\boldsymbol{\beta} + \mathbf{P}\boldsymbol{\varepsilon} \Rightarrow \hat{\boldsymbol{\beta}}_{FGLS} = \left[(\mathbf{P}\mathbf{X})' (\mathbf{P}\mathbf{X}) \right]^{-1} (\mathbf{P}\mathbf{X})' \mathbf{P}\mathbf{y}$$

$$\hat{\boldsymbol{\beta}}_{FGLS} = \left[\mathbf{X}'\mathbf{P}'\mathbf{P}\mathbf{X} \right]^{-1} \mathbf{X}\mathbf{P}'\mathbf{P}\mathbf{y} = \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1} \mathbf{X}'\hat{\Omega}^{-1}\mathbf{y}$$

\Rightarrow consistent and asympt'ly efficient if $C(\mathbf{X}, \boldsymbol{\varepsilon}) = 0$

$$\widehat{V\left(\hat{\boldsymbol{\beta}}_{FGLS}\right)}_{FGLS} = \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1} \mathbf{X}'\hat{\Omega}^{-1}\mathbf{V}(\mathbf{y})\hat{\Omega}^{-1}\mathbf{X} \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1}$$

$$\widehat{V\left(\hat{\boldsymbol{\beta}}_{FGLS}\right)}_{FGLS} = \hat{\sigma}^2 \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1} \mathbf{X}'\hat{\Omega}^{-1}\hat{\Omega}\hat{\Omega}^{-1}\mathbf{X} \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1}$$

$$\widehat{V\left(\hat{\boldsymbol{\beta}}_{FGLS}\right)}_{FGLS} = \hat{\sigma}^2 \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1} \mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1}$$

$$\widehat{V\left(\hat{\boldsymbol{\beta}}_{FGLS}\right)}_{FGLS} = \hat{\sigma}^2 \left[\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X} \right]^{-1}$$

\Rightarrow "consistent and asympt'ly efficient" (as above)