LECTURE 12: GLS II

Example 1: Grouping (or data on averages)

Suppose the "true" model is \( y = X\beta + \varepsilon \) where \( \text{E}\varepsilon = 0 \) and \( \text{V}(\varepsilon) = \sigma^2 I \).

Suppose that the available data are \( [\bar{y} \ \bar{X}] \) arranged in \( M (> K) \) groups and the group means are the only given (e.g. city or firm averages). Thus, we have to consider the model \( \bar{y} = \bar{X}\beta + \bar{\varepsilon} \) where \( \bar{y} \) is \( M \times 1 \) and \( \bar{X} \) is \( M \times K \).

Now: \( \bar{y} = Gy \) where \( G \) is \( M \times N \). \( \text{E}\bar{\varepsilon} = 0 \) and \( \text{V}(\bar{\varepsilon}) = \sigma^2 GG' \). Similarly, \( \bar{X} = GX \)

Then \( \hat{\beta}_G = (\bar{X}'(GG')^{-1}\bar{X})^{-1}\bar{X}'(GG')^{-1}\bar{\varepsilon} \) with variance \( \sigma^2 (\bar{X}'(GG')^{-1}\bar{X})^{-1} \). In terms of the unobserved \( X \) and \( y \), \( \hat{\beta}_G = (X'QX)^{-1}X'Qy \) with \( Q = G'(GG')^{-1}G \). \( Q \) has an interesting structure.

Let's see what \( GG' \) looks like.

With 3 observations in the first group, 4 in second and 2 in third, we have

\[
G = \begin{bmatrix}
\frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}
\]

and

\[
GG' = \begin{bmatrix}
\frac{1}{3} & 0 & 0 \\
0 & \frac{1}{4} & 0 \\
0 & 0 & \frac{1}{2}
\end{bmatrix}
\]
If \( P \) denotes the factor that will be used to transform the model to the standard case, we have

\[
P = \begin{bmatrix}
\frac{1}{\sqrt{3}} & 0 & 0 \\
0 & \frac{1}{\sqrt{4}} & 0 \\
0 & 0 & \frac{1}{\sqrt{2}} \\
\end{bmatrix}
\]

since \( PP' = GG' \). Note that \( P \) just divides each observation by its standard deviation. \( \text{(If we had the same number of observations in each group, what would this imply?)} \)

**Example 2:** GLS Prediction

Let \( Ey = X\beta \) and \( V(y) = \Sigma \). Suppose we know \( X_{N+1} \), and we want to predict \( y_{N+1} \).

Note that \( \hat{y}_{N+1} = X_{N+1} \hat{\beta} \) is unbiased. But \( \epsilon_{N+1} \) is correlated with \( \epsilon \). How can this correlation be used to improve the forecast?

Let \( E\epsilon_{N+1}\epsilon = w \) where \( \epsilon_{N+1} \) is 1x1 and \( \epsilon \) is Nx1.

Let \( \hat{y}_{N+1} = c'y \) be a linear predictor.

Unbiasedness implies that \( E(\hat{y}_{N+1} - y_{N+1}) = 0 = (c'X - X_{N+1})\hat{\beta} \). Thus \( c'X = X_{N+1} \). \( \text{(why?)} \)

The prediction error is \( c'\epsilon - \epsilon_{N+1} \) with variance \( c'\Sigma c + \sigma^2 - 2c'w \).

Minimize this variance subject to \( c'X = X_{N+1} \) using the multiplier \( 2\lambda \).

First order conditions yield

\[
\begin{bmatrix}
\Sigma & X \\
X' & 0
\end{bmatrix}
\begin{bmatrix}
c \\
-\lambda
\end{bmatrix}
= \begin{bmatrix}
w \\
X_{N+1}
\end{bmatrix}
\]

Solving for \( c \), we get
\[ c^* = \Sigma^{-1}[I - X(X'\Sigma^{-1}X)^{-1}X']w + \Sigma^{-1}X(X'\Sigma^{-1}X)^{-1}X_{N+1} \]

using the first part of the partitioned inverse.

Note: \[ \hat{y}_{N+1} = c^*y = X_{N+1}\hat{\beta}_G + w^{'}\Sigma^{-1}(y - X\hat{\beta}_G) \]

which uses the correlation between \( \epsilon_{N+1} \) and \( \epsilon \). The last term is the expectation of \( \epsilon_{N+1} \) gives \( \epsilon \).

\( \Sigma \) and \( w \) are usually modelled as functions of a small number of parameters.

**SEEMINGLY UNRELATED REGRESSION EQUATIONS (SURE):** (Zellner)

Let \( y_j = X_j\beta_j + \epsilon_j \quad j = 1, \ldots, M \) where \( y_j \) is Nx1, \( X_j \) is NxK, \( \beta_j \) is Kx1, and \( \epsilon_j \) is Nx1.

Stacking up these M regressions yields \( y = X\beta + \epsilon \) where \( y \) is MNx1, \( X \) is MNxMK, \( \beta \) is MKx1, and \( \epsilon \) is MNx1.

Note that

\[
\begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_M
\end{bmatrix}
= \begin{bmatrix}
X_1 & 0 & \cdots & 0 \\
0 & X_2 & \cdots & 0 \\
0 & 0 & \cdots & 0 \\
0 & 0 & \cdots & X_M
\end{bmatrix}
\begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_M
\end{bmatrix}
\]

and

\[
E\epsilon\epsilon^{'} = 
\begin{bmatrix}
E\epsilon_1\epsilon_1^{'} & E\epsilon_1\epsilon_2^{'} & \cdots & E\epsilon_1\epsilon_M^{'} \\
E\epsilon_2\epsilon_1^{'} & E\epsilon_2\epsilon_2^{'} & \cdots & E\epsilon_2\epsilon_M^{'} \\
\vdots & \vdots & \ddots & \vdots \\
E\epsilon_M\epsilon_1^{'} & E\epsilon_M\epsilon_2^{'} & \cdots & E\epsilon_M\epsilon_M^{'}
\end{bmatrix}
\]

Suppose \( E\epsilon_i\epsilon_i^{'} = \sigma_{ii}I \). (Notation convention: no square)

Then each equation satisfies the standard conditions but \( E\epsilon_j\epsilon_j^{'} = \sigma_{jj}I \neq 0 \) is the equations are
correlated with each other. 
Think of independent observations on a system of correlated equations.

Let the MxM matrix $\Sigma$ have elements $\sigma_{ij}$ and $\Sigma^{-1}$ have elements $\sigma^{-1}_{ij}$. (Note that $\sigma_{ij} \neq \sigma^{-1}_{ij}$.) Then

$$ E\varepsilon\varepsilon' = \Sigma \otimes I = \begin{bmatrix}
\sigma_{11} I & \sigma_{12} I & \ldots & \sigma_{1M} I \\
\sigma_{21} I & \sigma_{22} I & \ldots & \sigma_{2M} I \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{M1} I & \sigma_{M2} I & \ldots & \sigma_{MM} I
\end{bmatrix} 
$$

where $\otimes$ is the Kronecker product. Note $(\Sigma \otimes I)^{-1} = \Sigma^{-1} \otimes I$ (verify).

Thus $\hat{\beta}_G = (X' (\Sigma^{-1} \otimes I) X)^{-1} X' (\Sigma^{-1} \otimes I) y$. Here

$$ \Sigma^{-1} \otimes I = \begin{bmatrix}
\sigma_{11} I & \sigma_{12} I & \ldots & \sigma_{1M} I \\
\sigma_{21} I & \sigma_{22} I & \ldots & \sigma_{2M} I \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{M1} I & \sigma_{M2} I & \ldots & \sigma_{MM} I
\end{bmatrix}. $$

Writing out $\hat{\beta}_G$ gives

$$ \hat{\beta}_G = \begin{bmatrix}
\sigma_{11} X_1' X_1 & \sigma_{12} X_1' X_2 & \ldots & \sigma_{1M} X_1' X_M \\
\sigma_{21} X_1' X_1 & \sigma_{22} X_1' X_2 & \ldots & \sigma_{2M} X_1' X_M \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{M1} X_1' X_1 & \sigma_{M2} X_1' X_2 & \ldots & \sigma_{MM} X_1' X_M
\end{bmatrix}^{-1} \begin{bmatrix}
\sum_{j=1}^M \sigma_{1j} X_1' y_j \\
\sum_{j=1}^M \sigma_{2j} X_2' y_j \\
\vdots \\
\sum_{j=1}^M \sigma_{Mj} X_M' y_j
\end{bmatrix}. $$

where the first term on the right hand side is $(X' (\Sigma^{-1} \otimes I) X)^{-1}$ and the second term is $X' (\Sigma^{-1} \otimes I) y$.

The “unbalanced” case, with different sample sizes for different equations, is straightforward with appropriate changes in the dimensions of the “stacked” matrices.

Notes:

**Proposition 1:** If $\sigma_{ij} = 0$ for $i \neq j$, then $\hat{\beta}_G = \hat{\beta}$ obtained by estimating each equation by the LS method. In other words, when the equations are not correlated with each other, estimation of each
equation by the LS method gives the GLS estimators. (why?)

Proposition 2: If \( X_1 = X_2 = \ldots = X_M \), then \( \hat{\beta}_G = \hat{\beta} \) obtained by estimating each equation by the LS method.

Proof: Let \( X = I \otimes X_1 \) where \( X \) is MNxMK, \( I \) is MxM, and \( X_1 \) is NxK.

We know that \( \hat{\beta}_G = (X'(\Sigma^{-1} \otimes I)X)^{-1}X'(\Sigma^{-1} \otimes I)y \). Substituting for \( X \) yields

\[
\hat{\beta}_G = ((I \otimes X_1)'(\Sigma^{-1} \otimes I)(I \otimes X_1))^{-1}(I \otimes X_1)'(\Sigma^{-1} \otimes I)y.
\]

Using the property \((A_1 \otimes B_1)(A_2 \otimes B_2) = A_1A_2 \otimes B_1B_2\),

\[
\hat{\beta}_G = (\Sigma^{-1} \otimes X_1'X_1)^{-1}((\Sigma^{-1} \otimes X_1)'(\Sigma^{-1} \otimes I)y = (I \otimes (X_1'X_1)^{-1})X_1'y.
\]

Note that \((X_1'X_1)^{-1}X_1'y\) gives the vector of the LS estimators for the first equation.

Example: Here is an example which shows the efficiency gain over the LS estimators.

Consider a two-equation system with \( X_1'X_2 = 0 \), that is, the regressors in the equations are orthogonal, \( R[X_1] \cap R[X_2] = \emptyset \). Then

\[
\hat{\beta}_G = \begin{bmatrix} \sigma_{11}X_1'X_1 & 0 \\ 0 & \sigma_{22}X_2'X_2 \end{bmatrix}^{-1} \begin{bmatrix} \sigma_{11}X_1'y_1 + \sigma_{12}X_1'y_2 \\ \sigma_{21}X_2'y_1 + \sigma_{22}X_2'y_2 \end{bmatrix}
\]

Let \( \hat{\beta}_G^1 \) represent the vector of coefficients estimates for the first equation. Then

\[
\hat{\beta}_G^1 = (X_1'X_1)^{-1}X_1'y_1 + (\sigma_{12}/\sigma_{11})(X_1'X_1)^{-1}X_1'y_2.
\]

Note that \( E\hat{\beta}_G^1 = \beta_1 \).

We will show that \( V(\hat{\beta}_G^1) = (\sigma_{11} - \sigma_{12}^2/\sigma_{22})(X_1'X_1)^{-1} \)

Using the expression for \( \hat{\beta}_G^1 \), we can get
\[
V(\hat{\beta}_G) = \sigma_{11}(X'_1X_1)^{-1} + (\sigma_{12}/\sigma_{11})^2(X'_1X_1)^{-1}\sigma_{22} + 2(\sigma_{12}/\sigma_{11})\sigma_{12}(X'_1X_1)^{-1}. \quad (why?)
\]

Recall that
\[
\begin{bmatrix}
\sigma_{11} & \sigma_{12} \\
\sigma_{21} & \sigma_{22}
\end{bmatrix}
\begin{bmatrix}
\sigma_{11} & \sigma_{12} \\
\sigma_{21} & \sigma_{22}
\end{bmatrix}
= I.
\]

This implies that \(\sigma_{11} = \sigma_{22}/(\sigma_{11}\sigma_{22} - \sigma_{12}^2)\) and \(\sigma_{12} = -\sigma_{12}/(\sigma_{11}\sigma_{22} - \sigma_{12}^2)\). This is a simple trick to remember or reobtain the partitioned inversion formula. Thus

\[
V(\hat{\beta}_G) = [\sigma_{11} + (-\sigma_{12}/\sigma_{22})^2\sigma_{22} - 2(\sigma_{12}/\sigma_{22})\sigma_{12}](X'_1X_1)^{-1}. \quad \text{Hence}
\]

\[
V(\hat{\beta}_G) = (\sigma_{11} - \sigma_{12}/\sigma_{22})(X'_1X_1)^{-1} < \sigma_{11}(X'_1X_1)^{-1}.
\]

The second term in the variance gives the efficiency gain. It is useful to divide by the variance of the LS estimator, \(\sigma_{11}(X'_1X_1)^{-1}\), to get relative efficiency \(1 - \rho^2\) where \(\rho^2\) is the correlation squared.

\textit{Case of unknown covariance matrix (Feasible SURE):}

Let \(e_j = y_j - X_j\hat{\beta}_j\) be the vector of LS residuals from equation \(j\).

Define an \(M\times M\) matrix \(S\) such that \(S = \{S_{j\ell}\}_{j,\ell} = 1,2,\ldots,M\) where \(S_{j\ell} = e'_j e_\ell/(N - K)\).

Note that \(ES = \Sigma\). (That is, \(S_{j\ell}\) is an unbiased estimator of \(\Sigma_{j\ell} = \sigma_{j\ell}\).)

(If \(K\) and/or \(N\) are different in each equation, degrees of freedom have to be adjusted.)

Using \(S\) instead of \(\Sigma\) gives Zellner's estimator. This estimator will have the same asymptotic distribution as \(\hat{\beta}_G\) calculated with known \(\Sigma\).

Note that the LS estimator \(\hat{\beta}\) is the same as the ML estimator, even with \(\sigma^2\) unknown. This is not true in the case of a GLS estimator. \((why\ not?)\)
Suppose we iterate:
1. Calculate $S^k$ using $\beta^k$ (with $\beta^1$ the LS estimator).
2. Calculate $\beta^{k+1}$ using $S^k$ in the GLS formula.
3. If $|\beta^{k+1} - \beta^k| < \eta$ where $\eta$ is a small number, then stop. Else, go to 1.

On convergence this gives the ML estimator.

**Time-series of cross sections:**

Consider $y_t = X_t \beta_t + \epsilon_t$ with $t = 1, 2, ..., T$ where $y_t$ is $N \times 1$, $X_t$ is $N \times K$, $\beta_t$ is $K \times 1$, and $\epsilon_t$ is $N \times 1$.

Notes:
1. Each equation corresponds to a time period; usually $T$ is small and $N$ is large.
2. Allowing time correlation and estimating the $T \times T$ matrix $\Sigma$ is not difficult.
3. We often want to test $\beta_t = \beta_t'$ for all times or a subset.