

Seemingly Unrelated Regression (SUR) Models as a Generalized Least Squares (GLS) Solution to Path Analytic Models

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Multivariate Regression

$$\mathbf{Y}_{(N \times p)} = \mathbf{X}_{(N \times k)} \mathbf{B}_{(k \times p)} + \boldsymbol{\varepsilon}_{(N \times p)}$$

where \mathbf{Y} is a matrix of p dependent variables, \mathbf{X} is a k -dimensional design matrix, and $\boldsymbol{\varepsilon}$ is an error matrix, which is assumed to be distributed as:

$$\boldsymbol{\varepsilon}_{(N \times p)} \sim \mathbf{N}_{(N \times p)}(\mathbf{0}, \boldsymbol{\Sigma} \otimes \mathbf{I}_N)$$

Multivariate Regression

Multivariate regression theory using ordinary least squares (OLS) assumes that all of the \mathbf{B} coefficients in the model are unknown and to be estimated from the data as:

$$\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1} (\mathbf{X}'\mathbf{Y})$$

SUR Models

Zellner (1962) formulated the Seemingly Unrelated Regression (SUR) model as p correlated regression equations, which has also been referred to as multiple-design multivariate (MDM) models (Srivastava, 1967).

The p regression equations are “seemingly unrelated” because taken separately the error terms would follow standard linear OLS linear model form.

Multiple Univariate Regression

Calculating p separate standard OLS solutions ignores any correlation among the errors across equations; however, because the dependent variables are correlated and the design matrices may contain some of the same variables there may be “contemporaneous” correlation among the errors across the p equations.

SUR Models

SUR models are applied when there are several equations, which appear to be unrelated but are related by the fact that:

- (1) some coefficients are the same or assumed to be zero;
- (2) the disturbances are correlated across equations; and/or
- (3) a subset of right hand side variables are the same.

SUR Models

SUR Models allow each of the p dependent variables to have a **different design matrix** with some of the predictor variables being the same.

SUR models allow for a variable to be **both** in the **Y** and **X** matrices, which has particular relevance to **Path Analysis**.

SUR Model

$$E[\mathbf{Y}_{(N \times p)}] = \{ \mathbf{X}_1_{(N \times m_1)} \beta_1_{(m_1 \times 1)}, \mathbf{X}_2_{(N \times m_2)} \beta_2_{(m_2 \times 1)}, \mathbf{X}_j_{(N \times m_j)} \beta_j_{(m_j \times 1)}, \mathbf{X}_p_{(N \times m_p)} \beta_p_{(m_p \times 1)} \}$$

$$E(\mathbf{y}_v)_{(Np \times 1)} = \begin{bmatrix} \hat{\mathbf{y}}_1 & (N \times 1) \\ \hat{\mathbf{y}}_2 & (N \times 1) \\ \dots & \\ \hat{\mathbf{y}}_j & (N \times 1) \\ \dots & \\ \hat{\mathbf{y}}_p & (N \times 1) \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ (N \times m_1) & \mathbf{X}_2 & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \dots & (N \times m_2) & \dots & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{X}_j & \dots & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ (sym) & (N \times m_j) & \mathbf{X}_p & \dots & \mathbf{0} & \mathbf{0} \\ (Np \times M) & & (N \times m_p) & & & \end{bmatrix} \begin{bmatrix} \beta_1_{(m_1 \times 1)} \\ \beta_2_{(m_2 \times 1)} \\ \beta_j_{(m_j \times 1)} \\ \beta_p_{(m_p \times 1)} \end{bmatrix}$$

where M is the total number of parameters estimated over the p models,

$$M = \sum_{j=1}^p m_j$$

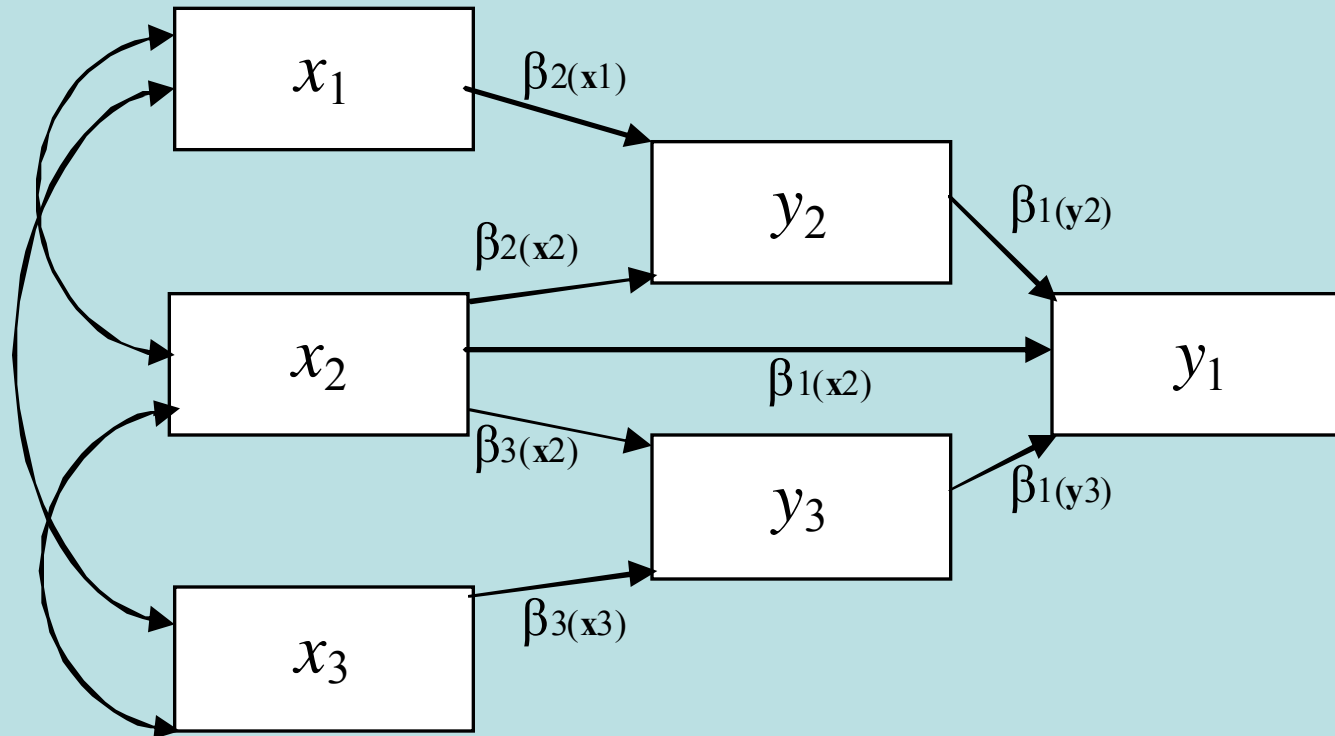
SUR Model

$$\hat{\mathbf{B}}_{(M \times 1)} = \begin{bmatrix} \mathbf{D}' & \mathbf{Q}^{-1} & \mathbf{D} \end{bmatrix}^{-1}_{(M \times Np) \quad (Np \times Np) \quad (Np \times M)} \begin{bmatrix} \mathbf{D}' & \mathbf{Q}^{-1} & \mathbf{y}_v \end{bmatrix}_{(M \times Np) \quad (Np \times Np) \quad (Np \times 1)}$$

\mathbf{Q} is weight matrix based on the residual covariance matrix of the \mathbf{Y} variables and is formed as:

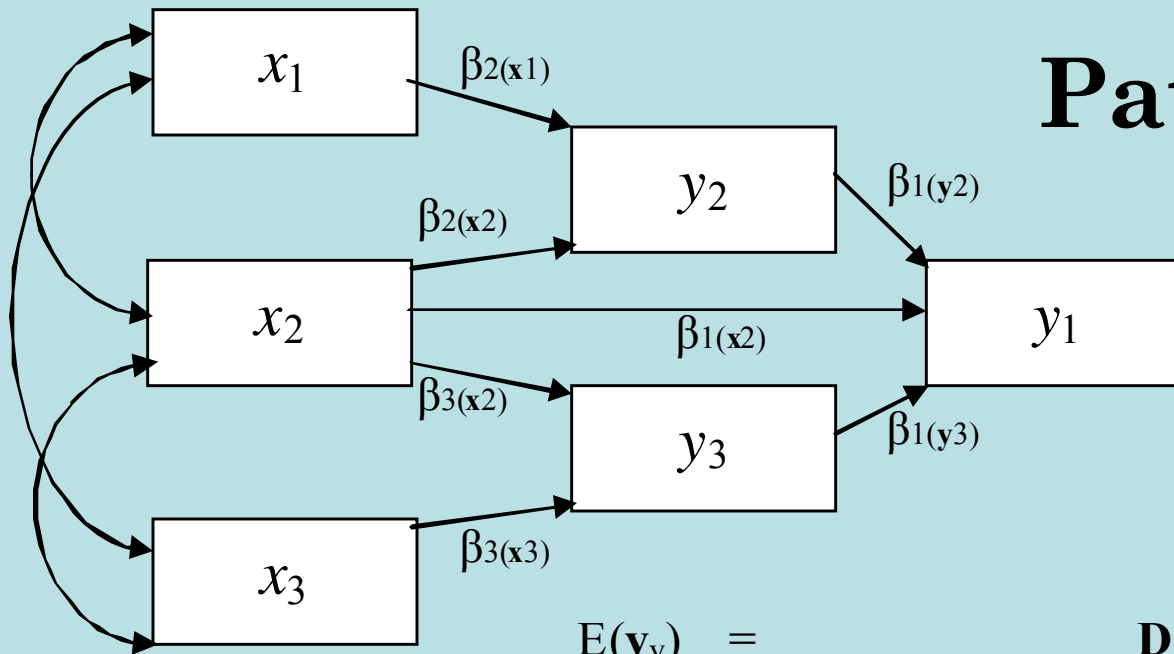
$$\mathbf{Q}_{(Np \times Np)} = \hat{\boldsymbol{\Sigma}}_{(p \times p)} \otimes \mathbf{I}_N$$

Path Model



$$\begin{aligned}
 \hat{y}_1 &= \beta_{1(y2)} y_2 + \beta_{1(y3)} y_3 + \mathbf{0} \mathbf{X}_1 + \beta_{1(x2)} \mathbf{X}_2 + \mathbf{0} \mathbf{X}_3 \\
 \hat{y}_2 &= \beta_{2(x1)} \mathbf{X}_1 + \beta_{2(x2)} \mathbf{X}_2 + \mathbf{0} \mathbf{X}_3 \\
 \hat{y}_3 &= \mathbf{0} \mathbf{X}_1 + \beta_{3(x2)} \mathbf{X}_2 + \beta_{3(x3)} \mathbf{X}_3
 \end{aligned}$$

Path Model



$$E(\mathbf{y}_v) = \begin{matrix} \hat{\mathbf{y}}_{11} \\ \hat{\mathbf{y}}_{12} \\ \dots \\ \hat{\mathbf{y}}_{1N} \\ \hat{\mathbf{y}}_{21} \\ \hat{\mathbf{y}}_{22} \\ \dots \\ \hat{\mathbf{y}}_{2N} \\ \hat{\mathbf{y}}_{31} \\ \hat{\mathbf{y}}_{32} \\ \dots \\ \hat{\mathbf{y}}_{3N} \\ (3N \times 1) \end{matrix} = \begin{matrix} \mathbf{y}_{21} & \mathbf{y}_{21} & \mathbf{x}_{21} \\ \mathbf{y}_{22} & \mathbf{y}_{22} & \mathbf{x}_{22} \\ \dots & \dots & \dots \\ \mathbf{y}_{2N} & \mathbf{y}_{21} & \mathbf{x}_{21} \\ (N \times 3) & & \\ (\text{sym}) & & \\ (N \times 2) & & \\ (N \times 2) & & \\ (3N \times 7) \end{matrix} \begin{matrix} \mathbf{D} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{x}_{11} & \mathbf{x}_{21} & \mathbf{0} & \mathbf{0} \\ \mathbf{x}_{12} & \mathbf{x}_{22} & \mathbf{0} & \mathbf{0} \\ \dots & \dots & & \\ \mathbf{x}_{1N} & \mathbf{x}_{2N} & \mathbf{0} & \mathbf{0} \\ \mathbf{x}_{21} & \mathbf{x}_{31} \\ \mathbf{x}_{22} & \mathbf{x}_{32} \\ \dots & \dots \\ \mathbf{x}_{2N} & \mathbf{x}_{3N} \\ (7 \times 1) \end{matrix} \mathbf{B}$$