

LinMod M1: 1A

Generally, for M ppm onto $\mathcal{L}(X)$, $M = X(X'X)^{-1}X'$

$$M_0: \text{orthogonal projection onto } \mathbf{1} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \Rightarrow M_0 = \mathbf{1}(\mathbf{1}'\mathbf{1})^{-1}\mathbf{1}' = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} (3)^{-1} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \\ = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \cdot \frac{1}{3} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$$

$$M_1: \text{orthog. proj. onto } X_1 = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \Rightarrow M_1 = X_1(X_1'X_1)^{-1}X_1' = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \left(\begin{bmatrix} 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} \\ = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} (2)^{-1} \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -1 \end{bmatrix} \cdot \frac{1}{2} = \begin{bmatrix} \frac{1}{2} & 0 & -\frac{1}{2} \\ 0 & 0 & 0 \\ -\frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}$$

$$M_2: \text{orthog. proj. onto } X_2 = \begin{bmatrix} \frac{1}{3} \\ -\frac{2}{3} \\ \frac{1}{3} \end{bmatrix} \Rightarrow M_2 = X_2(X_2'X_2)^{-1}X_2' = \begin{bmatrix} \frac{1}{3} \\ -\frac{2}{3} \\ \frac{1}{3} \end{bmatrix} \left(\begin{bmatrix} \frac{1}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} \frac{1}{3} \\ -\frac{2}{3} \\ \frac{1}{3} \end{bmatrix} \right)^{-1} \begin{bmatrix} \frac{1}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} \\ = \begin{bmatrix} \frac{1}{3} \\ -\frac{2}{3} \\ \frac{1}{3} \end{bmatrix} \left(\frac{6}{9} \right)^{-1} \begin{bmatrix} \frac{1}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} = \begin{bmatrix} \frac{1}{3} \\ -\frac{2}{3} \\ \frac{1}{3} \end{bmatrix} \begin{bmatrix} \frac{1}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} \cdot \frac{9}{6} = \begin{bmatrix} \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \end{bmatrix}$$

$$M_0 + M_1 + M_2 = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} + \begin{bmatrix} \frac{1}{2} & 0 & -\frac{1}{2} \\ 0 & 0 & 0 \\ -\frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix} + \begin{bmatrix} \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_3$$

Given $Y = 1 \cdot \beta_0 + X_1 \cdot \beta_1 + X_2 \cdot \beta_2 + \varepsilon$ with $\varepsilon \sim N(0, \sigma^2 I_3)$, if only 1 and X_1 are considered, are the OLS estimates of intercept (β_0) and slope (β_1) unbiased estimates of β_0 and β_1 in the true model?

Yes.

The OLS estimator for the simpler model, $Y = 1 \cdot \beta_0 + X_1 \cdot \beta_1 + \varepsilon$ is $\hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = (X'X)^{-1} X'Y$

$$\begin{aligned} \hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} &= \left(\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 1 & -1 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \quad \text{Here, } X = \begin{bmatrix} 1 & 1 \\ 1 & X_1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 1 & -1 \end{bmatrix} \\ &= \left(\begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \\ &= \frac{1}{6} \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \frac{1}{6} \begin{bmatrix} 2 & 2 & 2 \\ 3 & 0 & -3 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \frac{1}{6} \begin{bmatrix} 2Y_1 + 2Y_2 + 2Y_3 \\ 3Y_1 - 3Y_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{3}(Y_1 + Y_2 + Y_3) \\ \frac{1}{2}(Y_1 - Y_3) \end{bmatrix} \end{aligned}$$

The OLS estimator for the true model, $Y = 1 \cdot \beta_0 + X_1 \cdot \beta_1 + X_2 \cdot \beta_2 + \varepsilon$ is $\hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} = (X'X)^{-1} X'Y$

$$\text{Here, } X = \begin{bmatrix} 1 & 1 & 1 \\ 1 & X_1 & X_2 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1/3 \\ 1 & 0 & -2/3 \\ 1 & -1 & 1/3 \end{bmatrix}$$

$$\begin{aligned} \hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} &= \left(\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \\ 1/3 & -2/3 & 1/3 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1/3 \\ 1 & 0 & -2/3 \\ 1 & -1 & 1/3 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \\ 1/3 & -2/3 & 1/3 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \\ &= \left(\begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \\ 1/3 & -2/3 & 1/3 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} 1/3 & 0 & 0 \\ 0 & 1/2 & 0 \\ 0 & 0 & 1/2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & -1 \\ 1/3 & -2/3 & 1/3 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & -1/2 \\ 1/2 & -1 & 1/2 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{3}(Y_1 + Y_2 + Y_3) \\ \frac{1}{2}(Y_1 - Y_3) \\ \frac{1}{2}(Y_1 - 2Y_2 + Y_3) \end{bmatrix} \end{aligned}$$

In both cases, $\beta_0 = \frac{1}{3}(Y_1 + Y_2 + Y_3)$ and $\beta_1 = \frac{1}{2}(Y_1 - Y_3)$.

Let $\hat{\epsilon}_s$ denote residuals from fitting simpler model, $Y = 1\beta_0 + X_1\beta_1 + \epsilon_s$.

$\hat{\epsilon}_s = Y - (1\hat{\beta}_0 + X_1\hat{\beta}_1)$. Find $E[\hat{\epsilon}_t]$ where $\hat{\epsilon}_t = Y - (1\hat{\beta}_0 + X_1\hat{\beta}_1 + X_2\hat{\beta}_2)$

$$E[\hat{\epsilon}_t] = E[Y - 1\hat{\beta}_0 - X_1\hat{\beta}_1 - X_2\hat{\beta}_2]$$

$$\hat{\epsilon}_s = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} - \left(\frac{1}{3}(Y_1 + Y_2 + Y_3)\right) \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \left(\frac{1}{2}(Y_1 - Y_3)\right) \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} Y_1 - \frac{1}{3}(Y_1 + Y_2 + Y_3) - \frac{1}{2}(Y_1 - Y_3) \\ Y_2 - \frac{1}{3}(Y_1 + Y_2 + Y_3) \\ Y_3 - \frac{1}{3}(Y_1 + Y_2 + Y_3) + \frac{1}{2}(Y_1 - Y_3) \end{bmatrix} = \begin{bmatrix} \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \\ -\frac{1}{3}Y_1 + \frac{2}{3}Y_2 - \frac{1}{3}Y_3 \\ \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \end{bmatrix}$$

(3x1) (3x1)

Note: $\hat{\epsilon}_s$ is the residual after projecting Y onto 1 and X_1 .

$\hat{\epsilon}_t$ is the residual after projecting Y onto 1, X_1 , and X_2 .

Therefore, by subtracting out $\hat{\epsilon}_s$'s projection onto X_2 , what remains is the residual after projecting onto 1, X_1 , and X_2 . So $\hat{\epsilon}_t = \hat{\epsilon}_s - M_2\hat{\epsilon}_s$.

$$M_2\hat{\epsilon}_s = \begin{bmatrix} \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ \frac{1}{6} & -\frac{1}{3} & \frac{1}{6} \end{bmatrix} \begin{bmatrix} \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \\ -\frac{1}{3}Y_1 + \frac{2}{3}Y_2 - \frac{1}{3}Y_3 \\ \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{6}(\frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3) - \frac{1}{3}(-\frac{1}{3}Y_1 + \frac{2}{3}Y_2 - \frac{1}{3}Y_3) + \frac{1}{6}(\frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3) \\ -\frac{1}{3}(\downarrow) + \frac{2}{3}(\downarrow) - \frac{1}{3}(\downarrow) \\ \frac{1}{6}(\downarrow) - \frac{1}{3}(\downarrow) + \frac{1}{6}(\downarrow) \end{bmatrix}$$

(3x3) (3x1) (3x1)

$$\hat{\epsilon}_t = \hat{\epsilon}_s - M_2\hat{\epsilon}_s = \begin{bmatrix} \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \\ -\frac{1}{3}Y_1 + \frac{2}{3}Y_2 - \frac{1}{3}Y_3 \\ \frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3 \end{bmatrix} - \begin{bmatrix} \frac{5}{6}Y_1 - \frac{5}{3}Y_2 + \frac{5}{6}Y_3 \\ -\frac{2}{3}Y_1 + \frac{4}{3}Y_2 - \frac{2}{3}Y_3 \\ \frac{5}{6}Y_1 - \frac{5}{3}Y_2 + \frac{5}{6}Y_3 \end{bmatrix}$$

(3x1) (3x1)

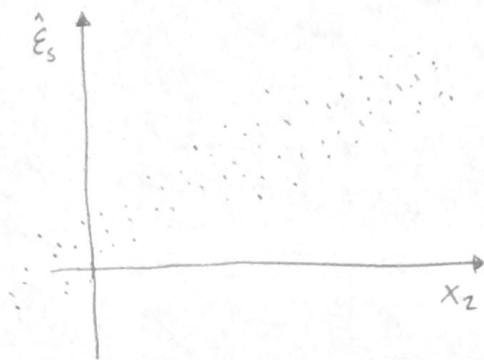
$$= \begin{bmatrix} \frac{5}{6}(\frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3) - \frac{1}{3}(-\frac{1}{3}Y_1 + \frac{2}{3}Y_2 - \frac{1}{3}Y_3) + \frac{1}{6}(\frac{1}{6}Y_1 - \frac{1}{3}Y_2 + \frac{1}{6}Y_3) \\ -\frac{1}{3}(\downarrow) + \frac{1}{3}(\downarrow) - \frac{1}{3}(\downarrow) \\ \frac{1}{6}(\downarrow) - \frac{1}{3}(\downarrow) + \frac{5}{6}(\downarrow) \end{bmatrix} = \begin{bmatrix} \frac{5}{12}Y_1 - \frac{5}{9}Y_2 + \frac{5}{12}Y_3 \\ -\frac{2}{9}Y_1 + \frac{4}{9}Y_2 - \frac{2}{9}Y_3 \\ \frac{5}{12}Y_1 - \frac{5}{9}Y_2 + \frac{5}{12}Y_3 \end{bmatrix}$$

$$\hat{\epsilon}_t = \begin{bmatrix} \frac{5}{18}(Y_1 - 2Y_2 + Y_3) \\ -\frac{2}{9}(Y_1 - 2Y_2 + Y_3) \\ \frac{5}{18}(Y_1 - 2Y_2 + Y_3) \end{bmatrix} = \begin{bmatrix} \frac{5}{18} \\ -\frac{2}{9} \\ \frac{5}{18} \end{bmatrix} (Y_1 - 2Y_2 + Y_3)$$

(3x1)

Lin Mod M1: 1D

Given $\hat{\epsilon}_s$ as residuals on the simple model, $Y = 1 \cdot \beta_0 + X_1 \beta_1 + \epsilon_s$; if the data comes from the true model, $Y = 1 \beta_0 + X_1 \beta_1 + X_2 \beta_2 + \epsilon_t$, then plotting $\hat{\epsilon}_s$ versus X_2 will show some correlation, since the information that "should" be expressed by X_2 is forced into the simple model's error term ϵ_s .



$\hat{\epsilon}_s \not\perp X_2$ if the data comes from the true model.