

Answer key for the midterm in 2014

1a.) OLS regression coefficient, square of standard error of regression, and uncentered coefficient of determination.

b.) $\mathbf{b} = (T^{-1} \sum \mathbf{x}_t \mathbf{x}'_t)^{-1} (T^{-1} \sum \mathbf{x}_t y_t) \xrightarrow{p} \mathbf{Q}^{-1} \boldsymbol{\lambda}$

c.) $s^2 = (T - k)^{-1} \sum (y_t^2 - 2y_t \mathbf{x}'_t \mathbf{b} + \mathbf{b}' \mathbf{x}_t \mathbf{x}'_t \mathbf{b})$
 $\xrightarrow{p} E(y_t^2) - 2E(y_t \mathbf{x}'_t) \mathbf{Q}^{-1} \boldsymbol{\lambda} + \boldsymbol{\lambda}' \mathbf{Q}^{-1} E(\mathbf{x}_t \mathbf{x}'_t) \mathbf{Q}^{-1} \boldsymbol{\lambda} = \gamma - 2\boldsymbol{\lambda}' \mathbf{Q}^{-1} \boldsymbol{\lambda} + \boldsymbol{\lambda}' \mathbf{Q}^{-1} \boldsymbol{\lambda}$

d.)

$$R^2 = 1 - \frac{T^{-1} \sum e_t^2}{T^{-1} \sum y_t^2} \xrightarrow{p} 1 - \frac{\gamma - \lambda Q^{-1} \lambda}{\gamma} = \frac{\lambda^2}{Q\gamma} = \frac{[E(x_t y_t)]^2}{E(x_t^2) E(y_t^2)} = \rho^2$$

2a.) $b = (\mathbf{X}' \mathbf{X})^{-1} \mathbf{X}' \mathbf{y}$

b.) $\hat{\beta}_{GLS} = (\mathbf{X}' \mathbf{V}^{-1} \mathbf{X})^{-1} \mathbf{X}' \mathbf{V}^{-1} \mathbf{y}$

$\mathbf{P} \mathbf{P}' = \mathbf{V}$

$\tilde{\mathbf{e}} = \mathbf{P}^{-1} (\mathbf{y} - \mathbf{X} \hat{\beta}_{GLS})$

$s^2 = (T - 1)^{-1} \tilde{\mathbf{e}}' \tilde{\mathbf{e}} = (T - 1)^{-1} (\mathbf{y} - \mathbf{X} \hat{\beta}_{GLS})' \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X} \hat{\beta}_{GLS})$

c.)

$$\frac{\hat{\beta}_{GLS}}{\sqrt{s^2 (\tilde{\mathbf{X}}' \tilde{\mathbf{X}})^{-1}}} = \frac{\hat{\beta}_{GLS}}{\sqrt{s^2 / (\mathbf{X}' \mathbf{V}^{-1} \mathbf{X})}} \sim \text{Student } t \text{ with } (T - 1) \text{ d.f.}$$

d.) $\xrightarrow{L} N(0, 1)$

3.) If $\mathbf{y} = \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$, $(\mathbf{X}' \mathbf{X})$ has full rank k , $E(\boldsymbol{\epsilon} | \mathbf{X}) = \mathbf{0}$, $E(\boldsymbol{\epsilon} \boldsymbol{\epsilon}' | \mathbf{X}) = \sigma^2 \mathbf{I}_T$, $\mathbf{b} = (\mathbf{X}' \mathbf{X})^{-1} \mathbf{X}' \mathbf{y}$, $\hat{\boldsymbol{\beta}} = \mathbf{A}_{\mathbf{X}} \mathbf{y}$, $E(\hat{\boldsymbol{\beta}} | \mathbf{X}) = \boldsymbol{\beta}$, then

$$E[(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta})(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta})' | \mathbf{X}] - E[(\mathbf{b} - \boldsymbol{\beta})(\mathbf{b} - \boldsymbol{\beta})' | \mathbf{X}]$$

is positive semidefinite.