

# EC402 classes

November 17, 2010

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## PS5 Question 1, out of sample prediction

Here is a detailed solution to exercise 1 (see also Johnston & Dinardo, p99).

We have 11 observations (1...11) of the model:

$$y_i = \beta_1 \cdot x_{1i} + \beta_2 \cdot x_{2i} + \varepsilon_i = x'_i \cdot \beta + \varepsilon_i. \text{ with } \varepsilon_i \text{ i.i.d } N(0, \sigma^2)$$

And we want to predict  $y_{12}$  and  $E(y_{12})$ .

We need to do three steps. **1/** First we need to find the predicted value at  $x_{12}$ ,  $\hat{y}_{12}$  and the precision of our estimates. **2/** Then we need to evaluate the variance and the distribution of  $\hat{y}_{12} - y_{12}$  if we are interested in predicting the value of observation 12. **3/** Finally, we need to evaluate the variance and the distribution of  $\hat{y}_{12} - E(y_{12})$  if we are interested in predicting the **expected** value of observation 12.

**1/** Using the OLS estimator formula, we get:

$$\hat{\beta}_{ols} = \begin{pmatrix} 1/3 \\ 1/3 \end{pmatrix}, \text{ thus, } \hat{y}_{12} := \hat{\beta}_1 \cdot x_{12} + \hat{\beta}_2 \cdot x_{12} = (5 - 2)/3 = 1$$

Moreover we know that:  $V(\hat{y}_{12}) = V(x'_{12} \cdot \hat{\beta}_{ols}) = x'_{12} \cdot V(\hat{\beta}_{ols}) \cdot x_{12}$ .

And that we can estimate  $V(\hat{\beta}_{ols})$  by  $\hat{V}(\hat{\beta}_{ols}) = \frac{RSS}{n-k} \cdot (X'X)^{-1}$ .

So we need to evaluate:

$$RSS = \hat{\varepsilon}' \hat{\varepsilon} = y' \cdot y - \hat{y}' \cdot \hat{y}.$$

$$\hat{y}' \cdot \hat{y} = \hat{\beta}'_{ols} \cdot X'X \cdot \hat{\beta}_{ols} = \frac{1}{9} \cdot \begin{pmatrix} 1 & 1 \end{pmatrix} \cdot \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 6/9 = 2/3$$

$$\text{Thus } RSS = 4/3 - 2/3 = 2/3 \text{ and } s^2 = \frac{RSS}{n-k} = \frac{2}{3} \cdot \frac{1}{11-2} = \frac{2}{27}$$

This gives us:

$$\hat{V}(\hat{\beta}_{ols}) = s^2 \cdot (X'X)^{-1} = \frac{2}{27} \cdot \frac{1}{3} \cdot \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix}$$

$\frac{2}{81}$

$$\text{So that: } \hat{V}(\hat{y}_{12}) = \frac{2}{81} \cdot \begin{pmatrix} 5 & -2 \\ -1 & 2 \end{pmatrix} \cdot \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix} \cdot \begin{pmatrix} 5 \\ -2 \end{pmatrix} = \frac{156}{81}$$

**2/** We want a confidence interval for  $y_{12} = \beta_1 \cdot x_{12} + \beta_2 \cdot x_{12} + \varepsilon_{12}$ . So we need to evaluate the variance of  $\hat{y}_{12} - y_{12} = x'_{12} \cdot (\hat{\beta}_{ols} - \beta) - \varepsilon_{12}$ .

$$V(\hat{y}_{12} - y_{12}) = \underbrace{V(\hat{y}_{12})}_{\simeq \frac{156}{81}} + \underbrace{V(y_{12})}_{\simeq \hat{V}(\varepsilon_{12})} + 2 \cdot \underbrace{Cov(\hat{y}_{12}, y_{12})}_{=0}$$

We know that the first term estimate is  $\frac{156}{81}$ , the second term is estimated by  $s^2 = \frac{2}{27}$  and the third term is 0 because we have assumed that  $\varepsilon_i$  is i.i.d, so  $y_{12}$  is independent of  $y_i$  for  $i \leq 11$

and it follows that  $y_{12}$  from  $\hat{y}_{12}$ . Thus,

$$\hat{V}(\hat{y}_{12} - y_{12}) = 2$$

Moreover, we have:

$$\frac{\hat{y}_{12} - y_{12}}{\sqrt{\hat{V}(\hat{y}_{12} - y_{12})}} \sim t_{n-k}$$

Because:

-  $\frac{\hat{y}_{12} - y_{12}}{\sqrt{V(\hat{y}_{12} - y_{12})}} \sim N(0, 1)$  (here A5Normality A3fixed regressors and A4 scalar covariance matrix are satisfied).

-  $(n - k) \cdot \frac{\hat{V}(\hat{y}_{12} - y_{12})}{V(\hat{y}_{12} - y_{12})} \sim \chi_{n-k}^2$

(To see this point, note that:  $\hat{V}(\hat{y}_{12} - y_{12}) = s^2 \cdot (1 + x'_{12} \cdot (X'X)^{-1} \cdot x_{12})$  and:

$V(\hat{y}_{12} - y_{12}) = \sigma^2 \cdot (1 + x'_{12} \cdot (X'X)^{-1} \cdot x_{12})$ . This implies:  $(n - k) \cdot \frac{\hat{V}}{V} = (n - k) \cdot \frac{s^2}{\sigma^2}$  so we can apply the results of the lecture notes p30.)

- The numerator and denominator are independent.

(For the fixed regressors case (or conditionnal on  $X$ ), the random part of the denominator is  $s^2$  computed with observations 1...11.  $s^2$  is independent of  $\hat{\beta}$  (see p30) and thus of  $\hat{y}_{12}$ . Moreover as  $s^2$  do not depend on observation 12, it is independent of  $y_{12}$ ).

This gives us,  $y_{12} \in [\hat{y}_{12} + / - \sqrt{\hat{V}(\hat{y}_{12} - y_{12})} \cdot t_{n-k}^*(10\%)]$

**3/** Now if we want a confidence interval for  $E(y_{12}) = \beta_1 \cdot x_{12} + \beta_2 \cdot x_{12}$ , we have to evaluate  $\hat{V}(\hat{y}_{12} - E(y_{12}))$ . This is  $\hat{V}(\hat{y}_{12}) = \frac{156}{81}$  by what we did before. By the previous arguments, we can construct the confidence interval using:

$$\frac{\hat{y}_{12} - E(y_{12})}{\sqrt{\hat{V}(\hat{y}_{12})}} \sim t_{n-k}$$