EC220 classes

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Why is the usual decomposition TSS = RSS + ESS not valid when we do not include an intercept in the model?

The idea is to look at a simple regression model.

(1) Y_i = β₁ + β₂.X_i + u_i
And to compare it with a model without the intercept β₁.
(2) Y_i = α₂.X_i + v_i

Fitting model (1) by OLS, we obtain, \hat{Y}_{1i} the first fitted line, the residuals, $e_{1i} = Y_i - \hat{Y}_{1i}$ and can compute RSS_1 and R_1^2 .

Now fitting model (2), we obtain \hat{Y}_{2i} the second fitted line and the residuals, $e_{2i} = Y_i - \hat{Y}_{2i}$. The R-squarred obtained fitting the first model by OLS can be defined as: $P_i^2 = \frac{ESS_i}{1 + C} (1 + C_i)$

$$R_1^2 = \frac{DSS_1}{TSS_1}$$
 (def. a.) or,
 $R_1^2 = 1 - \frac{RSS_1}{TSS_1}$ (def. b.)

From the course and PS3, you should know that in the case of model (1), definitions (a) and (b) are the same. Furthermore, we have the following equalities:

 $R_1^2 = r_{Y,\hat{Y}_1}^2 = r_{Y,X}^2$

In any case, the equality between definition (a) and definition (b) comes from the fact that in a model with intercept: $TSS_1 = ESS_1 + RSS_1$. In the case (1), we know that the equality:

 $TSS_1 = ESS_1 + RSS_1$ is valid (see the book, box 1.2 p.62). This is based on the fact that: $\bar{e}_{1i} = 0$ (which can be proved using the first order conditions of the minimization of the RSS). By definition of the residuals, this can be rewritten as: $\bar{Y}_{1i} = \bar{Y}$

In other words, the fitted line goes through the average sample observation: (\bar{X}, \bar{Y}) .

This fact does not hold if we fit model (2) by OLS. In this case, the OLS estimator of α_2 is: $c_2 = \frac{\sum_{i=1}^{n} X_i \cdot Y_i}{\sum_{i=1}^{n} (X_i)^2}$ (this has been proved in class).

Then the question is: does the second fitted line (\hat{Y}_{2i}) go through the average sample observation, (\bar{X}, \bar{Y}) ? The answer is **no in general**.

Obs	X_i	Y_i	$X_i - \bar{X}$	$Y_i - \bar{Y}$	$(X_i - \bar{X}).(Y_i - \bar{Y})$	$(X_i - \bar{X})^2$	$X_i.Y_i$
1	-1	0	-1	-1	1	1	0
2	0	1	0	0	0	0	0
3	1	2	1	1	1	1	2
$\operatorname{Sum}_{i=1\dots 3}$	0	3	0	0	2	2	2

The best is to look at a simple counter-example. Suppose we have the following data:

Then, $c_2 = b_2 = 1$ and $b_1 = \overline{Y} - b_2 \cdot \overline{X} = 1 - 0 = 1$. And $c_2 \cdot \overline{X} = 0 \neq 1$. Indeed, we have the following graph:



As a consequence, the two definitions of the R^2 are not the same in model (2). From the picture it is clear that $e_{2i} = 1$ for all the three observations and that $RSS_2 = 3$ but, $ESS_2 = \sum_{i=1}^{n} (\hat{Y}_{2i} - \bar{Y}_2)^2 = \sum_{i=1}^{n} (\hat{Y}_{2i} - 0)^2 = \sum_{i=1}^{n} (X_i)^2 = 2$ $TSS_2 = \sum_{i=1}^{n} (Y_i - \bar{Y})^2 = 2$ $RSS_2 = 3 \neq TSS_2 - ESS_2 = 2 - 2 = 0$ Moreover, $\bar{e}_2 = 1 \neq 0$.