1-2. More Issues in Linear Model

- Interpretation of coefficient
- Let $y_i = \alpha + \beta x_i + u_i$, $\triangle log(x) = \triangle x/x$

Υ	Χ	β	Interpretation
У	Х	$\triangle y/\triangle x$	1 more $x \Longrightarrow \beta$ more y
log y	X	$(\triangle y/y)/\triangle x$	1 more $x \Longrightarrow y$ increases by $(\beta \times 100)\%$
У	X	$\triangle y/(\triangle x/x)$	1% increase of $x \Longrightarrow \beta/100$ more y
log y	log x	$(\triangle y/y)/(\triangle x/x)$	1% increase of $x \Longrightarrow y$ increases by β %

p-value and One-Sided Test

p-value: the largest significance level at which we could carry out
the test and still fail to reject the null hypothesis. (If p-value is small
enough, we reject the null hypothesis. For example, at 5%
significance level, if p-value is less than 0.05, we reject the null
hypothesis.)

$$H_0: \beta_1 = 0, \ H_1: \beta_1 \neq 0 \text{ (two-sided)}$$

If $\widehat{\beta}_1$ is large or small enough, we reject H_0 .

$$H_0: \beta_1 = 0, \ H_1: \beta_1 > 0 \text{ (one-sided)}$$

If $\widehat{\beta}_1$ is large enough, we reject H_0 . If $\widehat{\beta}_1$ is small, doen not reject H_0 .

• p-value (two-sided) = $2 \times$ p-value (one-sided): easier to reject H_0 ? : You need a proper reason to use an one-sided test.

Dummy Variable

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\begin{split} \bullet & \mathsf{wage}_i = \beta_0 + \beta_1 \mathsf{educ}_i + \beta 2 \mathsf{female}_i + u_i \\ & \mathsf{where} \\ & \mathsf{female}_i = 1 \; \mathsf{if} \; \mathsf{the} \; \mathsf{person} \; i \; \mathsf{is} \; \mathsf{female} \\ & \mathsf{female}_i = 0 \; \mathsf{if} \; \mathsf{the} \; \mathsf{person} \; i \; \mathsf{is} \; \mathsf{male}. \\ & \mathsf{wage}_i = \beta_0 + \beta_1 \mathsf{educ}_i + \beta_2 \mathsf{female}_i + \beta_3 \mathsf{male}_i + u_i \\ \\ & \Rightarrow \mathsf{female}_i + \mathsf{male}_i = 1 \\ & \mathsf{Perfect} \; \mathsf{Collinearity} \end{split}
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- For data with seasonality, one can use dummy variables (quaterly/monthly) if seasonally adjusted data are unavailable.
- If your dependent variable is a dummy variable? (see probit model)

How Good Is the Fitting?

- Standard error of the regression
- Coefficient of determination R^2 : a measure of 'Goodness of Fit' $Y = X\beta + U$

Let
$$\widehat{Y} = X\widehat{\beta}$$
 and $\widehat{U} = Y - \widehat{Y}$
Then $Y'Y = (\widehat{Y} + \widehat{U})'(\widehat{Y} + \widehat{U}) = \widehat{Y}'\widehat{Y} + \widehat{U}'\widehat{U}$
because $\widehat{Y}'\widehat{U} = \widehat{U}'\widehat{Y} = 0$.
 $Y'Y$: total sum of squares (TSS)
 $\widehat{Y}'\widehat{Y}$: explained sum of squares (ESS)
 $\widehat{U}'\widehat{U}$: residual sum of squares (RSS)
 $R^2 = ESS/TSS = \frac{\widehat{Y}'\widehat{Y}}{Y'Y} = 1 - \frac{\widehat{U}'\widehat{U}}{Y'Y}$
 $\overline{R}^2 = 1 - \frac{\widehat{U}'\widehat{U}/(n-k-1)}{Y'Y/(n-1)}$

Projection

V vector space,

 $P:V \to V$ (linear transfromation)

P is a projection if $P(P_X) = P_X$.

If P is a projection, so is I - P.

Orthogonal Projection: null space and range of P are orthogonal.

Projection of Y on (the space spanned by) X is

$$P_X Y = X(X'X)^{-1}X'Y$$

Two step regression

Partitions of X

$$Y = X_1\beta_1 + X_2\beta_2 + u$$

$$\widehat{\beta}_2 = (X_2'(I - P_1)X_2)^{-1}X_2'(I - P_1)Y$$

$$\widehat{\beta}_1 = (X_1'X_1)^{-1}X_1'(Y - X_2\widehat{\beta}_2)$$
where $P_1 = X_1(X_1'X_1)^{-1}X_1'$
If $X_1'X_2 = 0$,
$$\widehat{\beta}_2 = (X_2'X_2)^{-1}X_2'Y$$

$$\widehat{\beta}_1 = (X_1'X_1)^{-1}X_1'Y$$

Omitted Variable

• Exclusion of a relevant variable W

True Model :
$$Y = W\alpha + X\beta + U$$

Estimate
$$Y = X\beta + U$$

$$\widetilde{\beta}_{OLS} = (X'X)^{-1}X'Y$$
$$= \beta + (X'X)^{-1}X'(W\alpha + U)$$

Unless
$$X'W = 0$$
, $E(\widetilde{\beta}_{OLS}) \neq \beta$

⇒ Omitted variable bias

Redundant Variable

ullet Inclusion of an irrelevant variable W

True Model :
$$Y = X\beta + U$$

Estimate $Y = W\alpha + X\beta + U$, $E(U|W) = 0$
 $\overline{\beta}_{OLS} = (X'(I - P_W)X)^{-1}X'(I - P_W)Y$
 $= \beta + (X'(I - P_W)X)^{-1}X'(I - P_W)U$
where $P_W = W(W'W)^{-1}W'$

⇒ Unbiased but Not Efficient

Multicollinearity

 Multicollinearity is different from perfect collinearity or perfect multicollinearity. Consider

$$y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + u_i$$

• Let $\frac{1}{n}X'X = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$, i.e., we assume $var(x_{1i}) = var(x_{1i}) = 1$ and $\rho = corr(x_{1i}, x_{2i})$. In this case,

$$\operatorname{var}\left(\widehat{\boldsymbol{\beta}}_{OLS}\right) = \frac{\sigma^2}{n} \left(\begin{array}{cc} 1 & \rho \\ \rho & 1 \end{array}\right)^{-1} = \frac{\sigma^2}{n(1-\rho^2)} \left(\begin{array}{cc} 1 & -\rho \\ -\rho & 1 \end{array}\right)$$

- If $|\rho|$ is closer to one \Rightarrow large standard error
- If sample size n is very small, we have the same problem. (better to have a large n).
- If two explanatory variables are highly correlated, they contain similar information and, therefore, an easy solution is to remove one variable