ECOM20001 Econometrics 1

Tutorial 7 (Week 7)

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Linear regression

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Indeed, the intercept is actually based on a variable only contains 1

$$y_i = \beta_0 1 + \beta_1 x_i + \epsilon_i$$

Multicollinearity

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we can only estimate $\beta_1 + \beta_2$ the combined coefficient, but not each of them.

⇒ perfect multicollinearity

Dummy Variable Trap

An example of perfect multicollinearity

• Occurs when we include all dummy variables for a categorical variable in a regression model along with the intercept.

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Two dummy variables:

$$D_{\mathsf{Auto},i} = egin{cases} 1 & \mathsf{if automatic} \\ 0 & \mathsf{otherwise} \end{cases}, \quad D_{\mathsf{Manual},i} = egin{cases} 1 & \mathsf{if manual} \\ 0 & \mathsf{otherwise} \end{cases}$$

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But since every car is either automatic or manual:

$$D_{\mathsf{Auto},i} + D_{\mathsf{Manual},i} = 1$$

Therefore

$$\begin{aligned} y_i &= \beta_0 1 + \beta_1 D_{\mathsf{Auto},i} + \beta_2 D_{\mathsf{Manual},i} + \varepsilon_i \\ &= \beta_0 1 + \beta_1 D_{\mathsf{Auto},i} + \beta_2 (1 - D_{\mathsf{Auto},i}) + \varepsilon_i \\ &= (\beta_0 + \beta_2) 1 + (\beta_1 - \beta_2) D_{\mathsf{Auto},i} + \varepsilon_i \end{aligned}$$

Again, we could only estimate the combined effect of $(\beta_0 + \beta_2)$ and $(\beta_1 - \beta_2)$, but not each of them.

⇒ perfect multicollinearity

Perfect Multicollinearity

- Note that $D_{Auto,i} + D_{Manual,i} = 1$ for all observations i.
- So, if we also include an intercept term, we have:

$$\mathsf{Intercept} = 1 = D_{\mathsf{Auto},i} + D_{\mathsf{Manual},i}$$

- ⇒ Perfect linear dependence among regressors.
- ⇒ OLS fails.

How to Avoid the Trap

- Drop one dummy variable use it as the reference category.
- Example: Include only $D_{\mathsf{Auto},i}$
- The omitted category $(D_{Manual,i})$ is captured in the intercept.

Correct Model:

$$y_i = \beta_0 1 + \beta_1 D_{\mathsf{Auto},i} + \varepsilon_i$$

Interpretation:

- β_0 : The mean value of y_i for manual cars.
- $\beta_0 + \beta_1$: The mean value of y_i for automatic cars.
- β_1 : The effect (or difference) of having an automatic transmission compared to a manual transmission.

How to Avoid the Trap: Alternatively

Less common: Drop the intercept

Recall before

$$y_i = \beta_0 1 + \beta_1 D_{\mathsf{Auto},i} + \beta_2 D_{\mathsf{Manual},i} + \varepsilon_i$$

Removing intercept

$$y_i = \beta_1 D_{\mathsf{Auto},i} + \beta_2 D_{\mathsf{Manual},i} + \varepsilon_i$$

No problem, but no reference group.

$$y_i = \beta_1 D_{\text{Auto},i} + \beta_2 (1 - D_{\text{Auto},i}) + \varepsilon_i$$
$$= \beta_2 1 + (\beta_1 - \beta_2) D_{\text{Auto},i} + \varepsilon_i$$