

# L4: Extensions of the two-variable linear regression model



**Feng Li**  
m@feng.li

**School of Statistics and Mathematics**  
**Central University of Finance and Economics**

## What we have learned last time...

- ① Normal assumptions of  $u_i$
- ② Constructing intervals, Hypothesis testing
- ③ Normality tests

# Today we are going to learn...

- 1 Regression through the origin
- 2 Scaling and units of measurement
- 3 Regression on standardized variables
- 4 Other models

# Regression through the origin

## ↳ The estimation

- 1 Assume the population regression function of the form

$$Y_i = \beta_2 X_i + u_i$$

- 2 The sample regression function is

$$Y_i = \beta_2 X_i + \hat{u}_i$$

- 3 Following the same procedure of OLS we have

$$\hat{\beta}_2 = \frac{\sum X_i Y_i}{\sum X_i^2}, \quad \text{var}(\hat{\beta}_2) = \frac{\sigma^2}{\sum X_i^2}, \quad \hat{\sigma}^2 = \frac{\sum \hat{u}_i^2}{n-1}$$

- 4 Comparing them with the model with intercept. **What can you find?**

## Regression through the origin

### ↪ Use with caution

- 1 The  $r^2$  defined for linear with intercept is not applied here. We defined that

$$r^2 = 1 - \text{RSS}/\text{TSS}$$

where

$$\text{RSS} = \sum u_i^2 = \sum Y_i^2 - \hat{\beta}_2^2 \sum X_i^2, \quad \text{TSS} = \sum (Y_i - \bar{Y})^2 = \sum Y_i^2 - n\bar{Y}^2$$

in the no intercept model. There is **no guarantee** that  $\text{RSS} \leq \text{TSS}$ . Hence  $r^2 < 0$  is possible.

- 2 Instead, people use **raw**  $r^2$  in this model,

$$\text{raw } r^2 = \frac{(\sum X_i Y_i)^2}{\sum X_i^2 \sum Y_i^2}$$

- 3 The **raw**  $r^2$  is not comparable with  $r^2$ .
- 4 Specification error may occur if you insist use this model. **See Chapter 7.**

# Scaling and units of measurement

## ↳ The model

- 1 Suppose that you want to model

$$Y_i = \hat{\beta}_1 + \hat{\beta}_2 X_i + \hat{u}_i$$

- 2 While you observe the data  $Y_i^* = w_1 Y_i$  and  $X_i^* = w_2 X_i$
- 3 So you have to consider instead

$$Y_i^* = \hat{\beta}_1^* + \hat{\beta}_2^* X_i^* + \hat{u}_i^*$$

where  $\hat{u}_i^* = w_1 \hat{u}_i$  (**why?**)

- 4 It is important to know that the two model are essentially the same because scaling the units will not change the data and the properties of the OLS not changed.

# Scaling and units of measurement

## ↳ The estimation

① It is easy to obtain the following occlusions (**homework!**)

①  $\hat{\beta}_2^* = \left(\frac{w_1}{w_2}\right)\hat{\beta}_2$

②  $\hat{\beta}_1^* = w_1\hat{\beta}_1$

③  $(\hat{\sigma}^*)^2 = w_1^2\hat{\sigma}^2$

④  $\text{var}(\hat{\beta}_1^*) = w_1^2\text{var}(\hat{\beta}_1)$

⑤  $\text{var}(\hat{\beta}_2^*) = \left(\frac{w_1}{w_2}\right)^2\text{var}(\hat{\beta}_2)$

⑥  $r_{xy}^2 = r_{x^*y^*}^2$

② Example:

$$\begin{aligned}\hat{\beta}_2^* &= \frac{\sum x_i^* y_i^*}{\sum (x_i^*)^2} = \frac{\sum (X_i^* - \bar{X}^*)(Y_i^* - \bar{Y}^*)}{\sum (X_i^* - \bar{X}^*)^2} = \frac{\sum (w_2 X_i - w_2 \bar{X})(w_1 Y_i - w_1 \bar{Y})}{\sum (w_2 X_i - w_2 \bar{X})^2} \\ &= \frac{w_2 w_1}{w_2^2} \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} = \frac{w_1}{w_2} \hat{\beta}_2\end{aligned}$$

# Regression on standardized variables

## ↳ The model

- 1 The same model as before, but the transformation are not

$$Y_i^* = \frac{Y_i - \bar{Y}}{S_Y}, \quad X_i^* = \frac{X_i - \bar{X}}{S_X}$$

- 2 The model is now as

$$Y_i^* = \beta_1^* + \beta_2^* X_i^* + u_i^* = \beta_2^* X_i^* + u_i^*$$

which goes through the origin.

- 3 The new coefficient

$$\hat{\beta}_2^* = \hat{\beta}_2 \frac{S_X}{S_Y}$$



## The log-linear model

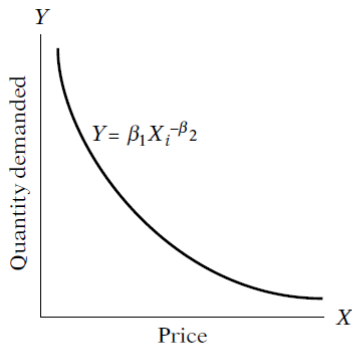
- 1 Consider the **exponential regression model**

$$Y_i = \beta_1 X_i^{\beta_2} e^{u_i}$$

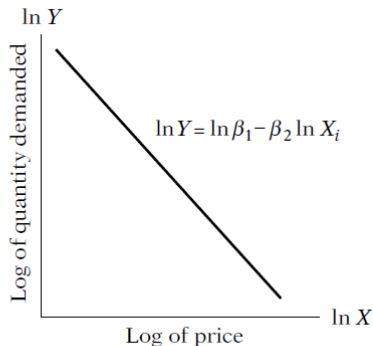
- 2 We express it as

$$\ln Y_i = \ln \beta_1 + \beta_2 \ln X_i + u_i$$

so that the linear model estimation can be used.



(a)



(b)

# The log-lin model

- 1 Consider the model

$$Y_t = Y_0(1 + r)^t$$

- 2 We express it as

$$\ln Y_t = \ln Y_0 + [\ln(1 + r)]t$$

- 3 Let  $\beta_1 = \ln Y_0$  and  $\beta_2 = \ln(1 + r)$  we have the following model

$$\ln Y_t = \beta_1 + \beta_2 t + u_t$$

# The lin-log model

- 1 The lin-log model

$$Y_i = \beta_1 + \beta_2 \ln X_i + u_t$$

where  $\hat{\beta}_2 = \frac{\Delta Y}{\Delta X/X}$  and  $\Delta$  means very small change.

- 2 Thus  $\Delta Y = \hat{\beta}_2 \cdot (\Delta X/X)$

- 3 The interpretation of this model:

If  $\Delta X/X$  changes by 1 percent, the absolute change in  $Y$  is  $0.01\beta_2$

## Summary of models

Model	Equation	Slope $\left( = \frac{dY}{dX} \right)$	Elasticity $\left( = \frac{dY}{dX} \frac{X}{Y} \right)$
Linear	$Y = \beta_1 + \beta_2 X$	$\beta_2$	$\beta_2 \left( \frac{X}{Y} \right)^*$
Log-linear	$\ln Y = \beta_1 + \beta_2 \ln X$	$\beta_2 \left( \frac{Y}{X} \right)$	$\beta_2$
Log-lin	$\ln Y = \beta_1 + \beta_2 X$	$\beta_2 (Y)$	$\beta_2 (X)^*$
Lin-log	$Y = \beta_1 + \beta_2 \ln X$	$\beta_2 \left( \frac{1}{X} \right)$	$\beta_2 \left( \frac{1}{Y} \right)^*$
Reciprocal	$Y = \beta_1 + \beta_2 \left( \frac{1}{X} \right)$	$-\beta_2 \left( \frac{1}{X^2} \right)$	$-\beta_2 \left( \frac{1}{XY} \right)^*$
Log reciprocal	$\ln Y = \beta_1 - \beta_2 \left( \frac{1}{X} \right)$	$\beta_2 \left( \frac{Y}{X^2} \right)$	$\beta_2 \left( \frac{1}{X} \right)^*$

*Note:* \* indicates that the elasticity is variable, depending on the value taken by  $X$  or  $Y$  or both. When no  $X$  and  $Y$  values are specified, in practice, very often these elasticities are measured at the mean values of these variables, namely,  $\bar{X}$  and  $\bar{Y}$ .

## Take home questions

- ① Verify the results in **slide 7**.
- ② Think about when you make log transformation, will it change the distribution of the error term?
- ③ Exercises (S2): **5.1, 5.5, 5.8, 5.14, 5.15, 6.1, 6.2, 6.7, 6.13, 6.14**