

Interpretation of regression coefficients for most common forms of regression models

① Linear regr. model

$$\underline{y_i} = b_1 + b_2 x_{2i} + \dots + \underbrace{b_j}_{\text{partial regr. coefficient}} \underline{x_{ji}} + \dots + b_k x_{ki} + e_i$$

partial
regr. coefficient

If x_j increases by 1 unit of measurement, then ^①on average, ^②ceteris paribus, y increases/decreases by b_j units of measurement.

Two relativisations, intercept: **S75**.

② Log-linear regression model

$$\underline{\ln y_i} = b_1 + b_2 \ln x_{2i} + \dots + \underbrace{b_j}_{\text{part. elasticity (approximation)}} \underline{\ln x_{ji}} + \dots + b_k \ln x_{ki} + e_i$$

part. elasticity
(approximation)

If x_j increases by 1 percent, then ^①on average, ^②ceteris paribus, y increases/decreases by b_j percent.

3. Log-lin regression model

$$\ln y_i = b_1 + b_2 x_{2i} + \dots + \underbrace{(b_j x_{ji})}_{\text{part. semi elasticity (approximation)}} + \dots + b_k x_{ki} + e_i$$

If x_j increases by 1 unit of measurement, then on average, ceteris paribus, y increases/decreases by $100 \cdot b_j$ percent.

4. Lin-log regression model

$$y_i = b_1 + b_2 \ln x_{2i} + \dots + \underbrace{(b_j \ln x_{ji})}_{\text{part. semi elasticity (approximation)}} + \dots + b_k \ln x_{ki} + e_i$$

If x_j increases by 1 percent, then on average, ceteris paribus, y increases/decreases by $b_j / 100$ units of measurement.

⑤ "Mixed" regression model

$$\text{EXAMPLE: } \ln y_i = b_1 + b_2 x_{2i} + b_3 \ln x_{3i} + e_i$$

Each regression coefficient is interpreted based on the **functional form of the relationship** between "y" and " x_j ".

Indirect effects, 577-78:

Indirect effect of x_j on y (through x_i):
total effect of x_j on x_i \odot direct effect of x_i on y .

(Note: In the original image, the 'total effect' and 'direct effect' are underlined in green, and the 'total effect' part includes a crossed-out 'y' at the end of the phrase 'total effect of x_j on x_i '.)

Example, c)

PDF, pp. 6-7.

$$L_i = c_1 + c_2 K_i + e_{Li}$$

$$\hat{Q}_i = d_1 + \underline{d_2} e_{Li} + d_3 K_i$$

↑ compute

$$\hat{Q}_i = b_1 + \underline{b_2} L_i + b_3 K_i$$

$d_2 = b_2$

$$K_i = f_1 + f_2 L_i + e_{Ki}$$

$$\hat{Q}_i = g_1 + g_2 L_i + \underline{g_3} e_{Ki}$$

↑ compute

$$\hat{Q}_i = b_1 + b_2 L_i + \underline{b_3} K_i$$

$g_3 = b_3$

Effects of L on Q:

- direct: $b_2 = d_2 = 9687.38$
- indirect: $f_2 \cdot b_3 = 4085.43 \cdot 2.279 = 9310.69$
- total: $b_2 + f_2 \cdot b_3 = 18,998.07$ ⊖
or $g_2 = 18,999.75$



Effects of K on Q:

- direct: $b_3 = g_3 = \underline{2.279}$
- indirect: $c_2 \cdot b_2 = 0.000176 \cdot 9,687.38 = \underline{1.705}$
- total: $b_3 + c_2 \cdot b_2 = 3.984$
or $d_3 = \underline{3.983}$



Example, d)

PDF, pp. 7-8.

$$Q_i = b_1 + b_2 L_i + \underline{b_3 K_i} + \underline{e_{1i}}$$

$$Q_i = c_1 + c_2 L_i + e_{qi}$$

$$K_i = d_1 + d_2 L_i + e_{ki}$$

FWL regression: $\underline{e_{qi}} = g_1 + \underline{g_2 e_{ki}} + \underline{e_{2i}}$

FWL theorem:

- (1) $b_3 = g_2$
- (2) $e_{1i} = e_{2i}, \forall i$