

Test for Heteroscedasticity

① Glejser Test :

$$|\hat{u}_i| = \beta_1 + \beta_2 x_i + v_i$$

$$|\hat{u}_i| = \beta_1 + \beta_2 \sqrt{x_i} + v_i$$

$$|\hat{u}_i| = \beta_1 + \beta_2 \frac{1}{x_i} + v_i$$

$$|\hat{u}_i| = \beta_1 + \beta_2 \frac{1}{\sqrt{x_i}} + v_i$$

$$|\hat{u}_i| = \sqrt{\beta_1 + \beta_2 x_i} + v_i$$

$$|\hat{u}_i| = \frac{\sqrt{\beta_1 + \beta_2 x_i^2}}{\sqrt{\beta_1 + \beta_2 x_i^2}} + v_i$$

Expression
 {
 E(\hat{u}_i) }
 E(u_i) } ①
 E($u_i u_j$) = 0

Non-linear.

② Goldfeld-Quandt Test : if one assume that the heteroscedastic variance, σ_i^2 is positively related to one of the explanatory variables in regression model $y_i = \beta_1 + \beta_2 x_i + v_i$ and σ_i^2 is positively related to x_i as

$$\sigma_i^2 = \underbrace{\sigma^2}_{\sim} x_i^2$$

- ① Order or rank the observation according to the value of x_i , beginning with lowest x value, where c is specified a priori and
- ② Omit 'c' central observations, divide the ~~remaining~~ remaining $(n-c)$ observations in two groups each of $\frac{n-c}{2}$ observations.

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③ Fit separate OLS regressions to the first $\frac{(n-c)}{2}$ observations and the last $\frac{(n-c)}{2}$ observations and obtain the respective residual sum of squares RSS_1 and RSS_2 . RSS_1 representing the RSS from the regression corresponding to the smaller x_i values and RSS_2 that from the larger x_i values. Then RSS each have $\frac{(n-c)}{2} - k$ or $\frac{(n-c-2k)}{2}$ degrees of freedom, where k is the no. of parameters to be estimated.

④ Compute the ratio $t = \frac{RSS_2/df}{RSS_1/df}$

If we assume v_i are normally distributed and if the assumption of homoscedasticity is valid then it can be shown that t follows F-distribution, with each numerator and denominator of $\frac{(n-c-2k)}{2}$.

If computed $t(F)$ is greater than critical F at a level of significance then H_0 is rejected & heteroscedasticity is likely present.

Functional forms of Regression

① Double-log, Log linear or Constant elasticity Model

$$\text{Eg: } y_i = \alpha_0 x_i^{\beta_1} e^{u_i}$$

$$\ln y_i = \ln \alpha_0 + \beta_1 \ln x_i + u_i$$

$$\ln Y_i = \alpha_0 + \beta_1 \ln x_i + u_i$$

$$Y_i^* = \alpha_0^* - \beta_1^* x_i^* + u_i$$

② Semi-log Model : ↳ elasticity coeff between x and y

$$(a) \ln Y_i = \alpha_0 + \alpha_1 x_i + u_i$$

$$\text{and } (b) Y_i = \beta_0 + \beta_1 \ln x_i + u_i$$

$$(a) \alpha_1 = \frac{d}{dx_i} (\ln Y_i) = \frac{1}{Y_i} \cdot \frac{dy_i}{dx_i} = \frac{dy/y}{dx} = \frac{\Delta y / y}{\Delta x}$$

$\alpha_1 = \frac{\text{prop change in } y}{\text{absolute change in } x}$

$$(b) \beta_1 = \frac{dy_i}{d \log x_i} = \frac{\Delta y}{\Delta x / x} = \frac{\text{absolute change in } y}{\text{proportional change in } x}$$

③ Reciprocal Transformation or Hyperbolic Models

$$(a) y_i = \alpha + \beta \left(\frac{1}{x_i} \right) + u_i$$

If α and β are positive, this model shows that
 y decreases non linearly as x increases

(b) Another form of hyperbolic model is log-hyperbolic model which is of form $\ln y_i = \alpha - \beta \left(\frac{1}{x_i} \right) + u_i$
or, $y_i = e^{\alpha - \beta/x_i}$

Name of function	Relation	Slope
1. Linear	(i) $y = \alpha + \beta x$ (ii) $y = \alpha - \beta x$	$+\beta$ $-\beta$
2. Quadratic	(i) $y = \alpha + \beta_1 x - \beta_2 x^2$ (ii) $y = \alpha - \beta_1 x - \beta_2 x^2$	$(+) (\beta_1, -2\beta_2 x)$ $\leftrightarrow (\beta_1, -2\beta_2 x)$
3. Hyperbolic	(i) $y = \alpha + \beta/x$ (ii) $y = \alpha - \beta/x$	$-\beta/x^2$ $(+) \beta/x^2$
4. Semilog	(i) $\log_e y = \alpha + \beta x$ or $y = e^{\alpha + \beta x}$ } (ii) $\log_e y = \alpha - \beta x$ or $y = e^{\alpha - \beta x}$	$(+) \beta y$ $\leftrightarrow \beta y$

$$(iii) y = \alpha + \beta \log_e x$$

or $e^y = \alpha + x^\beta$

$(+) \beta/x$

$$(iv) y = \alpha - \beta \log_e x$$

or, $e^y = \alpha + x^{-\beta}$

$\leftrightarrow \beta/x$

5. Log-quadratic	(i) $\log_e y = \alpha + \beta_1 x - \beta_2 x^2$	$(+) y (\beta_1, -2\beta_2 x)$
	(ii) $\log_e y = \alpha - \beta_1 x - \beta_2 x^2$	$\leftrightarrow y (\beta_1, -2\beta_2 x)$

6. Log-inverse	(i) $\log_e y = \alpha + \beta$ or $y = e^{\alpha + \beta/x}$	$- \phi \frac{\beta}{x^2} \cdot y$
	(ii) $\log_e y = \alpha - \beta/x$ or $y = e^{\alpha - \beta/x}$	$+ \beta/x^2 \cdot y$

7. Double-log	(i) $\log_e y = \alpha + \beta \log_e x$ or $y = \alpha x^\beta$	$+ \frac{\beta y}{x}$
	(ii) $\log_e y = \alpha - \beta \log_e x$ or $y = \alpha x^{-\beta}$	$- \frac{\beta y}{x}$

$\frac{dy}{dx}$
 $e^{\alpha + \beta x}$
 \downarrow
 y