

Multiple Regression Analysis: Heteroskedasticity

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k + u$$

BS1802 Statistics and Econometrics

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Roadmap

- Regression analysis with cross-sectional data
 - The multiple regression analysis
 - Basics: estimation, inference, analysis with dummy variables
 - More technically involved: asymptotics, heteroskedasticity, specification and data issues
- Advanced topics
 - Limited dependent variable models
 - Panel data analysis
 - Regression analysis with time series data

Outline (Wooldridge, Ch. 8.1 - 8.3)

- Consequences of heteroskedasticity
- Testing for heteroskedasticity
- Heteroskedasticity-robust inference

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Homoskedasticity and Heteroskedasticity

- Recall that the variance of OLS estimator is given by

$$\text{Var}(\hat{\beta}_j) = \frac{\sigma^2}{SST_j(1 - R_j^2)}, \quad j = 1, \dots, k,$$

where $SST_j = \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2$, $\bar{x}_j = n^{-1} \sum_{i=1}^n x_{ij}$, and R_j^2 is the R-squared from regressing x_j on all other independent variables.

- For the variance formula to be valid, we need

Assumption (homoskedasticity)

$\text{Var}(u_i | x_{i1}, \dots, x_{ik}) = \sigma^2$ for $i = 1, 2, \dots, n$. (It implies $\text{Var}(u_i) = \sigma^2$)

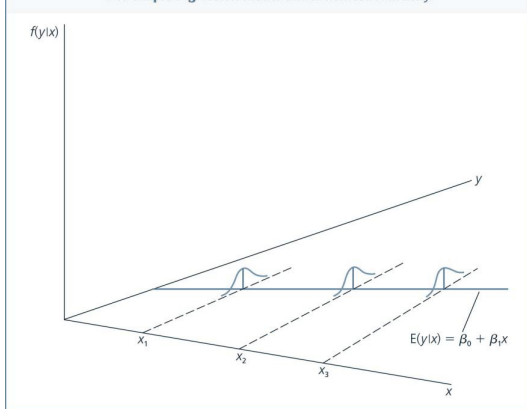
Homoskedasticity and Heteroskedasticity

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FIGURE 2.8

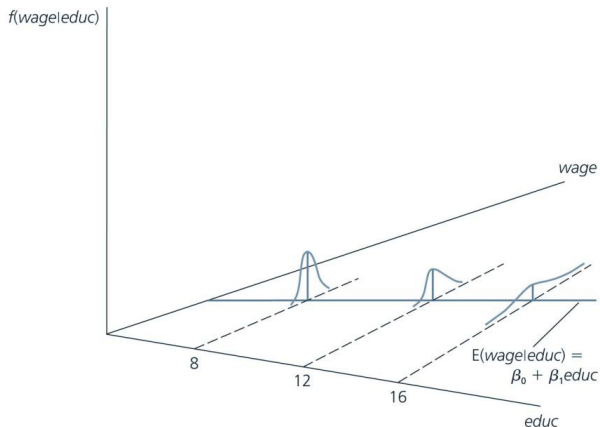
The simple regression model under homoskedasticity.



Homoskedasticity and Heteroskedasticity

FIGURE 2.9

$\text{Var}(\text{wage}|\text{educ})$ increasing with educ .



Consequences of Heteroskedasticity

- The OLS estimators are unbiased, even if we do not assume homoskedasticity
- Homoskedasticity is required for using the formula of the variance of the OLS estimator, which is important for inference
- The standard errors of the estimates are biased if we have heteroskedasticity
- If the standard errors are biased, we can not use the usual t statistics or F statistics for drawing inferences

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Heteroskedasticity Tests

- Essentially want to test $H_0 : \text{Var}(u|x_1, x_2, \dots, x_k) = \sigma^2$, which is equivalent to

$$H_0 : E(u^2|x_1, x_2, \dots, x_k) = E(u^2) = \sigma^2$$

Heteroskedasticity Tests: The Breusch-Pagan Test

- If assume a linear relationship between u^2 and x_j , i.e.,

$$u^2 = \delta_0 + \delta_1 x_1 + \cdots + \delta_k x_k + v,$$

the null hypothesis of homoskedasticity is equivalent to
 $H_0 : \delta_1 = \delta_2 = \cdots = \delta_k = 0$.

- The Breusch-Pagan test

- OLS $y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$ and save the squared residuals \hat{u}^2
- OLS $\hat{u}^2 = \delta_0 + \delta_1 x_1 + \cdots + \delta_k x_k + \text{error}$ and save the R-squared $R_{\hat{u}^2}^2$
- The test statistic

$$F = \frac{R_{\hat{u}^2}^2 / k}{(1 - R_{\hat{u}^2}^2) / (n - k - 1)} \sim F_{k, n-k-1} \quad \text{under the null}$$

- Reject the null if F is too large (or has a too-small p -value)

Heteroskedasticity Tests: The White Test

- The Breusch-Pagan test will detect any linear forms of heteroskedasticity
- The White test allows for nonlinearities by using squares and crossproducts of all the x 's
- The White test
 - OLS $y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$ and save the residuals and the fitted values, \hat{u} and \hat{y}
 - OLS $\hat{u}^2 = \delta_0 + \delta_1 \hat{y} + \delta_2 \hat{y}^2 + \text{error}$ and save the R-squared $R_{\hat{u}^2}^2$
 - The test statistic

$$F = \frac{R_{\hat{u}^2}^2 / 2}{(1 - R_{\hat{u}^2}^2) / (n - 3)} \sim F_{2, n-3} \quad \text{under the null}$$

- Reject the null if F is too large (or has a too-small p -value)

Heteroskedasticity Tests: An Example

- Eg. Log wage model (wage1.RData)

$$\widehat{\log(wage)} = .284 + .0920educ + .0041exper + .022tenure$$

(.104) (.0073) (.0017) (.003)

$$n = 526, R^2 = .316$$

- Breusch-Pagan test: $p\text{-value} = .013$
- White test: $p\text{-value} = .035$

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Heteroskedasticity-Robust Inference

- It is possible to adjust the OLS standard errors to make the t stat (or F stat) valid in the presence of heteroskedasticity of unknown form
- The adjustment is called [heteroskedasticity-robust procedure](#)
- The procedure is “robust” because the adjusted t stat (or F stat) is valid regardless of the type of heteroskedasticity in the population (even if there is no heteroskedasticity)

Robust Standard Errors

- Denote $r.se(\hat{\beta}_j)$ as **robust standard error**
- The **robust t stat** is

$$t \text{ stat} = \frac{\hat{\beta}_j - a_j}{r.se(\hat{\beta}_j)}$$

- These robust standard errors only have asymptotic justification
 - With small sample sizes, robust t stat will not have a distribution close to t , and inferences will not be correct
- The **robust F stat** must be computed using a formula different from the original one.
 - But the robust F stat is easily obtained in R, using `linearHypothesis`.

Robust Standard Errors: An Example

- Eg. Log wage model (wage1.RData)

$$\widehat{\log(wage)} = .284 + .0920educ + .0041exper + .022tenure$$

(.104) (.0073) (.0017) (.003)

The model with robust standard errors is

$$\widehat{\log(wage)} = .284 + .0920educ + .0041exper + .022tenure$$

[.112] [.0079] [.0017] [.004]

$n = 526, R^2 = .316$ (the robust results are in [])

- Hypotheses: $H_0 : \beta_{educ} - \beta_{exper} = 0$ vs $H_1 : \beta_{educ} - \beta_{exper} \neq 0$
 - F stat: (158.46), [143.46]

When to Use Robust Standard Errors in Practice?

- Always report robust standard errors for linear probability model and panel data model
- For other models,
 - Test for heteroskedasticity
 - Report robust standard errors only if there is evidence of heteroskedasticity, as robust standard errors only have asymptotic justification