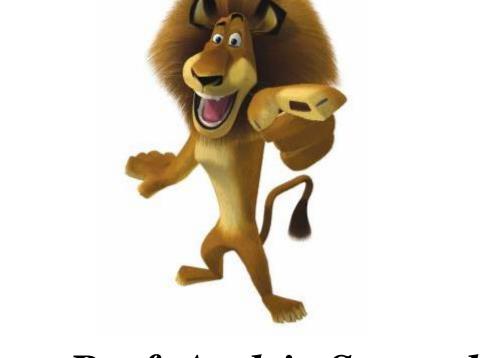
# Introduction to Econometric Analysis



Ass. Prof. Andriy Stavytskyy



# References

- Greene W. H., Econometric Analysis, 7th ed., Prentice Hall, 2011.
- Murray M. P. (2005) Econometrics: A Modern Introduction. Prentice Hall.
- Stock James H., Mark W. Watson (2010) Introduction to Econometrics (3rd Edition)





- Econometric review
- Econometric tests



# ECONOMETRIC REVIEW

0



# **Econometric analysis**

- Theoretical approach
- Empirical approach



# Types of Data and Notation

- ✓ Time series data
- Cross-sectional data
- Panel data, a combination of mentioned above types



# **Time series data**

### • The data may be

- > quantitative (e.g. exchange rates, stock prices, number of shares outstanding),
- > qualitative (e.g. day of the week).
- Examples of time series data

Series GNP or unemployment government budget deficit money supply value of a stock market index **Frequency** monthly or quarterly annually weekly

as transactions occur

# Examples of Problems Using Time Series Regression

- How the value of a country's stock index has varied with that country's macroeconomic fundamentals.
- 2. How the value of a company's stock price has varied when it announced the value of its dividend payment.
- 3. The effect on country's currency of an increase in its interest rate.

# **Cross-sectional data**

- Cross-sectional data is data on one or more variables collected at a single point in time, e.g.
  - A poll of usage of internet stock broking services
  - Cross-section of stock returns on the New York Stock Exchange
  - A sample of bond credit ratings for UK banks

# Examples of Problems Using a Cross-Sectional Regression

- The relationship between company **size** and the **return** to investing in its shares
- The relationship between a country's **GDP level** and the **probability** that the government will **default** on its sovereign debt.

# **Panel Data**

- Panel Data has the dimensions of both time series and cross-sections, e.g. the *daily prices of number of blue chip stocks over two years*.
- It is common to denote that each observation by the letter t and the total number of observations by T for time series data, and to denote each observation by the letter i and the total number of observations by N for cross-sectional data.



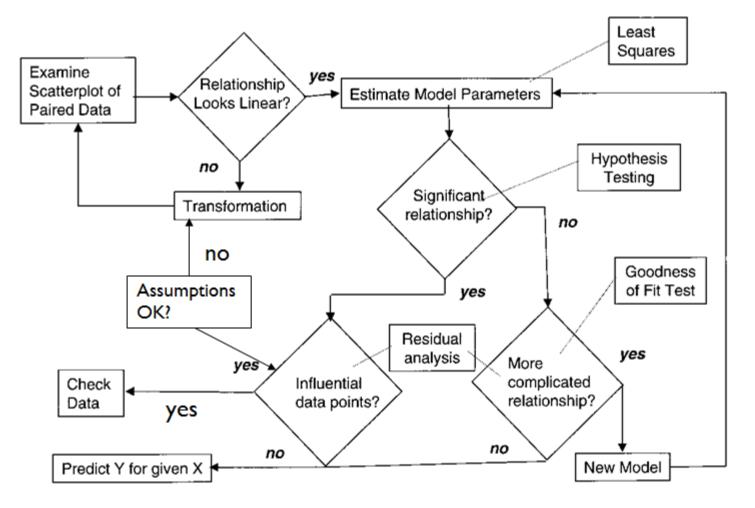
 Develop a statistical model that can predict the values of a dependent (response) variable based upon the values of the independent (explanatory) variables.



# Regression Modeling Steps

- Define a problem or question
- Specify model
- Collect data
- Do descriptive data analysis
- Estimate unknown parameters
- Evaluate model
- Use model for prediction

# How is a Linear Regression Analysis done?



# **Linear regression**

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{1t} + \dots + \beta_{k-1} x_{k-1t} + \varepsilon_t, t = 1, n$$

 $y_t$  - dependent variable;

 $X_{1t}, X_{2t}, \dots, X_{k-1t}$  independent variables;

 $\mathcal{E}_t$  - residuals.



# Assumptions

- **Linearity** the Y variable is linearly related to the value of the X variable.
- **Independence of Error** the error (residual) is independent for each value of X.
- **Homoscedasticity** the variation around the line of regression be constant for all values of X.
- **Normality** the values of Y be normally distributed at each value of X.

# **Method of Least Squares**

- The straight line that best fits the data.
- Determine the straight line for which the differences between the actual values (Y) and the values that would be predicted from the fitted line of regression (Y-hat) are as small as possible.

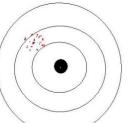
$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ij} \right)^2 \to \min$$

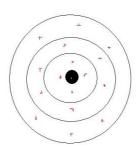
# The Three Desirable Characteristics

- Lack of bias  $E(\hat{\beta}) = \beta$
- Efficiency
  - Standard error will be minimum
    - Remember:

$$\operatorname{var}(\hat{\beta}) = \frac{1}{\sum x_i^2} \sigma^2 = \frac{\sigma^2}{\sum x_i^2}$$

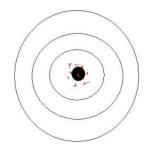
• OLS will minimize  $\sigma^2$  (the error variance)





### • Consistency

- As N increases the standard error decreases
  - Notice: as N increases so does  $\Sigma x_i^2$



# Inherently Linear Models

- Non-linear models that can be expressed in linear form
  - Can be estimated by least square in linear form
- Require data transformation

# Dummy-Variable Regression Model

- Involves categorical X variable with two levels
  - e.g., female-male, employed-not employed, etc.
- Variable levels coded 0 & 1
- Assumes only intercept is different
  - Slopes are constant across categories

### ECONOMETRIC TESTS



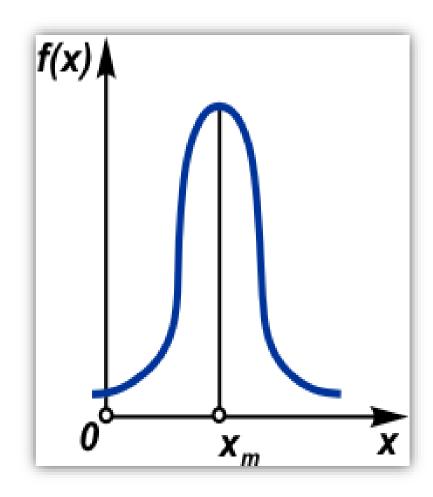
# **Multiple Regression Tests**

- Test residual for normality
- Test parameter significance
  - Overall model
  - Individual coefficients
- Test for multicollinearity
- Test for model stability
- Test for residuals autocorrelation
- Test for residuals homoscedasticity
- Test for specification
- Test for stationary process

# **Test residual for normality**

# Check normality of residuals:

- Jarque-Bera statistics
- Shapiro–Wilk test



### **Jarque-Bera statistics**

$$\overline{JB = \frac{n}{6} \left( S^2 + \frac{1}{4} \left( \left( K - 3 \right)^2 \right) \right)}$$

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \overline{x})^3}{\left( \frac{1}{n} \sum_{i=1}^n (x_i - \overline{x})^2 \right)^{3/2}} K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \overline{x})^4}{\left( \frac{1}{n} \sum_{i=1}^n (x_i - \overline{x})^2 \right)^{2/2}}$$

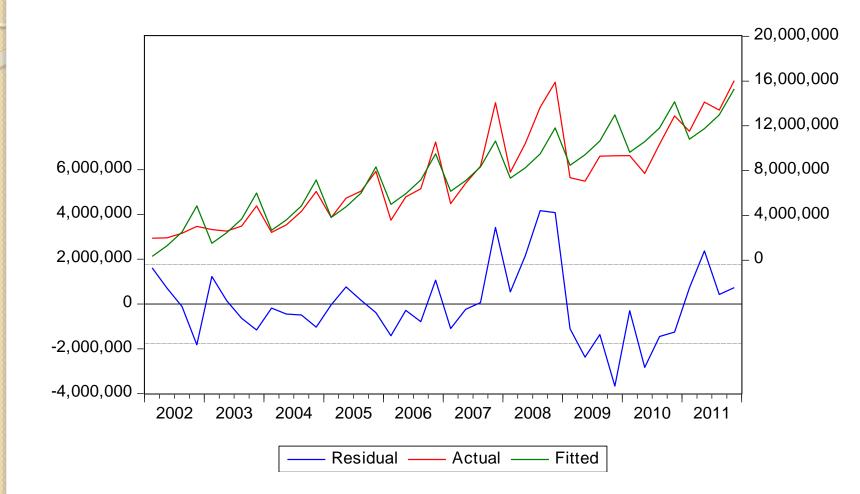
- *S* is the sample skewness,
- K is the sample kurtosis.

# Example

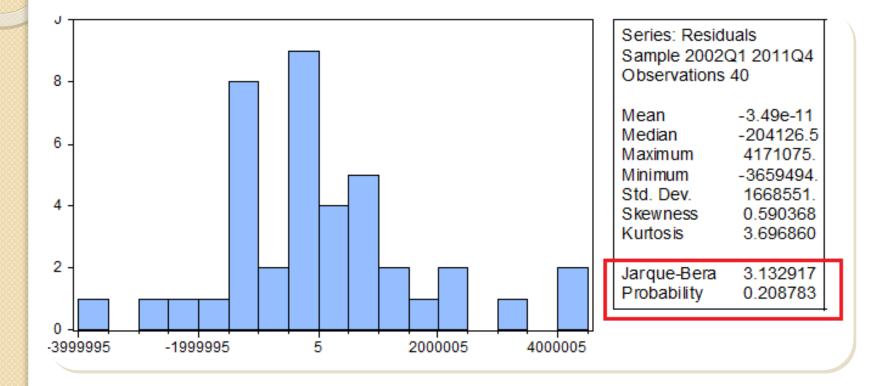
Dependent Variable: TAX\_ENT Method: Least Squares Date: 12/09/12 Time: 20:49 Sample: 2002Q1 2011Q4 Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C @TREND @SEAS(1) @SEAS(2) @SEAS(3)	3973770. 290525.1 -3627516. -2975920. -2032456.	754540.7 24239.34 791034.8 789175.7 788058.1	5.266475 11.98568 -4.585786 -3.770922 -2.579068	0.0000 0.0000 0.0001 0.0006 0.0143
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic	0.837415 0.818834 1761318. 1.09E+14 -629.3498 45.06800	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Durbin-Watson stat		7480035. 4138083. 31.71749 31.92860 31.79382 1.123746
Prob(F-statistic)	0.000000			

### Residuals



# **Check for normality**



## Test parameter significance: Overall model

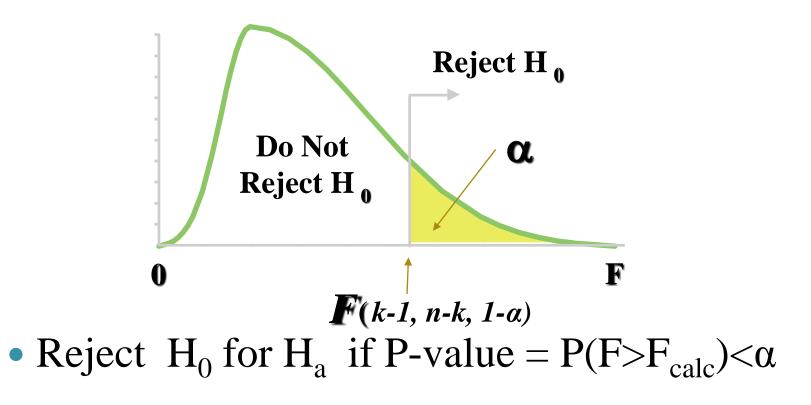
- Hypotheses
  - $H_0: \beta_1 = \beta_2 = \dots = \beta_{k-1} = 0$ 
    - No Linear Relationship
  - H<sub>a</sub>: At Least One Coefficient Is Not 0

• At Least One X Variable linearly Affects Y

$$F = \frac{RSS / (k-1)}{ESS / (n-k)} = \frac{R^2 / (k-1)}{(1-R^2) / (n-k)} \stackrel{H_0}{\sim} F_{k-1,n-k}$$

# **Overall Significance Rejection Rule**

• Reject  $H_0$  in favor of  $H_a$  if  $F_{calc}$  falls in colored area



# Example

Dependent Variable: TAX_ENT						
Method: Least Squares						
Date: 12/09/12 Time: 20:49						
Sample: 2002Q1 2011Q4						
Included observations: 40						

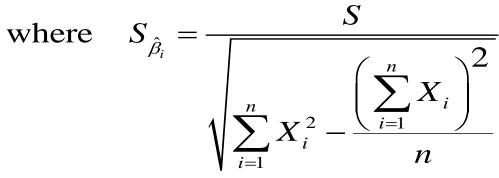
Included observations: 40						
Variable	Coefficient	Std. Error	t-Statistic	Prob.		
С	3973770.	754540.7	5.266475	0.0000		
@TREND	290525.1	24239.34	11.98568	0.0000		
@SEAS(1)	-3627516.	791034.8	-4.585786	0.0001		
@SEAS(2)	-2975920.	789175.7	-3.770922	0.0006		
@SEAS(3)	-2032456.	788058.1	-2.579068	0.0143		
R-squared	0.837415	Mean dependent var		7480035.		
Adjusted R-squared	0.818834	S.D. dependent var		4138083.		
S.E. of regression	1761318.	Akaike info criterion		31.71749		
Sum squared resid	1.09E+14	Schwarz criterion		31.92860		
Loa likelihood	-629.3498	Hannan-Quinn criter.		31.79382		
F-statistic	45.06800	Durbin-Watson stat		1.123746		
Prob(F-statistic)	0.000000					

# **Test of slope coefficients**

- •Hypotheses
  - $^{\circ}H_0: \beta_i = m$
  - • $H_a: \beta_i \neq m$



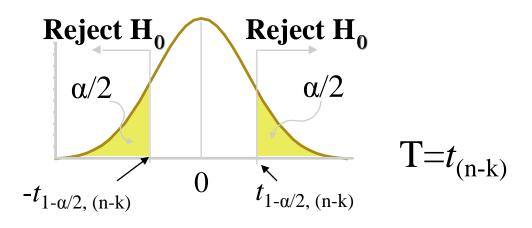




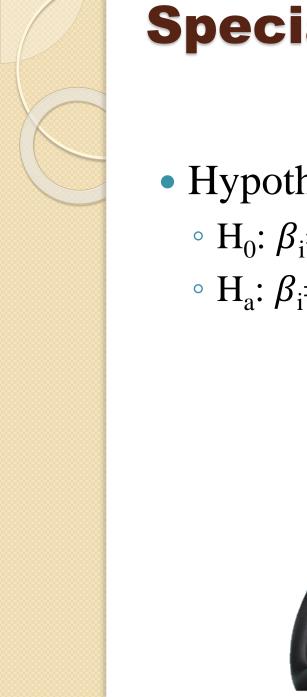
with 
$$S = \hat{\sigma} = \sqrt{\frac{RSS}{n-k}}$$
  
and  $RSS = \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 = \sum_{i=1}^{n} \left[Y_i - \left(\hat{\beta}_0 + \sum_{i=1}^{k-1} \hat{\beta}_i X_i\right)\right]^2$ 

# **Test of Slope Coefficient Rejection Rule**

• Reject  $H_0$  in favor of  $H_a$  if t falls in colored area

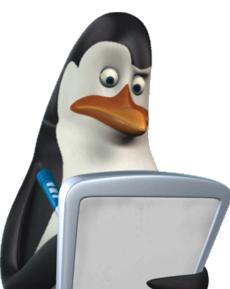


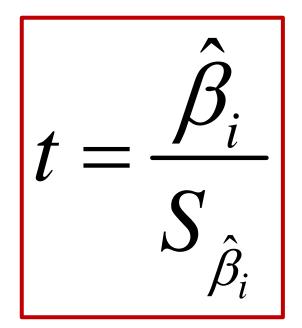
• Reject  $H_0$  for  $H_a$  if P-value = P(T>|t|) <  $\alpha$ 



### **Special case: significance** of coefficient

- Hypotheses
  - $H_0: \beta_i = 0$
  - H<sub>a</sub>:  $\beta_i \neq 0$





# Example

Dependent Variable: TAX_ENT Method: Least Squares Date: 12/09/12 Time: 20:49 Sample: 2002Q1 2011Q4 Included observations: 40							
Variable	Coefficient	Std. Error	t-Statistic	Prob.			
C @TREND @SEAS(1) @SEAS(2) @SEAS(3)	3973770. 290525.1 -3627516. -2975920. -2032456.		-4.585786	0.0000 0.0000 0.0001 0.0006 0.0143			
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.837415 0.818834 1761318. 1.09E+14 -629.3498 45.06800 0.000000	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Durbin-Watson stat		7480035. 4138083. 31.71749 31.92860 31.79382 1.123746			

# Wald test

Null Hypothesis:  $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ Alternative hypothesis  $H_1: \beta_1$  or  $\beta_2$  or  $\beta_3$ or any two of them or all are nonzero. At least one of them is significant.

In matrix notation

Hypothesis: 
$$Rb = r = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Test statistics with J numbers of restriction

$$F = \frac{\frac{(Rb-r)'[R\cos(b)R']^{-1}(Rb-r)}{J}}{\frac{RSS}{n-k}}$$

Calculate F and compare it with the critical values F(J, n-k) from the Table.

#### **Test for multicollinearity**

- High correlation between X variables
- Coefficients measure <u>combined effect</u>
- Leads to <u>unstable</u> coefficients depending on X variables in model
- <u>Always</u> exists; matter of degree
- *Example*: Using both total number of rooms and number of bedrooms as explanatory variables in same model

## **Detecting Multicollinearity**

- Farrar-Glauber Multicollinearity
- VIF-test

- Few remedies
  - Obtain new sample data
  - Eliminate one correlated X variable
  - Standardize your independent variables.

#### Example

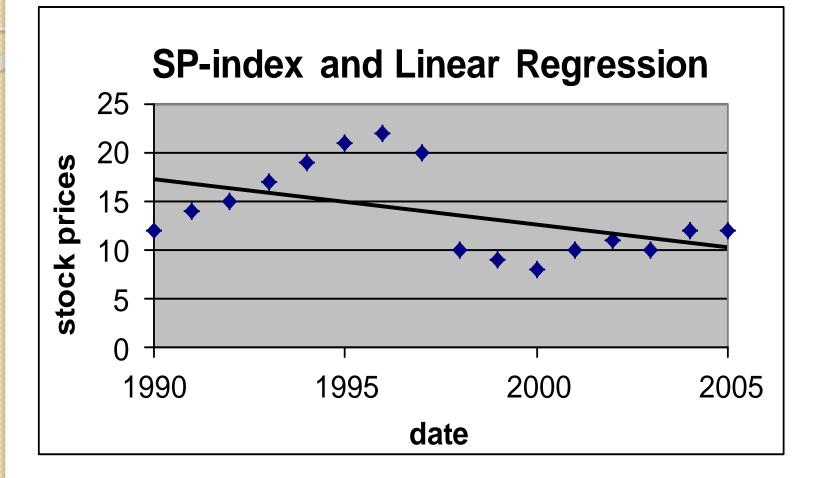
- $\hat{s}_t = 0.4 + 0.8 y_t + 0.2 li_t 0.1 si_t$ (0.9) (1.2) (0.4) (0.1)
- $\overline{R}^2 = 0.98$ , (standard errors in parentheses)

(n = 60). where :

- $s_t$  stock prices
- $y_t$  output
- $li_t$  long run interest rates
- $si_t$  short run interest rates



#### **Test for structural breaks**





#### **Chow Test**

• Tests whether the coefficients in two linear regressions on different data sets are equal.

$$F = \frac{RSS_c - (RSS_1 + RSS_2) / k}{(RSS_1 + RSS_2) / n - 2k} \sim F_{k,n-2k}$$

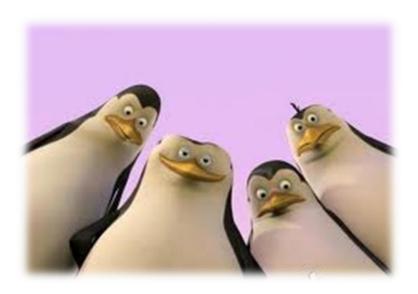
$$RSS_c - combined \_RSS$$

$$RSS_1 - pre - break \_RSS$$

$$RSS_2 - post - break \_RSS$$

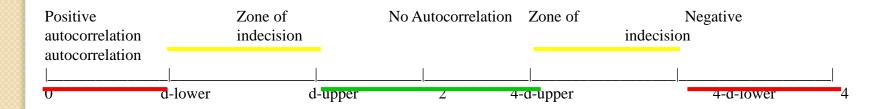
#### **Test for residuals autocorrelation**

- **Durbin-Watson test** (only checks for first order serial correlation in residuals)
- **Breusch-Godfrey Test** (checks for higher order autocorrelation AR(q) in residuals)



#### **Durbin-Watson statistic**

$$d = \frac{\sum (e_i - e_{i-1})^2}{\sum e_i^2}, \text{ for n and K - 1 d.f.}$$



- Autocorrelation is clearly evident
- Ambiguous cannot rule out autocorrelation
- Autocorrelation in not evident

## **Breusch-Godfrey Test**

Higher Order Autocorrelation model : AR(p)  $\mu_{t} = \rho_{1}\mu_{t-1} + \rho_{2}\mu_{t-2} + \dots + \rho_{p}\mu_{t-p} + \mathcal{E}_{t}$ Null Hypothesis  $H_0: \rho_1 = \rho_2 = ... = \rho_n = 0$ Test Model:  $\hat{\mu}_{t} = \delta_{1} + \delta_{2}X_{2t} + \dots + \delta_{k}X_{kt} + \lambda_{1}\hat{\mu}_{t-1} + \dots + \lambda_{n}\hat{\mu}_{t-n} + \omega_{t}$ **Test Statistic**  $LM = (n - p) R_{aux}^2 \sim \chi_p^2$ 

#### Tests for Heteroskedasticity

- There are two types of tests:
  - Tests for continuous changes in variance: *White test, Breusch–Pagan tests, etc.*
  - Tests for discrete (lumpy) changes in variance: the Goldfeld–Quandt test



## **The White Test**

- The White test for heteroskedasticity has a basic premise: *if disturbances are homoskedastic, then squared errors are on average roughly constant.*
- Explanators should **NOT** be able to predict squared errors, or their proxy, squared residuals.
- The White test is the most general test for heteroskedasticity.

## **Steps of the White Test**

- Regress Y against your various explanators using OLS, compute the OLS residuals,  $\epsilon_{1,...,}$   $\epsilon_{n}$
- Regress  $\epsilon_i^2$  against a constant, all of the explanators, the squares of the explanators, and all possible interactions between the explanators (p slopes total)
- Compute R<sup>2</sup> from the "auxiliary equation" in step 2
- Compare nR<sup>2</sup> to the critical value from the Chi-squared distribution with p degrees of freedom.

#### The Breusch–Pagan Test – 1

- The Breusch–Pagan test is very <u>similar</u> to the White test.
- The White test <u>specifies exactly which</u> <u>explanators</u> to include in the auxiliary equation. Because the test includes crossterms, the number of slopes (p) increases very quickly.
- In the Breusch–Pagan test the econometrician selects <u>which explanators to</u> <u>include</u>. Otherwise, the tests are the same.

#### The Breusch–Pagan Test – 2

- In the Breusch–Pagan test, the
  - econometrician selects **m** explanators to include in the auxiliary equation.
- Which explanators to include is a **judgment call**.
- A **good** judgment call leads to a more powerful test than the White test.
- A **poor** judgment call leads to a poor test.

#### The Goldfeld–Quandt Test – 1

- Both the *White* test and *the Breusch– Pagan* test focus on smoothly changing variances for the disturbances.
- *The Goldfeld–Quandt* test compares the variance of error terms across discrete subgroups.
- Under homoskedasticity, all subgroups should have the same estimated variances.

#### The Goldfeld–Quandt Test – 2

Divide the *n* observations into *h* groups, of sizes  $n_1..n_h$ 

Choose two groups, say 1 and 2.  $H_0: \sigma_1^2 = \sigma_2^2$  against  $H_a: \sigma_1^2 \neq \sigma_2^2$ 

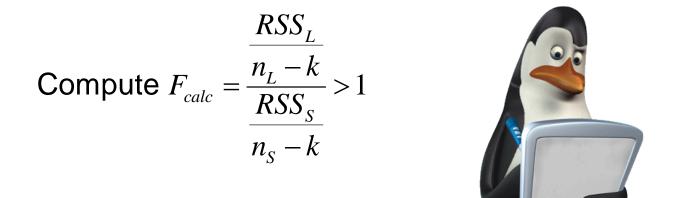
Regress *Y* against the explanators for group 1.

Regress *Y* against the explanators for group 2.



#### **Goldfeld–Quandt Test – 3**

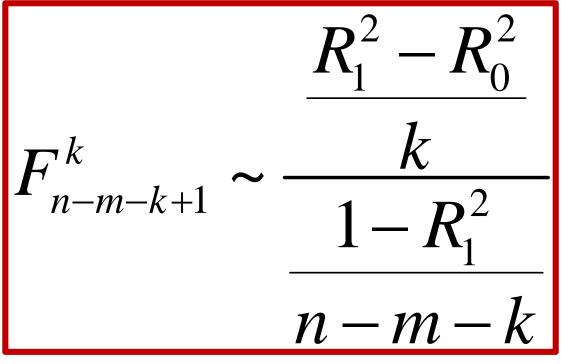
Relabel the groups as *L* and *S*, such that  $\frac{RSS_L}{n_L - k} > \frac{RSS_S}{n_S - k}$ 



Compare  $F_{calc}$  to the critical value for an *F*-statistic with  $(n_L - k)$  and  $(n_S - k)$  degrees of freedom.



#### **Test for specification**





## **Ramsey's RESET**

- RESET relies on a trick similar to the special form of the White test
- Instead of adding functions of the x's directly, we add and test functions of ŷ
- So, estimate  $y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \delta_1 \hat{y}_2 + \delta_2 \hat{y}_3 + \varepsilon$  and test H:  $\delta_1 - 0$ ,  $\delta_1 = 0$  using E~E.... or
- H<sub>0</sub>:  $\delta_1 = 0$ ,  $\delta_2 = 0$  using F~F<sub>2,n-k-3</sub> or LM~ $\chi^2(2)$ .

## **Stationary process**

- A stationary process is a stochastic process whose joint probability distribution does not change when shifted in time.
- Parameters such as the mean and variance, if they are present, also do not change over time and do not follow any trends.
   Solutions:
- Taking differences (Dickey-Fuller test)
- Trend-stationary processes

"What should we do, if we fail to find an appropriate model that satisfy all tests?"

#### Question



#### **Linear regression**

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{1t} + \dots + \beta_{k-1} x_{k-1t} + \varepsilon_t, t = 1, n$$

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 $X_{1t}, X_{2t}, \dots, X_{k-1t}$  independent variables;

 $\mathcal{E}_t$  - residuals.

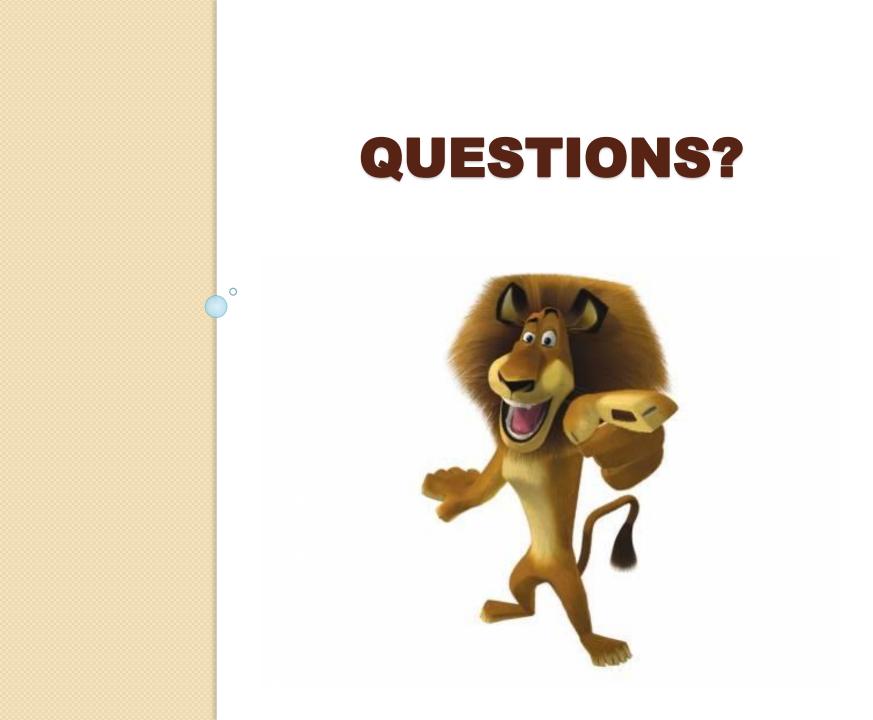


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- Estimate unknown parameters
- Evaluate model
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#### THANK YOU FOR YOUR ATTENTION!



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