



Measuring the Impact of Generating Electricity from Nuclear Energy Using the Panal Models

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Abstract

The research explains the economic theory of producing electricity from nuclear energy and its impact on sustainable development. This relationship is in the form of mathematical models that facilitate the quantitative measurement process. Considering that it is an essential tool that evaluates the features of economic theory by giving it estimates that make it more logical and acceptable, by relying on the econometric tools that we will use in our analysis of the results, and for this we will first indicating the models on which this study is based, which are the panel models, by identifying their advantages; Then, we recognize about the variables, their sources, and appropriate estimation methods for this type of model. As for the last part, it deals with identifying and estimating the appropriate model for analyzing the results of the estimation economically.

Panel data models are considered one of the important standard models in the field of economic sciences. Because it is of particular importance in increasing the number of observations, which allows access to more reliable standard results; In addition to the absence or regression of many

of the problems of econometrics, similar to the problem of instability of random error variance, and accordingly this topic was divided into three axes; The first axis included the theoretical framework of the longitudinal data model (Panel data), while the second axis measured the relationship between economic growth and electricity production from nuclear energy.

Keywords: Nuclear Energy, Sustainable Development, Panel Data, Econometric Study.

Part one: Theoretical framework of the panel data model

First: the concept of longitudinal data and its importance

The longitudinal data (Panel data) means the cross-sectional observations (countries or companies) observed during a specific period of time, meaning that this data has two dimensions, the first: for the time series, and the second: for the cross sections.

...., for a time series it describes the behavior of a single item over a given period of time; While the cross-sectional data describes the behavior of a number of singletons at one time period, and the longitudinal data is either balanced or unbalanced, if all observations are equal for the study sample, then the longitudinal data is balanced (Balanced Panel data); While it is unbalanced (Unbalanced Panel data) if there are missing observations for some of the study sample, and it should be noted that panel data has a synonymous term, it may also be called longitudinal data.

Longitudinal data models have gained increasing interest, particularly in economic studies. Because it considers the effect of the difference between cross-sections and the effect of time change. (Baltagi, 2005) mentioned a set of points that show the importance of longitudinal data, namely:

1. Controlling individual heterogeneity, which may appear in the case of time series or cross-sectional data, which may result in biased results.
2. Longitudinal data provide more additional information and less simultaneous linear relationship between variables. Longitudinal data are also characterized by a greater number of degrees of freedom and better efficiency.
3. Longitudinal data are better able to identify and quantify effects that simply cannot be detected in cross-sections or time-series data.
4. Longitudinal data models allow building and testing behavioral models that are more complex than cross-sectional data, or time series, eg technical competence is better studied.
5. Longitudinal data for individual units such as firms may be more accurate than similar data at the macroeconomic level.
6. Longitudinal data at the macro level have larger time series, and it is suggested to use co-integration methods for longitudinal data models with these data.

Second: unit root tests: (panel data unit root tests)

One of the most important stages of building the standard model is the stability tests of the longitudinal data. Because the presence of a unit root can lead to false results due to false regression between variables, the unit root tests for longitudinal data are:

Second: unit root tests: (panel data unit root tests) One of the most important stages of building the standard model is the stability tests of the longitudinal data. Because the presence of a unit root can lead to false results due to false regression between variables, the unit root tests for longitudinal data are:

$$\Delta y_{i,t} = \rho y_{i,t-1} + \varepsilon_{i,t} \dots\dots\dots (1)$$

$$\Delta y_{i,t} = \alpha_i + \rho y_{i,t-1} + \varepsilon_{i,t} \dots\dots\dots (2)$$

$$\Delta y_{i,t} = \alpha_i + \beta_{i,t} + \rho y_{i,t-1} + \varepsilon_{i,t} \dots\dots\dots (3)$$

Based on the previous models, the LLC proposes to test the following hypotheses:

$$H_0: \rho = 0 \quad H_1: \rho < 0$$

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In the general case and in the case of autocorrelation between the residuals, the LLC test is built on the basis of the Augmented Dickey - Fuller Test ADF model, as this test allows residuals to be placed in known distributions for individual t statistics, and the three models take the form following:

$$\Delta y_{i,t} = \rho y_{i,t-1} + \sum_{s=1}^p \gamma_{i,s} \Delta y_{i,t-s} + U_{it} \dots\dots\dots (4)$$

$$\Delta y_{i,t} = \alpha_i + \Delta y_{i,t} + \rho y_{i,t-1} + \sum_{s=1}^p \gamma_{i,s} \Delta y_{i,t-s} + U_{it} \dots\dots\dots (5)$$

$$\Delta y_{i,t} = \alpha_i + \beta_{i,t} + \Delta y_{i,t} + \rho y_{i,t-1} + \sum_{s=1}^p \gamma_{i,s} \Delta y_{i,t-s} + U_{it} \dots\dots\dots (6)$$

: Since $u_{i,t} \sim i.i.d(0, \sigma^2)$

2) Im, Pesaran and Shin test (IPS): IPS presented a model for the unit root test in longitudinal data through a study in (1997), which is unlike the LLC test as the IPS test allows for heterogeneity in the value of ρ_i under the alternative hypothesis and the formula for this model is as follows:

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{z=1}^p \beta_{i,z} \Delta y_{i,t-z} + \varepsilon_{i,t} \dots\dots\dots (7)$$

$$H_0: \rho_i = 0$$

$$H_1: \rho_i < 0$$

The IPS is based on the expanded Dekey-Fuller statistic averaged across groups, so the IPS statistic used for the unit root test of longitudinal data is:

$$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^N t_{p_{it}} \dots\dots\dots (8)$$

($t_{p_{it}}$): the individual statistic that relates to the (t) statistic associated with the null hypothesis.

3) The Wu and Maddala test:

This test is an illustration of Fisher's test that he developed in (1932), as Wu and Maddala's test in (1999) is simple and depends on a combination of the levels of significance of the study sample; Let $[P_i = F_{Ti}(G_i)]$ be the (p-value) related to the statistic G_i , which is the unit root null hypothesis test statistic, while F_{Ti} is the statistic density function G_i with respect to the time dimension T_i . Wu and Maddala developed the statistic for this test:

$$P = -2 \sum_{i=1}^N \ln p_i \dots\dots\dots(9)$$

The Wu and Maddala statistic follows the distribution of (χ^2) by the square of the degree of freedom in the case of $(\infty \rightarrow T)$, and accordingly, if the result of this statistic is greater than the value of (2χ) by the square of the degree of freedom, the null hypothesis of the unit root is rejected, and the alternative hypothesis is accepted, and the opposite occurs in the case that the result of the Wu and Maddala test statistic is less than (2χ) by the square of the degree of freedom, the null hypothesis of the unit root is accepted, and the alternative hypothesis is rejected.

Third: the basic models for analyzing longitudinal data

The general syntax for the Panel data form is:

$$y_{it} = \beta_0(i) + \sum_{j=1}^k \beta_j X_{j(it)} + \varepsilon_{it} \dots\dots\dots(10)$$

Since:

y_{it} : dependent variable.

$\beta_0(i)$: the point of intersection in observation i .

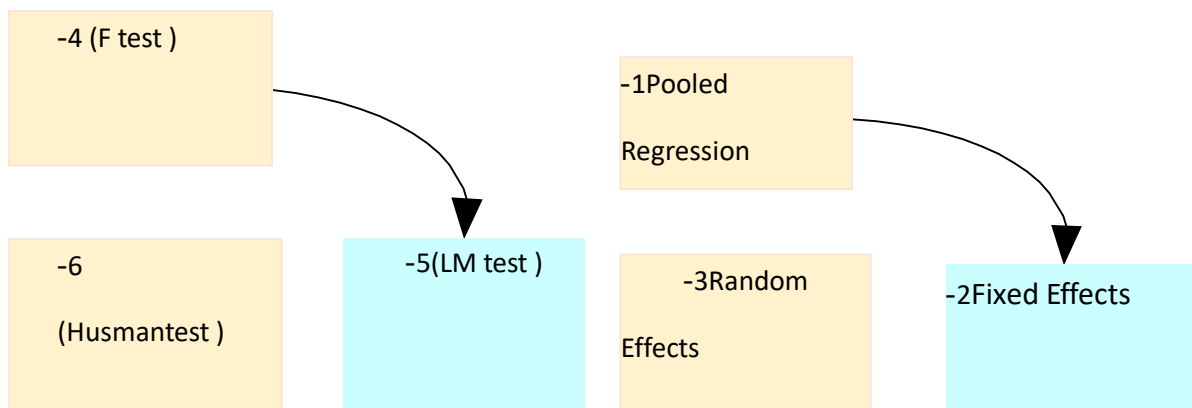
β_j : the value of the slope of the regression line.

$X_{j(it)}$: the value of the explanatory variable j in the observation i at the time period t .

ε_{it} : the random error.

The methods for estimating the panel models are as follows:

Figure 41 Steps for estimating panel data models



Gujarati, D. N. (2011). Econometrics by example

There are three models for longitudinal data, which are summarized as follows: 1) Pooled Regression Model PM The PM model is considered one of the simplest longitudinal data models, in which all coefficients $\beta_0(i)$ and β_j are constant over the length of time, and this means that this model neglects the effect of time, and by rewriting equation (10) the PM model is obtained as follows:

$$y_{it} = \beta_0 + \sum_{j=1}^k \beta_j X_{j(it)} + \varepsilon_{it} \dots\dots\dots (11)$$

since:

$$E(\varepsilon_{it}) = 0$$

$$\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$$

This means using the Ordinary Least Squares OLS method to estimate the model parameters in equation (11).

2) Fixed Effects Model FEM

(Gujarati and Porter, 2009, 596) indicated that what is meant by the term fixed effects is that the parameter β_0 is fixed for each cross sectional data set that does not change over time, and the change is only in the cross sectional data groups, and that the aim of the fixed effects model is to know the behavior of each data set sectional data, by making the parameter β_0 vary from group to group with the slope coefficients β_j remaining constant for each sectional dataset, and then the FEM model is in the following form:

$$y_{it} = \beta_{0(i)} + \sum_{j=1}^k \beta_j X_{j(it)} + \varepsilon_{it} \dots\dots\dots (12)$$

since:

$$E(\varepsilon_{it}) = 0$$

$$\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$$

To estimate the model parameters in equation (12) and to allow the cut-off parameter β_0 to vary between sectional aggregates, dummy variables of $(n-1)$ are used; To avoid perfect multicollinearity, the Ordinary Least Squares (OLS) method is used. It is worth noting that the

fixed-effects model is called the Least Squares Dummy Variable Model (LSDV), and after adding the dummy variable to equation (12), it becomes as follows:

$$y_{it} = \alpha_1 + \sum_{d=2}^N \alpha_d D_d + \sum_{j=1}^k \beta_j X_{j(it)} + \varepsilon_{it} \dots\dots\dots (13)$$

since:

$$\alpha_1 + \sum_{d=2}^N \alpha_d D_d \text{Change in sectional cross aggregates of the parameter : } \beta_0$$

3) Random Effects Model REM

Unlike the fixed effects model, the random effects model treats cross-sectional and temporal effects as random features, not fixed features. The random effects model will treat the cut-off factor $\beta_0(i)$ as a random variable with a rate of μ , i.e.:

$$\beta_{0(i)} = \mu + v_i \dots\dots\dots (14)$$

By substituting equation (5) into equation (12), the random effects model is obtained in the following form:

$$y_{it} = \mu + \sum_{j=1}^k \beta_j X_{j(it)} + v_i + \varepsilon_{it} \dots\dots\dots (15)$$

As:

v_i : error term of the cross-section dataset i .

Because of the presence of two components of error (v_i) and (ε_{it}), the random effects model is called the Error Components Model. When estimating the parameters of the random effects model, the usual least squares method is not relied upon; This is because it gives inaccurate results, and it has incorrect measurement errors, and this will affect the testing of the parameters, and accordingly, the Generalized least squares GLS method is used in estimating the parameters of the random effects model.

Fourth, choose the appropriate model

From the foregoing, it became clear that there are three models for longitudinal data, and a specific model must be chosen when conducting any tests. Accordingly, two methods will be presented to compare between longitudinal data models:

The first method: choosing between the combination regression model and the fixed effects model

When choosing between the combined regression model (PM) and the fixed effects model (FEM), the restricted F-test is used in the following form:

$$F(n-1, nT-n-K) = \frac{(R_{FEM}^2 - R_{PM}^2)/(n-1)}{(1 - R_{FEM}^2)/(nT-n-K)} \dots\dots\dots (16)$$

As:

K: the number of estimated parameters.

RFEM: coefficient of determination when using a fixed effects model (FEM)

RPM: coefficient of determination when using a pooled regression model (PM)

After obtaining the calculated value of F, it is compared to its tabular counterpart ($F(\alpha, N-1, Nt-N-k)$), and if it is greater than it, or the Cross-section Chi-square value is significant, the null hypothesis (H_0) is rejected. And accepting the alternative hypothesis (H_1), that is, the fixed or random effects model is suitable for the study, but if the calculated F value is less than the tabular one, or the Cross-section Chi-square value is not significant, then the null hypothesis (H_0) is accepted, and the hypothesis is rejected. Alternative (H_1), that is, the pooled regression model (PM) is appropriate for the study.

The second method: choosing between the fixed effects model and the random effects model

This method is done by the Hausman test, which is based on the difference between fixed effects and random effects, as it is the extent to which the individual effect is associated with variables; The Hausman test is used to find out which effects are more appropriate for model estimation, whether they are fixed-effects models or random-effects models. The Hausman test is based on two hypotheses, which take the following form:

H_0 : Null hypothesis the random effects model is appropriate, in which case the generalized least squares method (GLS) is relied upon.

H_1 : Alternative hypothesis, the fixed effects model is appropriate, in which case the OLS method is relied upon.

The formula for the Hausman test is as follows:

$$H = (\hat{\beta}_{FEM} - \hat{\beta}_{REM})' [\text{var}(\hat{\beta}_{FEM}) - \text{var}(\hat{\beta}_{REM})]^{-1} (\hat{\beta}_{FEM} - \hat{\beta}_{REM}) \dots \dots \dots (17)$$

Since:

$(\hat{\beta}_{FEM} - \hat{\beta}_{REM})$: The difference between the estimates of fixed effects and random effects.
 $[\text{var}(\hat{\beta}_{FEM}) - \text{var}(\hat{\beta}_{REM})]$: The difference between the covariance for each of the fixed effects estimators and for the random effects estimators.

The difference between the covariance for each of the fixed effects estimators and for the random effects estimators.

If the calculated value of the Hausman test is greater than the tabular value, or the Chi-Sq. Statistically, the null hypothesis (H_0) supporting the random effects model is rejected, and the alternative hypothesis (H_1) is accepted, which states that the fixed effects model is the best model, either if the calculated value of the Hausman test is less than the tabular value, or the statistical value Chi- Sq. Statistic is not significant, the null hypothesis (H_0) supporting the random effects model is accepted, and the alternative hypothesis (H_1) is rejected, meaning that the random effects model is the best model. Through this measurement, we will try to verify the following hypotheses:

The second part: the practical framework of the longitudinal data model (Panel data)

The first hypothesis: proving the first hypothesis that there is a significant positive relationship with statistical significance between economic growth, electricity production from nuclear energy, and the choice between different alternatives for energy generation.

A- Study variables: The variables used in estimating the model can be defined as follows: Table No. 23 Study variables

variable type	measuring unit	Definition	variable name
dependent variable	%)annually(	.GDP growth rate as an indicator of economic growth.	GDP
independent variable	%) annually(	Electricity production from nuclear sources	NUCLEAR
independent variable	%) annually(	Electricity production from natural gas sources	GAS
independent variable	%) annually(	Electricity production from coal sources	COAL
independent variable	%) annually(	Electricity production from oil sources	OIL
independent variable	%) annually(	Electricity production from renewable sources	Renewable sources

b- Study population and sample: The GDP rate was chosen as an indicator of economic growth for a sample of foreign countries and a response variable (dependent); While the production rates of nuclear, gas, coal, petroleum and renewable energy were included as an independent and explanatory variable, and the study covers foreign countries whose data are available, representing 03 countries during the period 2003 to 2018, and thus the number of observations used in the total sample is 480 observations.

Table No. 24 of the countries under study

Country	Country	Country
Netherlands-21	Spain-11	Argentina-1
Pakistan-22	Finland -12	Armenia-2
Romania-23	France -13	Belgium-3
Russian fede-24	United king-14	Bulgaria-4
South africa-25	Hungary-15	Brazil-5
Slovak republ-26	India-16	Canada-6
Slovenia-27	Japan-17	Switzerland-7
Sweden-28	Korea. Rep-18	China-8
Ukraine-29	Lithuania-19	Czeck Republ-9
United states-30	Mexico-20	Germany-10

B- Methods for estimating the model in the EVIEWS program: Firstly, an estimation of the regression pooling, fixed-effects, and random-effects model In order for the vision to become clear, to measure the impact of electricity production from nuclear energy on economic growth, the longitudinal data model was used through the application of three models, the aggregate regression model, the fixed effects model, and the random effects model. The results of these three models were reached as shown in the following table:

Table 25. Estimation of the combined regression, fixed and random effects model

Dependent Variable: GDP Sample: 2003 – 2018 Cross-sections included: 30 Total panel (balanced) observations: 480												
Variable	Pooled Regression Model				Fixed Effects Model				Random Effects Model			
	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob	Coefficient	Std. Error	t-Statistic	Prob
C	4.706	0.759	6.194	0.000	-3.834	3.070	-1.249	0.2123	2.751	1.455	1.891	0.059
GAZ	-0.013	0.012	-1.065	0.287	0.088	0.041	2.185	0.0294	0.002	0.019	0.102	0.918
COAL	0.008	0.009	0.889	0.374	0.074	0.049	1.532	0.1263	0.017	0.016	1.076	0.282
NUCLEAR	-0.027	0.011	-2.416	0.016	0.081	0.036	2.256	0.0246	-0.006	0.081	-0.382	0.702
OIL	-0.030	0.026	-1.152	0.249	0.066	0.053	1.259	0.2088	-0.005	0.034	-0.159	0.873
RENEWABLE_SOURCES	-0.175	0.033	-5.309	0.000	0.159	0.063	2.523	0.0120	0.001	0.042	0.046	0.963
R-square	0.08				0.61				0.006			
Adjusted R-squared	0.07				0.56				0.004			
F-statistic	8.91				13.82				0.57			
Prob(F-statistic)	0.000				0.000				0.61			

Source: prepared by the researcher based on the statistical program EViews, version ten.

Secondly, the F test and the Hausmann test for differentiation between the three models. The above table shows the results of the three panel models test (summative, fixed and random), which were reached based on the available data that show the countries of the research sample. After the model has been estimated, a comparison is now made between these methods in order to rely on the best method. In order to reach this goal, the F-test is used in order to compare between the aggregate regression model, the fixed-effects model, and the random-effects model. In order to choose the appropriate model to be used, Table (26) shows the F test.

Table 26 F test

Test Summary	Prob
Cross-section F	0.00

Source: prepared by the researcher based on the statistical program EViews, version ten

The results of the F test, as shown in Table (26), showed that the probability of the F test is significant at a level less than (0.01); Therefore, we reject the null hypothesis (H0), and accept the alternative hypothesis (H1), that is, the fixed or random effects model is the appropriate model for estimating the impact of electricity production from nuclear energy on economic growth, and accordingly the Hausman test is used.

Table 27. Hausmann test

Test Summary	Prob
Cross-section random	0.011

Source: prepared by the researcher based on the statistical program EViews, version ten

By observing Table (27), the results of the Hausmann test showed that the statistical value was significant at a level less than (0.05); Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), that is, the fixed effects model is the appropriate model for estimating the impact of electricity production from nuclear energy on economic growth, as shown in Table (27).

Third, the analysis of the results of the Fixed Effects Model test:

Table No. 45 Fixed Effects Model

Dependent Variable: GDP				
Method: Panel Least Squares				
Date: 10/30/19 Time: 23:23				
Sample: 2003 2018				
Periods included: 16				
Cross-sections included: 30				
Total panel (balanced) observations: 480				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.834231	3.069550	-1.249118	0.2123
GAS	0.088893	0.040681	2.185132	0.0294
COAL	0.074984	0.048951	1.531798	0.1263

NUCLEAR	0.081182	0.035986	2.255938	0.0246
OIL	0.066859	0.053114	1.258787	0.2088
RENEWABLE_SOURCES	0.159748	0.063318	2.522965	0.0120
	Effects Specification			
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
R-squared	0.611763	Mean dependent var		3.080462
Adjusted R-squared	0.567522	S.D. dependent var		3.855031
S.E. of regression	2.535186	Akaike info criterion		4.796744
Sum squared resid	2763.683	Schwarz criterion		5.231513
Log likelihood	-1101.218	Hannan-Quinn criter.		4.967642
F-statistic	13.82797	Durbin-Watson stat		1.256279
Prob(F-statistic)	0.000000			

In continuation of the results of table (52) and in the light of the results of estimating the fixed effects model, the researcher notes through the following equation:

$$\text{GDP} = -3.834 + 0.081 \text{ Nuclear} + 0.066 \text{ Oil} + 0.088 \text{ Gaz} + 0.074 \text{ Coal} + 0.159 \text{ Renewable} \dots\dots\dots(18)$$

1. Significance of the parameters: The statistically significant coefficients of the model are represented in the proportion of electricity produced from gas, nuclear and renewable energy, where we find the probability of the constant coefficient for each of them (0.0294), (0.0246), (0.0120), respectively, because they are less than the level of significance (0.05), as The non-significant coefficients are represented in coal and oil, where we find the probability of the constant coefficient for each of them (0.1263), (0.2088).
2. Total significance: Through the model, we find that the F-statistic probability value (0.000) less than (0.05) indicates the overall significance of the model, which is significant at the level of 5%, meaning that the model is entirely significant.
3. The quality of reconciliation: the value of R² amounted to 0.61, meaning that the independent variables explain changes in economic growth by 61%, and the rest is due to factors outside the model, i.e. explained by other variables that were not included in the model.
4. The positive sign of the coefficient of electricity produced from nuclear energy (0.081) indicates the positive relationship between economic growth and the percentage of electricity production from nuclear energy; When the production of nuclear electricity increases by one unit, it leads to an increase in the size of the gross national product by 0.081; In other words, increasing electricity generation by relying on nuclear reactors raises economic growth rates.

Conclusion

Using standard models and analyzing the relationship between growth and electricity consumption, it was found that there is a significant positive effect of generating electricity from nuclear energy on economic growth. This is consistent with the first hypothesis that there is a positive effect relationship between economic growth and the production of electricity from

nuclear energy, and therefore, through the results of estimating the fixed effects model, the model can be accepted from the economic point of view, given that the economic theory is consistent with the results obtained.

References

- Wooldridge, Jeffrey M (2016), Introductory Econometrics: A Modern Approach, Sixth Edition, Cengage Learning, United States of America, pp 756-769.
- Frees, Edward W (2004), Longitudinal and Panel Data Analysis and Applications in the Social Sciences, Cambridge University, United Kingdom, pp 2
- Baltagi , Badi H (2005), Econometric Analysis of Panel Data, Third Edition, John Wiley & Sons Ltd, England., 4-7.
- Diebold, Francis X (2017), Econometrics: A Predictive Modeling Approach, University of Pennsylvania, pp6.
- Levin , Andrew, Lin , Chien-Fu , and Chu, Chia-Shang James (2002) , Unit root tests in panel data :asymptotic and finite-sample properties, Journal of Econometrics , Vol. 108 , No. 1.pp 4.
- Strauss, Jack, and Yigit, Taner,(2003) Shortfalls of panel unit root testing, Economics Letters, Vol. 81, No. 3 , pp309.
- Hurlin, Christophe, and Mignon, Valerie (2007), Second Generation Panel Unit Root Tests, HAL Id: halshs-00159842.pp 5.
- Asteriou, Dimitrios, and Hall, Stephen G (2011) , Applied Econometrics, Second Edition, Palgrave Macmillan, England.,pp445 .
- Hsiao , Cheng (2003), Analysis of Panel Data, Second Edition, Cambridge University Press, United Kingdom, pp 9.
- Seddighi, Hamid R (2012), Introductory Econometrics: A Practical Approach, First published, Routledge, London., pp, 261.
- Cameron, A. Colin, and Trivedi, Pravin K (2005), Microeconometrics: Methods and Applications, First published, Cambridge University Press, United Kingdom., 734.
- Greene, William H (2012), Econometric Analysis, Seventh Edition, Pearson Education Limited, United States of America.pp 403.
- Wooldridge, Jeffrey M (2002), Econometric Analysis of Cross Section and Panel Data, First published, The MIT Press , London., pp 288 .
- Verbeek, Marno (2017) , A Guide to Modern Econometrics, Fifth Edition, John Wiley & Sons Inc, United States of America. pp394.