Academic Journal of Business & Management
ISSN 2616-5902 Vol. 5, Issue 18: 134-138, DOI: 10.25236/AJBM.2023.051821

Green GDP and Energy: A New Model of GGDP and Energy

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Abstract: *While the gross national/domestic product (GNP/GDP) index is a highly reliable indicator that reflects economic performance of a country, it still largely ignores the depreciation of assets, non-market economy and especially the damages to the environment caused by growth. Environmental sustainability of economic growth has come to be recognized as one of the most important pillars of sustainable growth and development. In order to tackle many challenges of the so-called green growth and sustainable development, we try to build a new/alternative Green GDP indicator that should give us a clearer perspective of the consequences of economic progress by offering a new approach in quantifying the cost of ecological and environmental degradation. Since the loss of natural resources is difficult to estimate, but the main purpose of natural resource loss is to obtain energy, the relationship between GGDP and energy is studied, including coal resources, natural gas resources and nuclear energy. Furthermore, the main factors affecting GGDP are indirectly explored, so as to provide reference opinions for the sustainable development of various countries. Since the obtained data is panel data, after preprocessing, logarithmic operations, F-test and Haussmann test, a random-effects model is selected, and the calculation concludes that GGDP is highly correlated with GDP, coal, natural gas and nuclear energy.*

Keywords: *GGDP; panel data; random-effects model; sustainable development*

1. Introduction

Nowadays, economic development and environmental protection meeting each other halfway has become a global concern in the fields of humanity, energy consumption and meteorology. However, Gross Domestic Product (GDP), the most widely used measure of national economic health at present, increasingly shows the following drawbacks: (1) Traditional GDP may be a misleading economic indicator, which often reflects the material and static conditions, but tends to ignore the problems in economic development [1]; (2) Traditional GDP lacks the measurement of sustainable growth (for example, it ignores energy consumption in the process of economic development ,thus causes climate change, etc. [2]). In this way, it is going to impede the sustainable development of resources and cannot continuously benefit the well-being of mankind in the long run.

In order to deal with the problems mentioned above, the concept of green GDP comes into being [3-5]. Compared with traditional GDP, the accounting method of green GDP not only considers the economic growth rate but also pays attention to the factors, such as resource consumption, environmental pollution and other aspects on society, so as to reflect the combined effect of economy, resources and environment more comprehensively and objectively, which is a larger overall effect on the whole society [6-10]. Nevertheless, as a new concept, green GDP also faces multiple challenges in its implementation and promotion. Therefore, the establishment, testing and universality analysis of its accounting model are of great practical significance under the world environment at that time.

2. The new model of GGDP analysis

2.1 Model Description

The collected data are divided into two dimensions, cross-section——country and time——2008-2014, that is, cross-sectional data, so assume that the cross-section is $i = 1,2,\dots,n$, and the hypothetical time is $t = 1,2,\dots,T$, corresponding to 2008-2014. The basic model is:

$$y_{it} = f(x_{1it}, x_{2it}, .., x_{kit}) + u_{it}, i = 1,2,\dots,n; t = 1,2,\dots,T \tag{1}$$

ISSN 2616-5902 Vol. 5, Issue 18: 134-138, DOI: 10.25236/AJBM.2023.051821

$$u_{it} = \alpha_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In general, without considering the time effect, that is, the role of λ_t is merged into ε_{it} .The original basic model can be changed to:

$$y_{it} = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_k x_{kit} + \varepsilon_{it}, i = 1,2,\ldots,n; t = 1,2,\ldots,T \tag{3}$$

Since there are three basic models for processing cross-sectional data, namely mixed effect models, fixed effect models, and random effects models, it is necessary to test the appropriate model, and the following are the basic models of the three models and their solution methods. The model structure is shown in Figure 1.

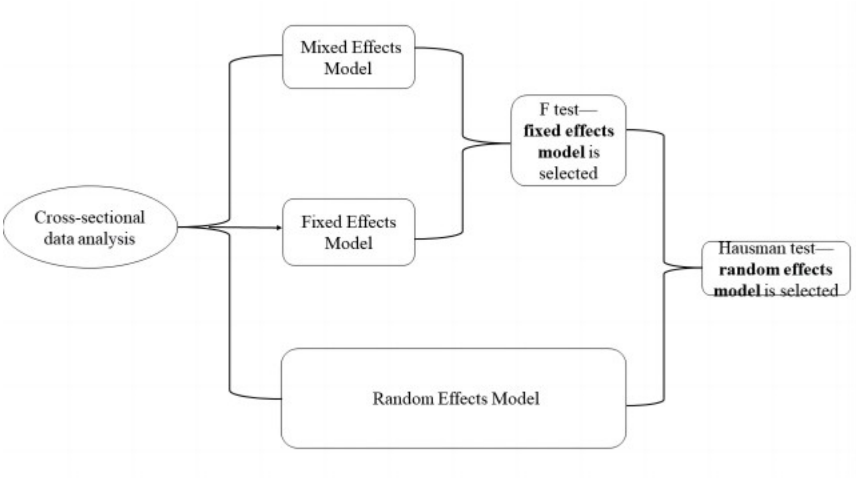

Figure 1: The logic of model structure

2.1.1 Mixed-effects model

The basic assumption is that all cross-section individuals have the same intercept and slope at different times.

The basic model is as follows:

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_k x_{kit} + \varepsilon_{it}, i = 1,2,\ldots,n; t = 1,2,\ldots,T \tag{4}$$

The OLS method can be used directly for parameter estimation.

2.1.2 Fixed effect model

The basic assumption is that each cross-section individual has a different intercept term, but the intercept and time of each cross-section individual are independent. General assumption: $Cov(\alpha_i, x_{it}) \neq 0$.

The basic model:

$$y_{it} = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_k x_{kit} + \varepsilon_{it}, i = 1,2,\ldots,n; t = 1,2,\ldots,T \tag{5}$$

Parameter estimation—Least squares dummy variable estimation LSDV.

Since fixed-effect models assume 'individual effects', each cross-sectional individual has its own individual intercept term. It is equivalent to introducing n-1 dummy variables to represent different individuals by addition in the classical linear regression model. If the constant term β0 of the model is omitted, n dummy variables are introduced.

If the unary fixed-effect model is set to:

$$y_{it} = \alpha_i + \beta_1 x_{it} + \varepsilon_{it} \tag{6}$$

Assuming there are intercept terms, n-1 dummy variables can be introduced, in which case the dummy variable model is:

$$y_{it} = \alpha_i + \beta_1 x_{it} + \gamma_1 D_1 + \gamma_2 D_2 + \ldots + \gamma_{n-1} D_{n-1} + \varepsilon_{it} \tag{7}$$

Performing OLS regression on the above equation yields the LSDV estimator $\hat{\beta}_1$.

F test can be used to test whether to choose a blended regression model or a fixed-effects model. Using the constrained regression model and the F-test, the constraint is $\gamma_1 = \gamma_2 = \ldots = \gamma_{n-1} = 0$. If you accept the null hypothesis, choose a blended regression model. If the null hypothesis is rejected, a fixed-effect model is chosen.

2.1.3 Random-effects model

Basic assumptions: $Cov(\alpha_i, x_{it}) = Cov(v_i, x_{it}) = 0$

Basic model:

$$y_{it} = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots + \beta_k x_{kit} + \varepsilon_{it}, i = 1,2,\ldots,n; t = 1,2,\ldots,T \tag{8}$$

$\alpha_i$is a random variable,$E(\alpha_i) = \alpha$.

The random-effects model classifies the individual heterogeneity of the fixed-effect model into the random error term, and the random error term that meets the basic assumptions needs to be constructed through transformation. Therefore, GLS is used for parameter estimation.

Still taking the univariate random-effects model as an example:

$$y_{it} = \beta_0 + \beta_1 x_{it} + u_{it} \tag{9}$$

Suppose the model contains intercept terms, let $u_{it} = v_i + \varepsilon_{it}$ be the non-observed error of the model

$$\text{Define}: \lambda = 1 - \frac{\sigma_\varepsilon}{\sqrt{\sigma_\varepsilon^2 + T\sigma_v^2}}, \bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \tag{10}$$

Make the following transformations:

$$y_{it} - \lambda\bar{y}_i = \beta_0(1-\lambda) + \beta_1(x_{it} - \lambda\bar{x}_i) + u_{it} - \lambda u_i \tag{11}$$

You can verify that there is no sequence correlation for the random error term at this time: $Cov(u_{it} - \lambda\bar{u}_i, u_{is} - \lambda\bar{u}_i) = 0$. OLS regression of the transformed equation yields GLS estimator $\beta_{1,re}$, also known as the random-effects estimator.

The random-effects estimator is valid when hypothesis $E(u_{it}|x_{it}) = 0$is satisfied.

2.2 Model selection

2.2.1 F test

First, the F test is carried out to determine whether to choose a fixed-effect model or a mixed-effect model, the theory is derived from LSDV, and the test results are shown in Table 1:

Table 1: F test for individual effects

statistical measure	value
F	18.639
df1	5.000
df2	31.000
p-value	1.569e-08

The null hypothesis was rejected and a fixed-effect model was selected.

Secondly, the Hausman test is carried out to determine whether to choose a fixed-effect model or a random-effects model, and the theoretical sources are as follows:

2.2.2 Hausman test

Here the Haussmann test is not an endogenous test, but a random-effects test. The basic idea of the test is:

If $Cov(\alpha_i, x_{it}) \neq 0$, the GLS estimator is biased and non-consistent, but the fixed-effect estimator is unbiased and consistent, so if the heterogeneity of the model is orthogonal to the explanatory variables, the model should be set to a random-effects model, otherwise it should be set to a fixed-effect model.

Here orthogonal is: if $E(XY) = 0$, then the random variables X and Y are said to be orthogonal

H_0: Individual heterogeneity is not correlated with x_{it}.

H_1: Individual heterogeneity is associated with x_{it}.

Construct the Wald statistic:

$$W = (\hat{\beta}_{fe} - \hat{\beta}_{re})^T [Var(\hat{\beta}_{fe} - \hat{\beta}_{re})]^{-1} (\hat{\beta}_{fe} - \hat{\beta}_{re}) \sim \chi^2(k) \quad (12)$$

where k is the number of explanatory variables.

The Haussmann test was carried out and the following results were obtained and shown in Table 2:

Table 2: Result of Hausman test

statistical measure	value
chisq df	10.377 4.000
p-value	0.345

The null hypothesis was rejected and a random-effects model was selected.

3. Results

3.1 The establishment of simulation model

3.1.1 Data Collection

This data comes from the World Bank's GDP, coal, natural gas and nuclear power station ratio, and per capita power generation and population in 26 countries from 2008 to 2014, estimates the GGDP of each year of the above countries, and estimates the power generation of coal, natural gas and nuclear respectively. Based on this data, model building and analysis are carried out.

3.1.2 Data preprocessing

Since the magnitude of each group of data is more than 10 to the power of 10, in order to reduce the magnitude, all data are logged at the same time to ensure the reversibility in the next matrix operation and improve the accuracy of model operation

3.2 Analysis of experimental results

The random-effects basic model can be used to obtain the following GGDP ~ GDP + coal + Ngas + nuclear model:

$$GGDP_{it} = \alpha_i + \beta_1 * GDP_{it} + \beta_2 * coal_{it} + \beta_3 * Ngas_{it} + \beta_4 * nuclear + \varepsilon_{it}, i = 1,2,\ldots n, t = 1,2\ldots, T \quad (13)$$

The calculation results are shown in Table 3:

In the table, the first column of data, from top to bottom, represents the intercept term and the estimated values of $\beta_1 - \beta_4$. Taking the estimated value of β_1 as an example, it represents the average increase in the value of GGDP when GDP increases by one unit, while holding coal, Ngas, and nuclear constant. The fourth column of data shows the p-values of this model. From the data in the table, it can be inferred that the p-values are all small, indicating good model significance.

Table 3: Coefficients of the GGDP model

	Estimate	Std.Error	Z-value	Pr(>|z|)
Intercept	-1.2936	0.2843	-4.5500	5.365e-06
GDP	1.0412	0.0137	75.8051	<2.2e-16
coal	-0.0166	0.0059	-2.8175	0.0048
Ngas	0.0172	0.0070	2.4409	0.0146
nuclear	0.0032	0.0032	1.0035	0.3156

Hence, the available models are:

$$GGDP_{it} = -1.2936 + 1.0412 * GDP_{it} - 0.0166 * coal_{it} + 0.0172 * Ngas_{it} + 0.0032 * nuclear i = 1,2,\ldots n, t = 1,2\ldots, T \quad (14)$$

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4. Conclusions

On the surface of this model, GGDP is closely related to GDP and has a positive correlation, but it has a negative correlation with coal use, and the correlation is strong, which is weak and positive with natural gas using, and has little correlation with nuclear energy use. Since the current GGDP algorithm is based on GDP to add factors related to environmental factors, GDP accounts for the main body of GGDP, so there is a strong positive correlation; In the use of coal, because the mining process will release a large amount of dust, and the mining process will destroy the local ecology, and a large amount of smoke and CO_2 will be generated in the combustion of power generation, which will lead to air pollution, water pollution and greenhouse effect, etc., resulting in serious environmental pollution, so coal has a strong negative correlation with GGDP; Natural gas is a clean energy source, and the CO_2 released is relatively small and easy to recover, so it has a weak positive correlation with GGDP. Nuclear energy does not cause problems such as atmospheric and water pollution and greenhouse effect, but nuclear leakage will cause a huge ecological disaster, but because the probability is too low and the disaster is huge and irreversible, it is difficult to assess whether it affects GGDP.

At present, GDP is still the world's mainstream indicator to measure a country's development level, but it covers up the ecological problems behind each country, although the current GGDP algorithm does not have a unified standard, but it can still be used as a reference indicator, and GDP together as an indicator to measure a country's economic development level, gradually promoted, and gradually persuaded countries to gradually adopt GGDP, after all, any emerging thing to replace the old thing takes time, let people accept it and love the convenience it brings to comfort.

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