

# **Energy Efficiency of Selected OECD Countries: A Slacks Based Model with Undesirable Outputs**

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**Abstract:** This paper presents an efficiency assessment of selected OECD countries using a Slacks Based Model with undesirable or bad outputs (SBM-Undesirable). In this research, SBM-Undesirable is used first in a two-stage approach to assess the relative efficiency of OECD countries using the most frequent indicators adopted by the literature on energy efficiency. Besides, in the second stage, GLMM-MCMC methods are combined with SBM-Undesirable results as part of an attempt to produce a model for energy performance with effective predictive ability. The results reveal different impacts of contextual variables, such as economic blocks and capital-labor ratio, on energy efficiency levels.

**Keywords:** Energy, OECD, SBM-Undesirable, Two-stage GLMM-MCMC

**JEL Codes:** C6, D2, Q4,

## **1. Introduction**

This paper analyzes the energy efficiency of selected OECD countries using SBM-Undesirable. Research on energy efficiency has adopted several methods. These range from the simple partial energy efficiency measures (e.g., energy usage per capita, ratio of GDP to energy consumption) to sophisticated composite index approaches (e.g., DEA - Data Envelopment Analysis-, distance functions, Malmquist productivity index). Therefore, the paper innovates on this context, first, by undertaking a review of energy efficiency and, second, by adopting as a research goal, SBM-Undesirable combined with MCMC generalized mixed models in a two-stage approach. The motivations for the present research originate from: First, this paper innovates on energy efficiency, evaluating the relative efficiency across selected OECD countries. Efficiency is the relative position of the units analyzed in the frontier of best practices, which is defined by the group of countries analyzed. In this research, this relative analysis is undertaken for a number of OECD countries, adopting for the first time the SBM-Undesirable and Markov chain Monte Carlo methodological approaches for GLMM. Furthermore, the present analysis enables a ranking of the relative efficiency of the countries and presents a predictive focus. Finally, the paper contributes to the literature of energy efficiency by analyzing, for the first time, 20 OECD countries with the above mentioned context of the SBM-Undesirable and MCMC generalized mixed modeling approaches.

Although there have been many papers on energy efficiency and productivity, there has been a very limited number of studies with reference to the OECD countries, in spite of their global importance in terms of energy consumption. The only closely related study is that of Zhou and Ang (2008) that makes use of three DEA-type linear programming modeling approach for measuring economy-wide energy efficiency performance across 21 OECD countries. While Zhou and Ang (2008) consider a joint production framework of desirable and undesirable output as in the current study, our study differs in a number of respects. First, Zhou and Ang (2008) consider energy consumption by different sources (coal, oil, gas and other energy) as separate inputs in the production of GDP, while we consider energy consumption in the context of renewable and non-renewable energy. Second, we use a much longer and recent sample (1985-2011) that enables us to track the

trend of energy efficiency over time, including the recent global crisis period, while their study uses only a five-year time span (i.e. 1997-2001). Finally, our study employs a different and more efficient methodology (SBM-Undesirable and MCMC generalized mixed models) that enables us not only to estimate energy efficiency levels, but also to analyze contextual factors that may influence efficiency levels.

The paper is structured as follows: The next Section presents the contextual setting, including a description of the energy sector across the OECD countries under investigation. The literature survey is then presented in Section 3, followed by the SBM-Undesirable methodology Section. Section 5 presents the data and the prediction of efficiency levels using MCMC generalized linear mixed models, followed by the discussion of the results and the conclusion.

## **2. Contextual Setting**

Energy is one of the major inputs in many production and related processes. Energy is needed in the industrial sector, transportation, street lighting, residential, commercial and government buildings, among others. The demand for energy is rising due to a rising population and the quest for economic growth, which has consequently led to rising energy prices. The UNEP (2011) report highlights that in the 20th century, the world population grew by 4 times, economic output by 22 times and fossil fuel consumption by 14 times. The Organisation for Economic Co-operation and Development (OECD) population stood at 27% between 1980 and 2012, while its Gross National Income (GNI) grew by 455% over the same period. Its world share of the electricity consumption as at 2011 was about 50% (International Energy Agency (IEA, 2013). Under the WEO-2011 New Policies Scenario (OECD, 2011), the Global primary energy demand is projected to increase on average by 1.3% per year from 2009 to 2035, while the average IEA crude oil import prices will approach USD 120 per barrel (in year-2010 dollars) in 2035. The report also indicates that while the demand is rising, nearly 20% of the global population lack access to electricity. Due to increasing globalisation and international competitiveness, more emphasis is being placed on reducing production costs, including those related to energy. Moreover, in addition to energy security issues, an increasing cause of concern over the increasing

demand for energy is the environmental footprints of energy use, particularly CO<sub>2</sub> emissions from fossil fuel use (Gielen and Taylor, 2009). The current energy system is highly dependent on fossil fuels, whose combustion accounted for 84% of global greenhouse gas emissions in 2009 (OECD, 2011). As at 2011, the OECD's world share of CO<sub>2</sub> emission was about 39.4% (IEA, 2013). With a looming global climate change threat, many countries across the globe, and OECD countries in particular, are expected to encounter difficulties in continuing with increasing energy demand towards achieving high economic growth. Hence, a trade-off may be required between economic growth gains from energy consumption and environmental deterioration, if appropriate strategies and policies are not put in place.

Although the current energy demand is driven mainly by non-OECD and emerging countries, such as China and India, the repercussions are felt globally. Hence, the above highlighted challenges have led several countries formulating political, economic and technical strategies across all sectors of the economy, with the aim of reducing energy demand (Martínez, 2009). The transition to a greener model of growth is being actively supported by OECD and IEA. At its 50<sup>th</sup> Anniversary Ministerial Council Meeting in May 2011, the OECD launched a Green Growth Strategy to help policy makers and stakeholders to address the major environmental challenges of today's world, while expanding economic opportunities. The Strategy encompasses both policy recommendations to make economic growth "greener" and a set of indicators to monitor progress towards green growth (OECD, 2011). The OECD set of indicators that are relevant to the energy sector are those that measure the carbon productivity or intensity of energy production and consumption (on various levels, including both national and sectoral energy consumption), energy intensity and efficiency, "clean" energy-related research and development and patents, as well as measures of energy related taxes and subsidies (OECD, 2011). This study focuses on energy efficiency.

The reason is that energy efficiency is considered as one of the vital strategies to addressing the challenges posed by increasing energy demand (Ang, 2006; Zhou and Ang, 2008). Improving energy efficiency is important from various policy perspectives. Conservation of energy derived from fossil fuels in order to prevent their depletion in the

near future is a very crucial objective (Mukherjee, 2008a). Moreover, energy security can be enhanced by improving energy efficiency. Furthermore, reduction in energy use, especially coming from burning fossil fuels, is important for preventing a further deterioration of environmental quality, through increasing CO<sub>2</sub> emissions (Balachandra et al., 2010). Energy efficiency also plays a vital role in achieving the underlying economic objective of cost minimization. For cost effectiveness, it is very important to reduce energy use during periods of high energy prices and also to suitably substitute other inputs for energy (Mukherjee, 2008a). Energy efficiency makes available additional energy resources, which can help in addressing the issues of energy inadequacy or insecurity as well as equity concerns (Balachandra, et al. 2010). According to IEA (2008) and IPCC (2007), energy efficiency improvements represent the largest and least-cost opportunities to meet the growing energy needs and for reducing CO<sub>2</sub> emissions. The importance of energy efficiency to attain overall sustainable economic development cannot be relegated to the background.

Given the importance of energy efficiency, a number of indicators for monitoring economy-wide energy efficiency trends over time or comparing energy efficiency performances across countries/regions have emerged. This is evident in the literature review section.

### **3. Literature Review**

Research in frontier models for energy efficiency encompasses several scientific methods to analyze performance in a quantitative manner. The summary of previous studies is presented in Table 1. Several methods have been used, ranging from simple indexes such as the traditional measure of energy efficiency (energy intensity) to composite indexes. The majority of these studies have used DEA and DEA-based modeling approaches. In many cases, multiple inputs, including energy consumption, are used, while output differs depending on whether the analysis focuses on specific sectors or on the entire economy. It has also been observed that only two of the studies, that is Zhou and Ang (2008) and Xie et al. (2014) consider both desirable and undesirable outputs in their modeling of energy efficiency. Further, there are only few studies in OECD countries namely Zhou and Ang (2008) which is an economy wide study as in this study, as well as Azadeh et al. (2007) and

Xie et al. (2014) which are sector specific studies. In general the results from previous studies are mixed. While a number of countries and/or sectors are found to be energy efficient, others are energy inefficient, implying that the latter group are operating below the frontier and, as such would need to reduce energy input and increase output simultaneously. Moreover, while energy efficiency has slowly improved in certain countries and sectors over time, it has declined considerably in others. Furthermore, in some countries energy efficiency has remained constant over time. Overall, these findings point to the need for more empirical studies on energy efficiency for specific regions, countries, sectors and industries, since it will be hard to generalize the empirical results. Finally, there is the need to employ more efficient methodologies, capable of estimating energy efficiency with little or no bias.

Table 1: Literature review

| Author            | Sample characteristic                                    |   |   | Method                              |
|-------------------|--|---|---|-------------------------------------|
|                   | Unit/Time period   | Input   | Output  |                                     |
| Ramanathan (2000) | Indian rail and road transport modes:<br>1980/81-1993/94 | Energy consumption  | (1) Passenger kilometres<br>(2) Tonne-kilometres  | DEA CRS                             |
| Ramanathan (2005) | 17 MENA countries:<br>1992 & 1996                        | (1) CO2 emissions per capita<br>(2) Fossil fuel energy consumption  | (1) Gross domestic product per capita (GDP per cap)<br>(2) Non-fossil fuel energy consumption | DEA CRS<br>DEA VRS<br>DEA Malmquist |
| Wei et al. (2007) | China's iron and steel sector by region:<br>1994–2003    | (1) Energy consumption (i.e. oil equivalent of fuel oil, natural gas and electricity)<br>(2) Coal<br>(3) Coke | (1) Pig iron<br>(2) Crude steel<br>(3) Finished steel   | DEA Malmquist                       |
| Azadeh et al.     | Manufacturing  | (1) Electricity consumption   | (1) Gross output  | An integrated approach based        |

|                                 |  |  |   |                              |
|---------------------------------|--|--|---|------------------------------|
| (2007)                          | sectors in 10 OECD countries:<br>Various years   | (2) Aggregated fossil fuels consumption  | (2) Value added<br>(3) Some sector specific outputs   | DEA, PCA and NT              |
| Banaeian and Namdari (2011)     | Watermelon farms in Hamadan province of Iran: cross sectional                                      | (1) Human labor<br>(2) Machinery<br>(3) Diesel fuel consumption<br>(4) Fertilizer<br>(5) Farmyard manure<br>(6) Seed<br>(7) Water<br>(8) Chemicals | Yield   | DEA CRS DEA VRS              |
| Hu and Kao (2007)               | 17 APEC economies:<br>1991–2000  | (1) Energy consumption<br>(2) Labor<br>(3) Capital   | GDP   | DEA CRS                      |
| Taghizadeh and Pourrabbi (2013) | Automobile and Autoparts producing companies listed in Tehran Stock Exchange:<br>2003-2008         | (1) Cost of electricity<br>(2) Cost of natural gas<br>(3) Cost of natural gas<br>(4) Cost of compressed air<br>(5) Cost of gasoline                | (1) Net sales<br>(2) Increase (decrease) in produced goods stock<br>(3) Increase (decrease) in stock goods in production process<br>(4) Investment profit | DEA CRS and DEA VRS          |
| Mukherjee (2008a)               | U.S. aggregate manufacturing sector and six highest energy consuming 2-digit sectors:<br>1970-2001 | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br>(4) Materials<br>(5) Services  | quantity index of gross output for the sector   | DEA CRS                      |
| Mukherjee (2008b)               | Indian States manufacturing sector:<br>1998–99 to 2003–04  | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br>(4) Materials  | Real gross value of manufacturing production in the state   | DEA CRS                      |
| Boyd and Pang (2000)            | Container glass and Flat glass   | (1) Capital<br>(2) Labor<br>(3) Consumption of   | Value of shipments  | Shephard's distance function |

|                          |  |  |  |  |
|--------------------------|--|--|--|--|
|                          | industries:<br>1987-1995   | electricity<br>(4) Cost of combustible fuels<br>(5) Cost of raw materials  |  |  |
| Gielen and Taylor (2009) | Indian industrial sectors  | Energy consumption   | GDP  | IEA energy efficiency index based on BAT/BPT                                   |
| Zhou and Ang (2008)      | 21 OECD countries:<br>1997-2001                                  | (1) Labor<br>(2) Capital<br>(3) Coal consumption<br>(4) Oil consumption<br>(5) Gas consumption<br>(6) Other energy consumption   | (1) GDP<br>(2) CO <sub>2</sub> emission  | Environmental CRS DEA  |
| Mukherjee (2010)         | Manufacturing sector in Indian states:<br>2000/2001 to 2004/2005 | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br>(4) Materials  | Gross value of manufacturing production in the state   | Directional distance function  |
| Grösche (2009)           | US single-family homes:<br>1997-2001                             | Households' total energy consumption<br><br>Second stage regression covariates:<br>-Local climatic condition variables<br>-Attached structure<br>-Construction decade dummy<br>- Main heating fuel<br>-Interaction variables | (1) Living space<br>(2) Number of Persons<br>(3) Number of electric appliances<br>(4) Number of Fridges and freezers<br>(5) Heating degree days<br>(6) Cooling degree days | Two stage bootstrap DEA  |
| Zhang et al. (2011)      | 23 developing countries:<br>1980–2005                            | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br><br>Second stage regression covariate: national income per capita and national income per capita squared   | GDP  | VRS DEA (full & window analysis)<br>Tobit regression for second stage analysis |
| Hu and Wang (2006)       | 29 administrative regions in China: 1995–2002                    | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br>(4) Total sown area of farm crops  | Real GDP   | CRS DEA  |
| Honma and Hu             | 47   | (1) Labor  | Real GDP   | CRS DEA  |



|                               |  |   |   |   |
|-------------------------------|--|---|---|---|
| (2008)                        | administrative regions in Japan: 1993–2003                           | (2) Private capital stocks<br>(3) Public capital stocks<br>(4) Electric power for commercial and industrial use<br>(5) Electric power for residential use<br>(6) Gasoline<br>(7) Kerosene<br>(8) Heavy oil<br>(9) Light oil<br>(10) City gas<br>(11) Butane gas<br>(12) Propane gas<br>(13) Coal<br>(14) Coke |   |   |
| Honma and Hu (2009)           | 47 administrative regions in Japan: 1993–2003                        | Same as in Honma and Hu (2008)  | Real GDP  | The total-factor energy productivity change index (TFEPI)             |
| Chang and Hu (2010)           | 29 provinces in China: 2000–2004                                     | (1) Labor<br>(2) Capital<br>(3) Energy consumption<br>(4) Total sown area of farm crops   | Real GDP  | TFEPI   |
| Mandal and Madheswaran (2009) | Indian states cement industry: 2000/01–2004/05                       | (1) Capital<br>(2) Energy consumption<br>(3) Labor<br>(4) Raw materials   | Real value of ex-factory products and by-products | DEA with Sequential Frontier<br><br>DEA with Contemporaneous Frontier |
| Khoshnevisan et al. (2013)    | Wheat farmers in Fereydonshahr region, Esfahan Iran: cross sectional | (1) Labor<br>(2) Chemical fertilizers<br>(3) Farmyard manure<br>(4) Bocides<br>(4) Machinery<br>(5) Diesel fuel<br>(6) Water for irrigation<br>(7) Electricity<br>(8) Seeds   | Wheat produce                                     | CRS and VRS DEA   |
| Iribarren et al. (2014)       | Wind farmers in Castile-La Mancha and Andalusia, Spain: 2010         | (1) Fossil resources use<br>(2) Metal ores<br>(3) Mineral resources<br>(4) Nuclear energy<br>(5) Renewable energy<br>(6) Water and<br>(7) Land resource   | Wind power  | Emergy + DEA (i.e Em + DEA model)                                     |
| Xie et al. (2014)             | Electric power   | (1) Labor   | (1) Electric power                                | SBM-DEA and   |

|  |  |   |                     |  |
|--|--|---|---------------------|--|
|  | Industries in 26 OECD and BRIC countries | (2) Installed capacity<br>(3) Fuel consumption<br>(4) Nuclear energy consumption<br><br>Second stage regression for determinants of TFP and its decompositions using population density, GDP per capita, the proportion of second industry, GDP growth, the proportion of research and development investment in GDP, energy consumption per unit of GDP, electricity consumption per capita and the thermal power proportion | (2) CO <sub>2</sub> | Tobit regression for second stage regression |
|--|--|---|---------------------|--|

Based on the literature review, it is verified that, thus far, no paper has adopted simultaneously SBM-Undesirable and the GLMM modeling approaches using MCMC, while there is not any relevant paper that has performed an analysis focusing solely on selected OECD countries within this methodological context, which renders an additional novelty of this empirical work.

#### 4. An SBM with undesirable outputs

Several authors have proposed efficiency measures in the presence of undesirable outputs. A conventional and traditional way to handle this problem is to shift undesirable outputs to inputs and to apply traditional DEA models. In the VRS (variable returns to scale) environment, Seiford and Zhu (2002) propose a methodological approach that first, multiplies each undesirable output by  $-1$  and then finds a proper translation vector so as all negative undesirable outputs are positive. Interestingly, Scheel (2001) point out that these two transformations (i.e., position changes and translations) provide the same efficient frontiers, though the Seiford and Zhu methodology is valid only under the VRS conditions. However, resulting efficiency scores for inefficient DMUs are different by the modeling approach followed. Another conventional way is to invert the undesirable output value and treat into a desirable one. This operation may cause the deformation of the efficient

frontiers due to the non-linear transformation and hence give a different identification of the efficiency status as well as of the efficiency score.

Färe *et al.* (1989) is the first paper to treat this subject systematically. They treat desirable and undesirable outputs asymmetrically, resulting in an enhanced hyperbolic output efficiency measure. This approach needs to solve a non-linear programming problem. In terms of the non-separable models, Scheel (2001) proposes a radial and output-oriented methodology, whereas Färe *et al.* (2003) develop a directional vector approach in output-orientation. The non-separable outputs models have efficient frontiers than the separable outputs case.

According to Copper *et al.* (2007), the majority of DEA models can be categorized into four classes: (1) radial and oriented, (2) radial and non-oriented, (3) non-radial and oriented, and (4) non-radial and non-oriented. Here, ‘radial’ implies that a proportional reduction or enlargement of inputs/outputs is the main concern in measuring efficiency, while ‘oriented’ denotes input-oriented or output-oriented. Consequently, radial models neglect slacks and, hence, when dealing with undesirable outputs, slacks in undesirable outputs are not accounted for in the efficiency measure, which constitutes a crucial shortcoming of radial models. By contrast, the major concern of input (output)-oriented models focuses on the input (output)-side efficiency, while output (input)-side turns out to be a minor issue in measuring efficiency. Thus, only the non-radial and non-oriented models can capture the whole aspects of efficiency.

Let us assume that there are  $n$  DMUs (decision making units), each being associated with three factors: inputs, good outputs and bad (undesirable) outputs, represented by three vectors:  $\mathbf{x} \in R^m$ ,  $\mathbf{y}^g \in R^{s_1}$  and  $\mathbf{y}^b \in R^{s_2}$ , respectively. We define the matrices  $X$ ,  $Y^g$  and  $Y^b$  as follows.  $X = [x_1, \dots, x_n] \in R^{m \times n}$ ,  $Y^g = [y_1^g, \dots, y_n^g] \in R^{s_1 \times n}$ , and  $Y^b = [y_1^b, \dots, y_n^b] \in R^{s_2 \times n}$ . We assume  $X > 0$ ,  $Y^g > 0$  and  $Y^b > 0$ . The production possibility set ( $P$ ) is defined as:

$$P = \{(\mathbf{x}, \mathbf{y}^g, \mathbf{y}^b) | \mathbf{x} \geq X \boldsymbol{\lambda}, \mathbf{y}^g \leq Y^g \boldsymbol{\lambda}, \mathbf{y}^b \geq Y^b \boldsymbol{\lambda}, \boldsymbol{\lambda} \geq \mathbf{0}\}, \quad (1)$$

where  $\boldsymbol{\lambda} \in R^n$  is the intensity vector. Notice that the above definition corresponds to the constant returns to scale technology. A DMU<sub>0</sub> ( $x_0, y_0^g, y_0^b$ ) is efficient in the presence of

undesirable outputs, if there is no vector  $(x, y^g, y^b) \in P$  such that  $x_0 \geq x, y_0^g \leq y^g$  and  $y_0^b \geq y^b$  with at least one strict inequality. In accordance with this definition, the SBM is modified as follows:

$$\text{[SBM-Undesirable]} \quad p^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b} \right)} \quad (2)$$

$$\text{Subject to} \quad x_0 = X\lambda + s^- \quad (3)$$

$$y_0^g = Y^g\lambda - s^g \quad (4)$$

$$y_0^b = Y^b\lambda + s^b \quad (5)$$

$$s^- \geq \mathbf{0}, s^g \geq \mathbf{0}, s^b \geq \mathbf{0}, \lambda \geq \mathbf{0} \quad (6)$$

The vectors  $s^- \in R^m$  and  $s^b \in R^{s_2}$  correspond to the excesses in inputs and bad outputs, respectively, while  $s^g \in R^{s_1}$  highlights shortages in good outputs. The objective function (2) is strictly decreasing with respect to  $s_i^- (\forall i)$ ,  $s_r^g (\forall r)$  and  $s_r^b (\forall r)$  and the objective value satisfies  $0 < p^* \leq 1$ . Let an optimal solution of the above program be  $(\lambda^*, s^{-*}, s^{g*}, s^{b*})$ .

Although the bad outputs model is presented under the constant returns to scale (CRS) assumption, other returns-to-scale RTS features can be also incorporated by adding the following constraint to the [SBM-Undesirable] scheme and, hence, to the definition of the production possibility set  $P$ :

$$L \leq e\lambda \leq U, \quad (7)$$

where  $e = (1, \dots, 1) \in R^n$  and,  $L (\leq 1)$  and  $U (\geq 1)$  are respectively the lower and upper bounds to the intensity  $\lambda$ . The cases  $(L = 1, U = 1)$ ,  $(L = 0, U = 1)$  and  $(L = 1, U = \infty)$  correspond to the variable (VRS), the decreasing (DRS) and the increasing (IRS) RTS, respectively.

## 5. Data and efficiency prediction using GLMM-MCMC

### 5.1. Data

Data on OECD selected countries span the period 1985 to 2011 for the following countries: Australia, Austria, Belgium, Canada, Switzerland, Denmark, Spain, Finland, France, Iceland, Italy, Japan, Korea, Netherland, Norway, New Zealand, Portugal, Sweden, the U.K. and the U.S. These countries are selected based on common data availability. The variables obtained are the inputs and outputs usually found in the literature review, based on data availability. These are: labor (number of employees), renewable and non-renewable energy consumption (in thousand tonnes of oil equivalent), and the productive capital stock (in constant US dollars) considered as inputs; Income (GDP, in constant US dollars) and the CO<sub>2</sub> emissions (in thousands of metric tonnes of Carbon), considered as the good and the bad output, respectively. Data on labor, capital and GDP are obtained from the OECD Economic Outlook. CO<sub>2</sub> (sourced from <http://cdiac.ornl.gov/>); total and renewable energy data are from the OECD database. Non-renewable energy is calculated as the difference between total and renewable energy. Their descriptive statistics are reported in Table 2.

In addition, a number of contextual variables are collected to explain differences in the efficiency levels; they are also presented in Table 2 and are related to major demographics/economics of each country under study. Dummies are created to assess whether the country is an European Union (EU) member, whether the country is signatory of the North-American Free-Trade Agreement (NAFTA), whether the country is an Asian Tiger, and whether the country belongs in the G7 group. Finally, the capital-labor ratio is computed by dividing the stock of productive capital by the total number of employees in the economy, while a trend variable is also explicitly considered.

Table 2: Descriptive statistics for the TOPSIS criteria and the contextual variables

|                      | Variables  | Min                | Max                      | Mean                   | SD                     |
|----------------------|--|--------------------|--------------------------|------------------------|------------------------|
| Inputs               | Productive Capital Stocks (USD constant prices)                      | 156,486,000,000.00 | 3,911,080,000,000,000.00 | 180,463,298,144,444.00 | 590,902,257,251,102.00 |
|                      | Labour (Number of Employees)   | 131,433.16         | 146,050,166.70           | 18,089,044.06          | 29,350,971.65          |
|                      | Renewable Energy Consumption (thousand tonnes of oil equivalent)     | -                  | 72,769.00                | 4,895.41               | 10,834.82              |
|                      | Non Renewable Energy Consumption (thousand tonnes of oil equivalent) | 876.38             | 1,527,404.06             | 138,032.32             | 297,640.36             |
| Outputs              | GDP (USD constant prices)  | 77,643,201,161.00  | 1,311,890,000,000,000.00 | 62,051,855,231,543.60  | 200,981,194,666,638.00 |
|                      | CO2 Emissions (thousands of metric tonnes of Carbon) - Bad           | 444.00             | 1,589,500.00             | 132,159.01             | 310,774.29             |
| Contextual Variables | EU   | -                  | 1.00                     | 0.60                   | 0.49                   |
|                      | NAFTA  | -                  | 1.00                     | 0.10                   | 0.30                   |
|                      | Asian Tiger  | -                  | 1.00                     | 0.10                   | 0.30                   |
|                      | G7   | -                  | 1.00                     | 0.30                   | 0.46                   |
|                      | Trend  | 1.00               | 27.00                    | 14.00                  | 7.80                   |
|                      | Squared Trend  | 1.00               | 729.00                   | 256.67                 | 224.92                 |
|                      | Capital-Labor ratio  | 37,690.64          | 161,333,824.40           | 6,458,751.38           | 21,733,493.54          |

## 5.2. Generalized Linear Mixed Models using Markov chain Monte Carlo methods

GLMMs combine a generalized linear model with normal random effects on the linear predictor scale to give a rich family of models that have been used extensively in many applications in the empirical literature (Diggle et al., 2002; Verbeke and Molenberghs, 2000, 2005; McCulloch et al., 2008). This flexibility comes at a price, however, of analytical tractability, which has a number of implications, including computational complexity and an unknown degree to which inference is dependent on modeling assumptions (Fong et al., 2009). For instance, although likelihood-based inference may be carried out relatively easily within many software platforms, inference is dependent on asymptotic sampling distributions of estimators, with few guidelines available as to when such theoretical approximations will generate accurate inferences.

More precisely, GLMMs extend the generalized linear model, proposed by Nelder and Wedderburn (1972) and comprehensively described in McCullagh and Nelder (1989), by adding normally distributed random effects on the linear predictor scale. Assume that  $Y_{ij}$  is described by an exponential form:  $Y_{ij} | \theta_{ij}, \varphi_l \sim p(\cdot)$ , where  $p(\cdot)$  is a member of the exponential family, that is:

$$p(y_{ij} | \theta_{ij}, \varphi_l) = \exp[(y_{ij} \theta_{ij} - b(\theta_{ij})) / a(\varphi_l) + c(y_{ij}, \varphi_l)], \quad (8)$$

for  $i = 1, \dots, m$  units (clusters) and  $j = 1, \dots, n_i$ , measurements per unit, and where  $\theta_{ij}$  is the (scalar) canonical parameter. Let  $\mu_{ij} = E[Y_{ij} | \beta, b_i, \varphi_l] = b'(\theta_{ij})$  with:

$$g(\mu_{ij}) = \eta_{ij} = x_{ij} \beta + z_{ij} b_i, \quad (9)$$

where  $g(\cdot)$  is a monotonic “link” function,  $x_{ij}$  is  $1 \times p$ , and  $z_{ij}$  is  $1 \times q$ , with  $\beta$  a  $p \times 1$  vector of fixed effects and  $b_i$  a  $q \times 1$  vector of random effects, hence  $\theta_{ij} = \theta_{ij}(\beta, b_i)$ . Assume  $b_i | Q \sim N(0, Q^{-1})$ , where the precision matrix  $Q = Q(\varphi_2)$  depends on parameters  $\varphi_2$ . It is assumed that  $\beta$  is assigned a normal prior distribution. Let  $\gamma = (\beta, b)$  denote the  $G \times 1$

vector of parameters assigned Gaussian priors. We also require priors for  $\varphi_1$  (if not a constant) and for  $\varphi_2$ . Let  $\varphi = (\varphi_1, \varphi_2)$  be the variance components for which non-Gaussian priors are assigned, with  $V = \dim(\varphi)$ .

Although a Bayesian approach is attractive, it requires the specification of prior distributions, which is not straightforward, particularly for variance components. Recall that we assume  $\beta$  is normally distributed. Often there will be sufficient information in the data set for  $\beta$  to be well estimated, with a normal prior characterized by large variance. The use of an improper prior for  $\beta$  will often lead to a proper posterior, though care should be taken. If we wish to use informative priors, we may specify independent normal priors, with the parameters for each component being obtained via a specification of 2 quantiles with associated probabilities. For logistic and log-linear models, these quantiles may be given on the exponentiated scale since these are more interpretable (as the odds ratio and rate ratio, respectively). If  $\theta_1$  and  $\theta_2$  are the quantiles on the exponentiated scale and  $p_1$  and  $p_2$  are the associated probabilities, then the parameters of the normal prior are given as:

$$\mu = z_2 \log(\theta_1) - z_1 \log(\theta_2) / (z_2 - z_1), \quad (11)$$

$$\sigma = \log(\theta_2) - \log(\theta_1) / (z_2 - z_1), \quad (12)$$

where  $z_1$  and  $z_2$  are the  $p_1$  and  $p_2$  quantiles of a standard normal random variable.

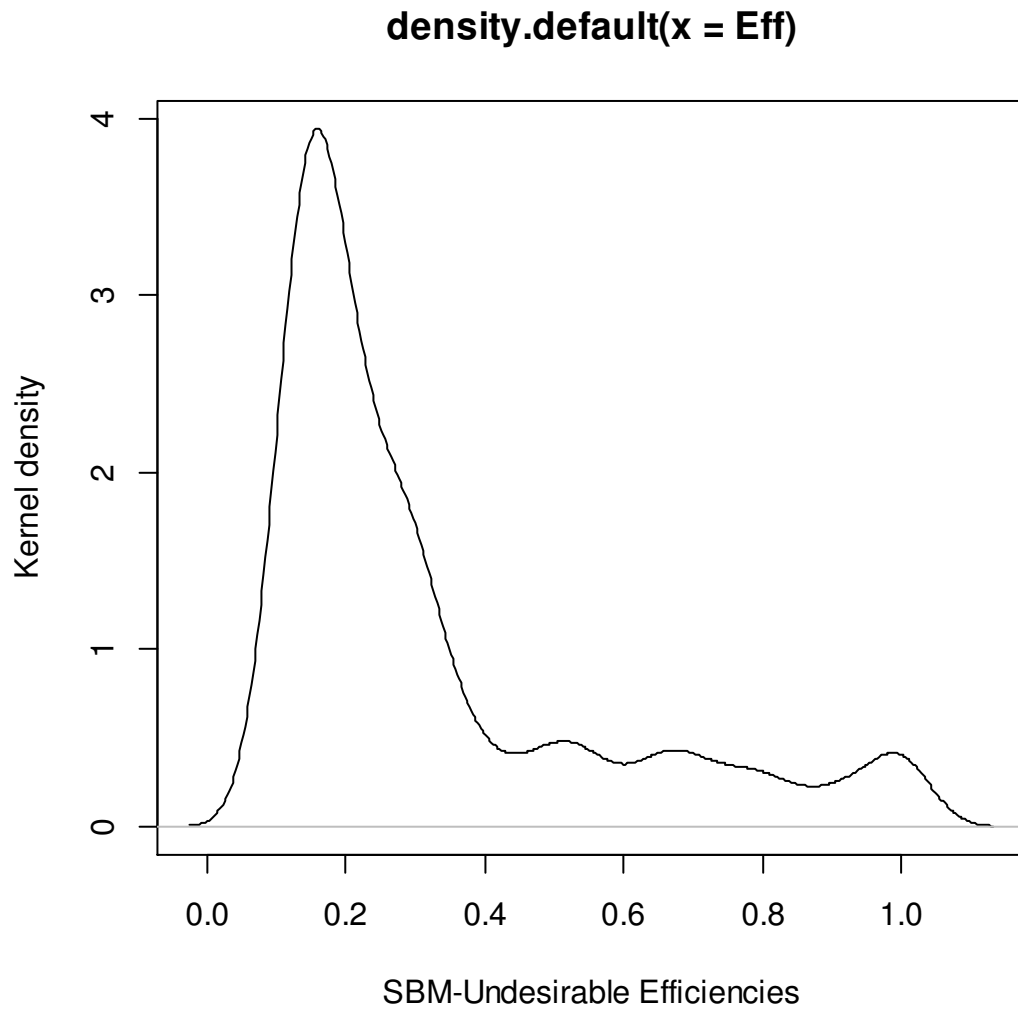
The most prominent application in the entire arena of simulation based estimation is the current generation of Bayesian econometrics based on Markov Chain Monte Carlo methodologies. In this area, intractable estimators of posterior means are routinely estimated with the assistance of simulation methodologies and the Gibbs sampler (Greene and Hill, 2010). These techniques offer stand-alone approaches to simulated likelihood estimation, but can also be integrated with traditional estimators (Korsgaard et al., 2003). Computation is also an issue since the usual implementation via MCMC carries a large computational overhead. A detailed discussion on the Gibbs sampler can be found in Gamerman (1996), Lange (2010) and Zhu and Lee (2002).



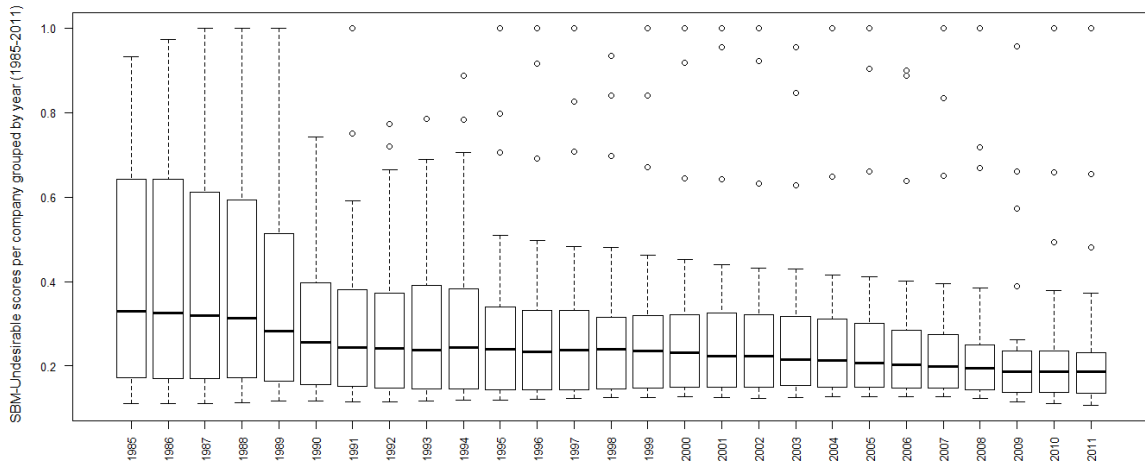
Finally, it is worth mentioning that limited dependent variable models can deal with censored outcomes that can arise in longitudinal settings. To enable inference in this class of models, however, one must address a central problem in multivariate discrete data analysis, namely, the evaluation of the outcome probability for each observation (Korsgaard et al., 2003). Outcome probabilities are required in constructing the likelihood function and involve multivariate integration, constrained to specific regions that correspond to the observed data. This latent variable framework is a generic probabilistic construct in which different threshold-crossing mappings from  $\eta_{ij}$  to the observed responses  $y_{ij}$  can produce various censored (Tobit) outcomes. For example, the relationship  $y_{ij}=1\{0<\eta_{ij}<1\}$  leads to a Tobit model with censoring from below 0 and from up to 1. In censored Gaussian and ordered categorical threshold models, the Gibbs sampling, in conjunction with data augmentation (Sorensen et al., 1998; Tanner and Wong, 1987), leads to fully conditional posterior distributions which are easy to sample from. This was demonstrated in Wei and Tanner (1990) for the Tobit model (Tobin, 1958), and in right censored and interval censored regression models.

## **6. Results and Discussion**

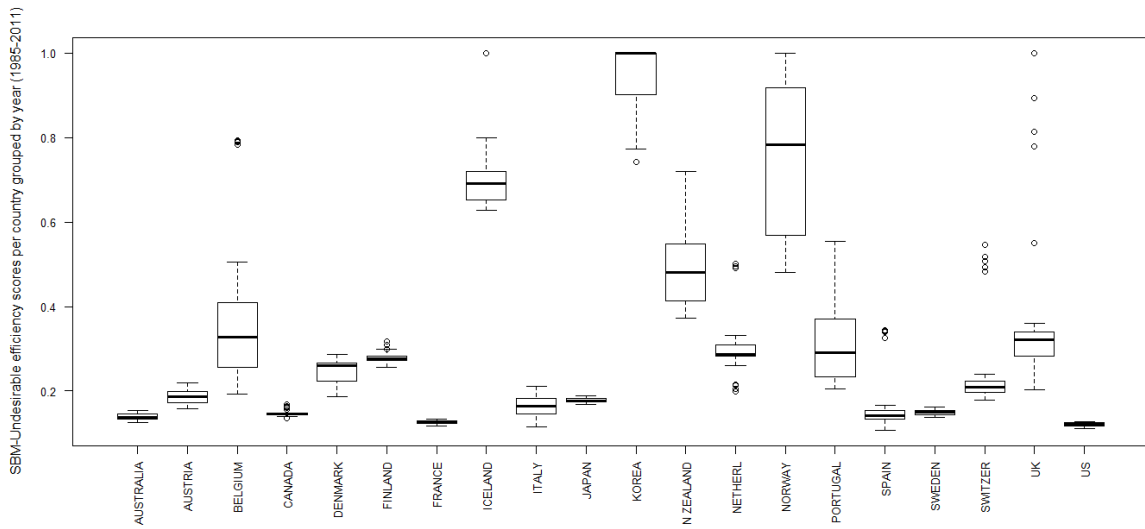
The efficiency levels calculated for 20 selected OECD countries from 1985 to 2011, using the SBM-Undesirable model and considering different grouping criteria, are presented in Figures 2, 3, and 4. The plot of the kernel density of the SBM-Undesirable efficiency scores not only reflects the fact that these scores are censored at 0 and 1, but also that a Gaussian shape around the mean, despite its asymmetry to the right. It is noteworthy that, although median efficiency levels are decreasing over the period under investigation, the dispersion on energy efficiency results increases across our country sample. For instance, efficiency level results are highly dispersed, not only in territorially large, populated countries, but also in small ones, despite their income and development levels, recommending the eventual impact of contextual variables that may be embedded within these grouping schemes. In other words, a group of countries is detaching of the common pattern of lower efficiency levels.



**Fig 2.** Kernel densities of the SBM-Undesirable efficiency scores



**Fig. 3.** Efficiency levels grouped by year



**Fig. 4.** Efficiency levels grouped by country

Therefore, a generalized linear mixed model is used to model this set of different contextual variables, ranging from nominal to metric scales. In addition, albeit with non-Gaussian response variables (which is the case of SBM-Undesirable efficiency scores), the likelihood cannot be obtained in a closed form. Markov chain Monte Carlo methodologies solve this problem by sampling from a series of simpler conditional distributions (Hadfield, 2010). In this paper, the response variable is assumed to follow a Gaussian distribution censored at

zero (left) and one (right). The following model defines a set of simultaneous (linear) equations:

$$E(y) = X\beta + Zb, \tag{13}$$

where  $X$  and  $Z$  are design matrices, containing the predictor information depicted in Table 3; that is, the whole set of variables is related to the demographics/economics that surrounds the countries, on the top of the trend effect.  $\beta$  and  $b$  are vectors of parameters, discussed in Section 5.1. It is worth noting that the simultaneous equations defined by Equation (13) cannot be solved directly, because the expected value of  $y$  is not known a priori. Only the observed values, presumed to be censored Gaussian at 0 and 1, are known. This system is solved using the MCMCglmm R package, which implements Markov chain Monte Carlo routines for fitting generalized linear mixed models (Hadfield, 2010).

Table 3 presents the MCMC-GLMM results for the TOPSIS scores under the censored Gaussian assumption considering cost structure, quality of the services provided, ownership, market positioning, mileage program offered, and trend as fixed effects and the demographic/economic variables as random effects. Summary plots containing the traces and densities for the fixed effects are presented in Figure 5.

We should recall that the first factor levels of the fixed effects are absorbed into the global intercept  $\beta_0$ , which is fitted by default in R. Furthermore, in terms of the Bayesian analysis, when an effect is treated as fixed, the only information regarding its value comes from data associated with that particular level. Very often, effects with few factor levels are candidates to be fixed effects (Hadfield, 2014). When effects are treated as random, they are weighted by what other data describe about the likely values that the effects could take. In addition, it should be put into perspective that in a Bayesian analysis all effects are technically random, as fixed effects are those associated with a variance component which has been set *a priori* to something large ( $10^8$  in MCMCglmm R package), while random effects are associated with a variance component which is not set *a priori*, but rather estimated from the data (Hadfield, 2010).

Table 3: Results for the MCMC-GLMM on the SBM-Undesirable scores

|             | post.mean  | l-95% CI   | u-95% CI   | eff.samp | pMCMC      |
|-------------|------------|------------|------------|----------|------------|
| (Intercept) | 5.067e-01  | 4.458e-01  | 5.665e-01  | 1000.0   | <0.001 *** |
| EU          | -6.418e-02 | -1.042e-01 | -1.927e-02 | 1000.0   | 0.002 **   |
| NAFTA       | -1.219e-01 | -1.975e-01 | -5.160e-02 | 1000.0   | 0.004 **   |
| ASIAN TIGER | -1.512e-01 | -2.514e-01 | -4.120e-02 | 1000.0   | <0.001 *** |
| G7          | -1.265e-01 | -1.684e-01 | -8.147e-02 | 923.5    | <0.001 *** |
| Trend       | -1.251e-02 | -2.144e-02 | -3.266e-03 | 1000.0   | 0.004 **   |
| Trend^2     | 1.928e-04  | -1.501e-04 | 4.866e-04  | 1000.0   | 0.216      |
| K/L.Ratio   | 6.934e-09  | 5.733e-09  | 8.207e-09  | 0.0      | <0.001 *** |

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Iterations = 25001:74951 / Thinning interval = 50 / Sample size = 1000

DIC: -289.3708

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R-structure

|       | post.mean | l-95% CI | u-95% CI | eff.samp |
|-------|-----------|----------|----------|----------|
| units | 0.03373   | 0.02996  | 0.0377   | 911.2    |

The results reveal different impacts of economic blocs on energy efficiency levels. Higher efficiency levels are found in EU countries, followed by NAFTA, G7, and the Asian Tigers. With respect to the capital-labor ratio, capital-intensive countries are more energy efficient than labor-intensive countries. These results confirm that efficiency levels are getting more dispersed across nations. In contrast, the findings with respect to trend confirm the qualitative perspectives derived by Figure 3, i.e. efficiency is lowering over time.

## 7. Conclusions

This paper presented an analysis of the energy efficiency of selected OECD countries and MCMC-GLMM. The results show that efficiency levels are high and are reducing over time. The analysis of the effect of contextual variables on the efficiency level showed that higher efficiency levels are found in EU countries, followed by NAFTA, G7, and the Asian Tigers. Moreover, capital-intensive countries are more energy efficient than labor-intensive countries. The declining efficiency level in the OECD countries calls for concern. The need for policies that could enhance energy efficiency cannot be overemphasized, given the role of energy efficiency in ensuring energy conservation, security, cost minimization and reduced CO<sub>2</sub> emissions. Policies that focus on the provision of renewable energy technologies are vital for achieving these goals. Barriers to the large scale spread of energy efficiency technologies are often related to governance, institutions and information, among others, rather than economic justifications. Hence, carefully designed regulations policies and strategies, policy measures and enforcement mechanisms are significantly needed to overcome barriers to the spread and use of superior and advanced technologies that could help to shift the efficiency frontier outwards across OECD countries. Moreover, programs and strategies targeting at reducing current energy intensities in these countries are also expected to assist with the improvement of energy efficiency. There is a need to remove or rationalize inefficient fossil fuel subsidies that promote wasteful consumption. This can be done in conjunction with effective targeted policies that could reduce the effect of such removals on low income households.

It is believed that sustainable development with sufficient energy supply can be achieved only if the goal of economic growth and efficiency in energy consumption is balanced. This is because failure to address energy efficiency may lead to a further deterioration of the environment, the impairment of public health, the resource degradation and energy insecurity, which in the long run could lead to slow or declining economic growth. In line with OECD (2011), improving energy efficiency could extensively assist to reduce the need for investments in energy infrastructure, reduced fuel costs, a lessen exposure to fuel price volatility, increased competitiveness, increased energy affordability for low-income households, reduced local and global pollutants, and improved consumer

welfare. As data and more information become available, future research venues may extend the empirical analysis to measure energy efficiency on industry levels.

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