Full length article

Production efficiency measurement and its determinants across OECD countries: The role of business sophistication and innovation
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A B S T R A C T

Increasing efficiency and productivity should be at the core of the policy agendas of all governments. Knowing whether or not OECD economies optimize their resources in production is, therefore, an important policy issue. The purpose of this paper was to make cross-country comparisons of production efficiency, and its determinants, using mainly a parametric approach. Our proposed model was a stochastic frontier version of Battese and Coelli's (1995) which includes both a stochastic error term and a term that can be characterized as inefficiency. The non-negative technical inefficiency effects are assumed to be a function of explanatory variables. The empirical analysis of macroeconomic performance done in this paper confirmed that OECD countries with a greater sophistication of their production processes and a higher capacity for innovation tend to be less inefficient. Alternative non-parametric methods for evaluating the impact of process/contextual variables on efficiency also corroborated that business sophistication and innovation contribute to efficiency improvements across OECD countries.

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1. Introduction

Most studies in the literature on macroeconomic performance across countries have mainly focused on explaining economic growth using standard growth equations derived from the Solow model (Mankiw et al., 1992; Solow, 1956). Typically, growth accountants attempt to break down total real-output growth into components attributable to growth in labor input, growth in capital input, and growth in total factor productivity — the so-called “Solow residual” that measures the increase in output that cannot be explained by input growth (Weil, 2013). Other works, controlling for capital and labor inputs (or human capital adjusted labor), have added variables or macro indicators to explain economic growth. For example, Fischer (1991) found a strong negative effect of inflation on growth; or Andrés et al. (1996) showed that exports growth had a significant and positive impact on growth for OECD countries.

The purpose of this paper was to examine the production efficiency across OECD countries and its determinants. Knowing whether or not OECD economies optimize their resources in production is relevant in itself. The analysis done in this paper showed what the suboptimal use of resources was, and in what percentage countries could increase their output without consuming more resources. From the social point of view, it is relevant to know if a country could produce more with the same resources and, therefore, could increase per capita income and welfare. In this type of analysis what matters is to identify what factors or variables explain that greater or lesser ability of a country to convert its resources into...
aggregate production. Our central hypothesis is that productive efficiency of OECD countries is strongly affected by their competitiveness. A nation’s competitiveness can be viewed as its position in the international marketplace compared to other countries of similar economic development (Önse et al., 2008). The Global Competitiveness Report of the World Economic Forum defines competitiveness as “the set of institutions, policies, and factors that determine the level of productivity of a country” (Sala-i Martin et al., 2011 p.4).

The current research has highlighted two key findings in the literature. On the one hand, an outstanding macroeconomic environment alone – such as a low inflation rate – cannot guarantee a high level of national competitiveness unless firms create valuable goods and services with a commensurately high level of productivity at the micro-level (Önse et al., 2008). To be competitive in the global market, organizations must continuously develop innovative and high-quality products and improve the techniques of production (Dosi, 1988). Technological innovation is, in fact, the source of both incremental improvements and transformational step changes in efficiency and productivity. And, in the long run, standards of living can be largely enhanced by technological innovation. Adler and Shenbar (1990, p. 26) defined technological innovation capability as consisting of four aspects: “(i) the capacity of developing new products satisfying market needs; (ii) the capacity of applying appropriate process technologies to produce new products; (iii) the capacity of developing and adopting new product and process technologies to satisfy future needs; and (iv) the ability of responding to accidental technology activities and unexpected opportunities created by competitors”. Evangelista et al. (1997) regarded research and development (R&D) activities as a central component of the technological innovation activities of firms and as the most important intangible innovation expenditure. Since the pioneering studies of Griliches (1980), and Griliches and Mairesse (1984), the existence of a significant relationship between R&D at the firm level and productivity was pointed out. On the other hand, innovative solutions are not sufficient. Major changes in business processes, organizational structures, and even talent are necessary to capture the full potential of innovation processes. Business sophistication concerns two elements that are intricately linked: the quality of a country’s overall business networks and the quality of individual firms’ operations and strategies (Sala-i Martin et al., 2011). Individual companies’ advanced operations and strategies (branding, marketing, distribution, advanced production processes, and the production of unique and sophisticated products) spill over into the economy and lead to sophisticated and modern business processes across the country’s business sectors (Sala-i Martin et al., 2011).

Our work on the empirical analysis of macroeconomic performance across countries differs from other macroeconomic studies in some aspects. First, our goal is not to explain the aggregate output growth of a sample of countries but to investigate the efficiency of aggregate production process (and its determinants) for a cross-section sample of OECD countries. Although much research has been done on efficiency measurement, it has focused on the firm or industry level; very few of these studies have considered the issue of multi-country efficiency. Second, although convergence equations seem to provide an adequate framework for the analysis of growth, the efficiency of resource utilization was measured in this paper using mainly a parametric production function. Our proposed model is a stochastic frontier version of Battese and Coelli’s (1995) which includes both a stochastic error term and a term that can be characterized as inefficiency. The non-negative technical inefficiency effects are assumed to be a function of explanatory variables (process/contextual variables) that affect the aggregate production process of the conversion of resources into the output. In particular, this paper showed that OECD countries with better business sophistication and capacity for technological innovation were more efficient in their macroeconomic activity, after controlling for contextual variables such as the efficiency of goods, labor, and financial markets:

If greater innovation and business sophistication lead to efficiency gains at the national level, the question to be asked is: what should be the government policies to encourage efficiency? The economic justification for government support for science and technology has been commonly based on the concept of market failure. Economic theory argues that governments should intervene in cases where the free market fails in achieving an efficient allocation of resources (Joseph and Johnston, 1985). If innovation in products and methods increases production efficiency, governments can do much supporting and funding business projects of research and development. In 2011, research and development expenditure in the OECD was 2.46 (% of GDP). Although there were countries such as Japan and Germany which invested more than the average (3.39% and 2.89%, respectively). Other countries, on the contrary, spent less than the average such as Portugal and Spain (1.52% and 1.36%, respectively). But in the process of research and development, the transfer of knowledge is important too – for example in the form of patents. In this regard, it is also important to see in different countries how patent and copyright laws protect invention and if this implies a greater effort in R&D, mainly company spending on R&D.

The rest of the article was structured as follows. Next section overviewed the two primary methods used in the literature for the efficiency measurement (parametric and non-parametric). Section 3 presented the principal methodology proposed in this paper. Following the pioneering work of Battese and Coelli (1995), we have proposed a parametric method to construct a world frontier that serves as a benchmark to compare the relative position of each country. Afterward, we described the data and variables (Section 4). The results of the empirical analysis were reported in Section 5. We found robust results for the effect of competitiveness – business sophistication and innovation – on productive efficiency. In Section 6 we presented alternative methods for evaluating the impact of process/contextual variables on efficiency. The paper concluded and outlined future work in Section 7.

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1 In italics in the original document.
2 Business sophistication and innovation are two pillars of the twelve that the World Economic Forum uses to build its Global Competitiveness Index.
3 Source: World Development Indicators (http://data.worldbank.org). Expenditures for research and development are current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge. R&D covers basic research, applied research, and experimental development.


2. Background

2.1. Production efficiency measurement

The concept of efficiency is related to the manner in which resources are used in the production. Among the early studies on efficiency, it highlights the work of Debreu (1951) who measured the inefficiency of resource allocation in an economy by calculating how much fewer resources could attain the same level of satisfaction to the consumers. Other relevant studies, such as Koopmans (1951) and Farrell (1957), developed specific methods to analyze productive efficiency at microeconomics level.

Full efficiency, in an engineering sense, means that a production process has achieved the maximum amount of output that is physically achievable with current technology, and given a fixed amount of inputs (OECD, 2001). The technically efficient result of the production process is represented by a production function, a frontier. In most empirical studies, the efficient frontier is unknown and has to be estimated from data on which efficiency is to be measured. The nature of the assumptions made in estimating the frontier divides the efficiency measurement into parametric and non-parametric methods. The former ones estimate frontier functions by using econometric (statistical) methods, while the latter ones build the efficient production function by applying mathematical programming. Mostly, two popular methods can be distinguished respectively: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). A standard feature of both approaches is that information is extracted from a body of data to determine the best-practice production frontier. In contrast to other approaches that evaluate producers relative to an average producer, methods such as SFA and DEA compare each producer with only the “best” producers (Fried et al., 2008).

DEA was introduced by Farrell (1957) and extended by Charnes et al. (1978), Färe et al. (1994), and Färe and Primont (1995). Farrell (1957) suggested that one could usefully analyze technical efficiency regarding realized deviations from an idealized frontier isoquant. In practice, the form of the production function is taken as unknown. A piecewise frontier is constructed based on data points that use the least inputs in producing a particular level of output (input-oriented version). Relative efficiency is measured by comparing observed performance against best-practice performance. However, some weaknesses of DEA include: (i) it is deterministic, and attributes all deviations from the frontier to inefficiencies; and (ii) its efficiency scores are relative to the study sample; data from additional entities may thus affect the sample efficiency scores.\

Conversely, the stochastic production frontier proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) was motivated by the idea that deviations from the production frontier might not be entirely under the control of the firm being studied. Under the interpretation of the deterministic frontier of the preceding paragraph, some external events, even bad weather, might ultimately appear as inefficiency. Worse yet, any error or imperfection in the measurement of its component variables, including the output, could likewise translate into increased inefficiency measures (Greene, 2008). This is an unattractive feature of any deterministic frontier specification. This one of the main reasons why our analysis uses SFA to measure how efficiently production inputs, such as labor and capital, are being employed by OECD countries to maximize their aggregated output. This approach falls naturally into an econometric approach in which the inefficiency is identified with disturbances in a regression model.

2.2. Macroeconomic performance in OECD countries

Although most of the published works have focused on the analysis of efficiency at the firm level – mainly to study the efficiency of financial institutions (e.g. Mia and Soltane, 2016) – the problem of measuring the productive efficiency of an economy (or country) is also important to governments. Analysis of the production efficiency of industrialized countries, questioning whether certain countries perform better than others in producing more output with the same or fewer inputs, is an example of the importance of estimating production relationships (Emrouznejad, 2003). It is important to know how far a given economy can be expected to increase its output by simply increasing its efficiency, without absorbing further resources. Nevertheless, efficiency studies using aggregated data from OECD countries and applying the above methodologies are rare in the literature of efficiency. Some exceptions are found using non-parametric methods (Arcelus and Arocena, 2000; Färe et al., 1994). Arcelus and Arocena (2000) used a non-parametric frontier approach to analyzing multi-factor productivity across time and countries over the 1970–1990 period, under the assumption of variable returns to scale. The evidence obtained from a sample of 14 OECD countries indicated a high degree of catching-up among these countries for the total industry and the manufacturing and services sectors. But we have not found any article using parametric methods.

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4 See Emrouznejad et al. (2008) for a detailed literature review on DEA.
5 The non-parametric DEA does not require a specification of the production process and only certain formal properties need to be defined that verify the points of the production set. However, the parametric SFA techniques require specification of the technological characteristics of the production process (Hjalmarsson et al., 1996).
3. Methodological framework: A model for technical inefficiency effects in a stochastic frontier production function for cross-sectional data

This paper proposed a cross-country production model for evaluating the relative efficiency of production. We used parametric techniques to construct the best practice macroeconomic performance frontier and to measure the performance of each country relative to the frontier. This type of analysis assumes that production technology is similar across producers. However, there are some problems in doing cross-country comparisons because there are differences in how the production processes are implemented in the firms. Although OECD countries enjoy a high degree of political, social and cultural similarities, they may differ from one another in their technological readiness which measures the agility with which an economy adopts existing technologies to enhance the productivity of its industries (Sala-i Martin et al., 2011). Of the initial sample of 20 countries for which the OECD estimates capital services, we finally worked with 19 (Italy behaved like an outlier), after undertaking a cluster analysis (k-means method) that considered the technological adoption in each country (see more details in Annex A). It is important to note, according to Sala-i Martin et al. (2011), that the level of technology available to firms in a country needs to be distinguished from the country’s ability to innovate and expand the frontiers of knowledge (innovation).

The stochastic frontier estimation method, developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), generates a production frontier with a stochastic error term that consists of two components: a conventional random error ("white noise") and an asymmetric component that measures inefficiency.

Formally, the basic stochastic frontier model is given by

\[ y_i = f(x_i) + \varepsilon_i \]

where: \( y_i \) is the production (output) of the producer \( i \); \( x_i \) is the vector of factors or resources used in production; \( f(\cdot) \) is a measurable production function; and \( \varepsilon_i \) is an error term, which is composed of two separate elements, \( u_i \) and \( v_i \), so that

\[ \varepsilon_i = v_i - u_i. \]

The component \( u_i \) collects those production variations due to random factors beyond the control of the producer. The model assumes that each \( u_i \) is distributed as a normal random variable with mean zero and variance \( \sigma^2_u \). The \( u_i \) component represents the technical efficiency relative to the stochastic frontier and takes only positive values (\( u_i \geq 0 \)). The original model assumes that each \( u_i \) is distributed independently as a skewed distribution, half-normal with zero mean and variance \( \sigma^2_u \). Technical efficiency is reached when \( u_i = 0 \), and there is technical inefficiency if \( u_i > 0 \), regardless of the value taken by \( v_i \).

3.1. One-step maximum likelihood estimates procedure

This paper used a stochastic frontier production function defined for cross-sectional data on countries in which the non-negative technical inefficiency effects are assumed to be a function of country-specific variables. Our proposed model of the production and inefficiency is a stochastic frontier version of Battese and Coelli’s (1995) and is given by Eq. (1), the stochastic production frontier, and Eq. (2), the inefficiency function. The inefficiency effects are assumed to be independently distributed as truncations of normal distributions with constant variance, but with means which are a linear function of observable variables.

The first equation specifies the stochastic frontier production function. A Cobb–Douglas production model for one output and \( K \) inputs would be specified as

\[ \ln y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{ki} + v_i - u_i \]  

where: \( y_i \) denotes the production of the \( i \)th country; \( x_{ki} \) is a vector of input quantities of the \( i \)th country; \( \beta \) is a vector of unknown parameters to be estimated. The \( v \) term takes care of the stochastic nature of the production process and possible measurement errors of the inputs and output, and the \( u \) term is the possible inefficiency of the producer; \( u_i 's \) are assumed to be iid \( N(0, \sigma^2_u) \) random errors independently distributed of the \( u_i 's \). It is also assumed a truncated-normal distribution for the inefficiency term.

\[ u_i \sim iidN^+ (\mu, \sigma^2_u) \text{ (truncated normal)}. \]

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6 As already indicated, SFA uses regression analysis to construct relative efficient production frontiers defined by “best-practice” producers.

7 The OECD only estimates capital services, a key input in our analysis, for 20 countries. The paper used finally cross-section data for a sample of 19 OECD countries.

8 Parameters in both equations are estimated simultaneously by maximum likelihood.

9 The choice of the distributional specification is sometimes a matter of computational convenience; theoretical considerations may also influence the choice of the distributional specification (Coelli et al., 2005).

10 The truncated-normal frontier model is due to Stevenson (1980).
Table 1
Variables and descriptive statistics.

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Output</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>19</td>
<td>1923910.42</td>
<td>3430799.93</td>
<td>139685.00</td>
<td>15204019.53</td>
</tr>
<tr>
<td><strong>Inputs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPITAL</td>
<td>19</td>
<td>2.44</td>
<td>1.33</td>
<td>0.10</td>
<td>5.66</td>
</tr>
<tr>
<td>LABOR</td>
<td>19</td>
<td>37115.01</td>
<td>57499.65</td>
<td>3187.22</td>
<td>245009.00</td>
</tr>
<tr>
<td><strong>Explanatory variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Process variables (business sophistication and innovation)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>19</td>
<td>5.64</td>
<td>0.63</td>
<td>4.39</td>
<td>6.55</td>
</tr>
<tr>
<td>MANAGEMENT</td>
<td>19</td>
<td>5.62</td>
<td>0.60</td>
<td>4.13</td>
<td>6.43</td>
</tr>
<tr>
<td>INNOVATION</td>
<td>19</td>
<td>4.76</td>
<td>0.79</td>
<td>3.47</td>
<td>5.84</td>
</tr>
<tr>
<td><strong>Control variables (contextual variables)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>19</td>
<td>4.86</td>
<td>0.32</td>
<td>4.24</td>
<td>5.31</td>
</tr>
<tr>
<td>LABOR_MARKET</td>
<td>19</td>
<td>4.74</td>
<td>0.77</td>
<td>3.45</td>
<td>6.03</td>
</tr>
<tr>
<td>FINANCIAL_MARKET</td>
<td>19</td>
<td>4.76</td>
<td>0.55</td>
<td>3.44</td>
<td>5.38</td>
</tr>
</tbody>
</table>

4. Data and variables

The two primary databases used for the empirical analysis have been the OECD and the World Economic Forum. Table 1 gives more details and presents the descriptive statistics.

4.1. Output and input variables in Eq. (1)

To perform our estimation exercise, we needed appropriate data on aggregate output and the two principal inputs into production activity, namely labor, and capital. Data were obtained from the OECD’s database (OECD.Stat).

Output measure

The measurement of output is a crucial part of assessing performance for any organization. Output in economics is the quantity of goods or services produced in a given period by a firm, industry, or country. In the latter case, national accounts...
measure the performance of entire economies in the commonly quoted measure gross domestic product (GDP). Calculating GDP is the most popular measure of national output. In this paper, total GDP (2011, US Dollar, constant prices 2010, constant PPPs) was used as a proxy for economic results of OECD countries.

Input measures
To take into account of the role of capital input, an appropriate measure is the flow of productive services that can be drawn from the cumulative stock of past investments (such as machinery and equipment). These services were estimated by the OECD using the rate of change of the productive capital stock, which takes into account wear and tear, retirements and other sources of reduction in the productive capacity of fixed capital assets. The price of capital services per asset is measured as their rental price. In principle, the latter could be directly observed if markets existed for all capital services. In practice, however, rental prices have to be imputed for most assets, using the implicit rent that capital goods’ owners “pay” to themselves (or the “user costs of capital”). In our analysis, we included the total capital services in 2011.

On the other hand, we also needed information on labor input. Labor remains the single most important input to many production processes. From a perspective of production analysis, the quantity of labor input in production is most appropriately measured as the total number of hours worked (OECD, 2001). Simple headcounts of employed persons will hide changes in average hours worked, caused by the evolution of part-time employment or the effect of variations in overtime, absence from work or shifts in regular hours. We included in the analysis the total of hours worked in 2011.

4.2. Explanatory variables in Eq. (2)

The influence of process/contextual variables on the production efficiency has been a major topic of economic research especially for managers and policy makers (e.g. Banker and Natarajan, 2008). In this paper, the identification of the factors that explain differences in efficiency across OECD economies is essential for improving the results of the countries. Fig. 1 summarized the explanatory variables used in Eq. (2), and Table 1 described the variables and presented the descriptive statistics. All information for the explanatory variables comes from the World Economic Forum (WEF). Since 2005, the WEF has based its competitiveness analysis on the Global Competitiveness Index (GCI), a comprehensive tool that measures the microeconomic and macroeconomic foundations of national competitiveness. The competitiveness measure (GCI) is calculated based on twelve pillars. In order to avoid problems of multicollinearity, and based on both economic theory and applied research, we have included only some dimensions of the GCI (edition 2011–2012): (a) business sophistication (11th pillar; only production process sophistication and reliance on professional management); (b) innovation (12th pillar; only capacity for innovation); (c) goods market efficiency (6th pillar; only competition); (d) labor market efficiency (7th pillar; only flexibility); and (e) financial market development (8th pillar).

Sophisticated business practices are conducive to greater efficiency in the production of goods and services (Sala-i Martin et al., 2011). Business sophistication is mainly distinguished by high levels of sophistication of production processes and professional management. We incorporated the variable PROD_PROCESS_SOPHISTICATION. In reality, competitive advantage that is based on the technological sophistication of production leading to products which incorporate high levels of technical knowledge is difficult to attain (Vinhas da Silva, 2013). Second, we included the variable MANAGEMENT. Applied research has documented that higher-quality management practices are correlated with several measures of productivity and firm performance, including labor productivity (Bloom and Van Reenen, 2007). Third, we included in the analysis the variable INNOVATION. Technological innovation is particularly important for economies as they approach the frontiers of knowledge (Acemoglu et al., 2006).

Moreover, we considered the relationships between the goods market, the labor market, and the money market – medium-term macroeconomic equilibrium (Dornbusch et al., 2004) – by incorporating the variables GOODS_MARKET, LABOR_MARKET, and FINANCIAL_MARKET. Regulations affecting product, labor and credit markets – which tend to vary significantly across OECD countries – affect indeed resource flows and can thus explain why some countries are more successful at channeling resources to high productivity firms than others (Andrews and Cingano, 2014).

5. Macroeconomic performance: Evidence from a multi-country study

5.1. Model specification

Many models of growth and development assume that output \( Y \) is generated by a two-factor, Cobb–Douglas specification for the aggregate production function with physical capital \( K \) and labor \( L \) serving as inputs (Duffy and Papageorgiou, 2000). If the input–output relationship is characterized by a Cobb–Douglas specification for the aggregate production
function, then log $Y$ should be a linear function of log $K$ and log $L$. Using cross-sectional data for 19 OECD countries ($i = 1, 2, \ldots, 19$), a two-input Cobb–Douglas production function is formulated (Eqs. (3) and (5)) in which the non-negative technical inefficiency effects are assumed to be a function of country-specific variables (Eqs. (4) and (6)).

**MODEL 1**

$$\ln (GDP_i) = \beta_0 + \beta_1 \ln (CAPITAL_i) + \beta_2 \ln (LABOR_i) + v_i - u_i$$

$$\mu_i = \delta_0 + \delta_1 (PROD\_PROCESS\_SOPHISTICATION_i) + \delta_2 (GOODS\_MARKET_i) + \delta_3 (LABOR\_MARKET_i)$$

$$+ \delta_4 (FINANCIAL\_MARKET_i) + \omega_i.$$  

**MODEL 2**

$$\ln (GDP_i) = \beta_0 + \beta_1 \ln (CAPITAL_i) + \beta_2 \ln (LABOR_i) + v_i - u_i$$

$$\mu_i = \delta_0 + \delta_1 (MANAGEMENT_i) + \delta_2 (INNOVATION_i) + \delta_3 (GOODS\_MARKET_i)$$

$$+ \delta_4 (LABOR\_MARKET_i) + \delta_5 (FINANCIAL\_MARKET_i) + \omega_i.$$  

Following Battese and Coelli (1995), the stochastic frontier production function and the technical inefficiency effects model must be jointly estimated by maximum-likelihood ((3) with (4); (5) with (6)). We derived maximum likelihood estimates of the parameter vectors $\beta$ and $\alpha$ from the simultaneous estimation of the production function and inefficiency term equations using the Stata14 statistical package — this software allows us to use the one-stage procedure when a truncated-normal distribution is specified.

### 5.2. Empirical findings

The results obtained by estimating Eqs. (3) and (4), on the one hand (Model 1), and (5) and (6) on the other hand (Model 2), were presented in Table 2. First, the estimated coefficients associated with the inputs are all positive and statistically significant, confirming that, all else being equal, a greater amount of one input has a positive effect on aggregate output. The output elasticity of labor was equal to one in both cases. In other words, in the period of study, holding the capital input constant, a 1% increase in the labor input led, on average, to a 1% increase in the output. Second, the estimated coefficients in the inefficiency models are of particular interest to this study. Table 2 shows which country-specific factors influence the efficiency of production. The negative estimate for business sophistication and innovation imply that OECD countries with a greater production process sophistication (Model 1) and capacity for innovation (Model 2) tend to be less inefficient.

As we said before, there is no doubt that sophisticated business practices are conducive to greater efficiency in the production of goods and services (Sala-i-Martin et al., 2011). The same applies to the technological innovation. Efficiency gains can be achieved through acts of innovation. Firms in these countries must design and develop cutting-edge products and

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14 The high collinearity between the three process variables forced us to estimate two different models.

15 A negative sign indicates lower levels of inefficiency for higher values in the production process sophistication (Model 1) and capacity for innovation (Model 2).
Table 2
Parameter estimates of stochastic production frontier and technical inefficiency model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(CAPITAL)</td>
<td>$0.1195^{**}$</td>
<td>0.0370</td>
</tr>
<tr>
<td>ln(LABOR)</td>
<td>$1.0013^{**}$</td>
<td>0.0155</td>
</tr>
<tr>
<td>Constant</td>
<td>$4.0250^{**}$</td>
<td>0.3769</td>
</tr>
</tbody>
</table>

Frontier production function

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>$-0.5092^{**}$</td>
<td>0.2253</td>
<td>$-0.4494^{*}$</td>
<td>0.2487</td>
</tr>
<tr>
<td>MANAGEMENT</td>
<td>$0.0464$</td>
<td>0.4449</td>
<td>$-0.3616$</td>
<td>0.6939</td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>$-0.0630$</td>
<td>0.2004</td>
<td>$-0.0933$</td>
<td>0.2607</td>
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<tr>
<td>LABOR_MARKET</td>
<td>$0.0265$</td>
<td>0.1941</td>
<td>$0.1703$</td>
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<tr>
<td>FINANCIAL_MARKET</td>
<td>$2.8502$</td>
<td>1.4534</td>
<td>$2.9931$</td>
<td>1.9153</td>
</tr>
</tbody>
</table>

Technical inefficiency function

A two-input Cobb–Douglas production function/truncated-normal distribution for the inefficiency term

Log likelihood 12.2335 11.9768
Number of obs. 19 19
Wald chi2(2) 4241.34 4372.47
Prob > chi2 0.0000 0.0000

$^a$ output $= \ln(\text{GDP})$.

$^{**}$ Represents 5% level of significance.

$^{*}$ Represents 10% level of significance.

processes to maintain a competitive edge. They approach innovation in its broadest sense, including both new technologies and new ways of doing things. Innovation can be manifested in a new product design, a new production process, a new marketing approach, or a new way of conducting training. Studies have shown that innovation, measured regarding new product introductions, was associated with business performance (Hall and Bagchi-Sen, 2002).

Nonetheless, emerging innovations in technology are important but are not sufficient in themselves to drive productivity and efficiency gains. It requires an environment that is conducive to innovative activity. In particular, it means sufficient investment in R&D, supported by both the public and the private sectors; the presence of high-quality scientific research institutions; extensive collaboration in research between universities and industry; and the protection of intellectual property (Sala-i Martin et al., 2011).

Stimulating robust productivity growth and increased innovation also require a profound reform of product markets. For example, barriers to entry and exit are substantial in the Mediterranean countries and need to be drastically reduced to allow a more efficient allocation of resources. Among the range of barriers to entry, specific attention should be devoted to anti-competitive barriers. These are a particularly severe problem for small businesses. If competition is expected to increase efficiency, governments can consider the abolition of monopolies and/or relieve companies of the constraints imposed by an overly regulatory legal framework. For example, competition in telecommunications tends to be associated with enhanced production efficiency (Lien and Peng, 2001).

There are still some fundamental principles that governments should embrace to play the proper supportive role for national competitiveness. If innovation increases efficiency: how much scientists and engineers should produce a country to develop its innovative capacity? How much should public money be allocated to support research and development in the public sector (e.g. universities) and the private sector? These are crucial questions that underpin the research in economics in its role of how to allocate scarce resources to ensure social welfare, including full employment and high living standards. Researchers still are interested in knowing what factors can contribute the most to a nation’s economic growth and prosperity.

5.3. Hypothesis testing

The appropriateness of the stochastic frontier approach should be tested for the absence of inefficiency effects (the null hypothesis)

$$H_0 = \text{There is no component of inefficiency in the composite error.}$$

A likelihood-ratio (LR) test can be used to this end. In the case of the truncated-normal model, the null hypothesis $H_0: \mu = \sigma_u^2 = 0$ should be rejected at the 5% level of significance if the LR test statistic exceeds 5.138 (Coelli et al., 2005). We computed

$$LR = 19.955 \text{ (Model 1)}; \ LR = 19.442 \text{ (Model 2)}.$$
Table 3
SFA and DEA estimates of productive efficiency.

<table>
<thead>
<tr>
<th>Country</th>
<th>(1) SFA efficiency scores (Model 1)</th>
<th>(2) SFA efficiency scores (Model 2)</th>
<th>(3) DEA efficiency scores</th>
<th>(4) Reciprocals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.683</td>
<td>0.674</td>
<td>1.293</td>
<td>0.773</td>
</tr>
<tr>
<td>Austria</td>
<td>0.807</td>
<td>0.798</td>
<td>1.216</td>
<td>0.822</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.952</td>
<td>0.949</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Canada</td>
<td>0.728</td>
<td>0.721</td>
<td>1.324</td>
<td>0.755</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.977</td>
<td>0.979</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Finland</td>
<td>0.888</td>
<td>0.879</td>
<td>1.187</td>
<td>0.843</td>
</tr>
<tr>
<td>France</td>
<td>0.926</td>
<td>0.926</td>
<td>1.079</td>
<td>0.927</td>
</tr>
<tr>
<td>Germany</td>
<td>0.953</td>
<td>0.952</td>
<td>1.079</td>
<td>0.927</td>
</tr>
<tr>
<td>Ireland</td>
<td>0.928</td>
<td>0.919</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Japan</td>
<td>0.921</td>
<td>0.915</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Korea</td>
<td>0.456</td>
<td>0.451</td>
<td>2.017</td>
<td>0.496</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.943</td>
<td>0.941</td>
<td>1.039</td>
<td>0.962</td>
</tr>
<tr>
<td>New Zealand</td>
<td>0.552</td>
<td>0.550</td>
<td>1.713</td>
<td>0.584</td>
</tr>
<tr>
<td>Portugal</td>
<td>0.509</td>
<td>0.508</td>
<td>1.948</td>
<td>0.513</td>
</tr>
<tr>
<td>Spain</td>
<td>0.688</td>
<td>0.686</td>
<td>1.382</td>
<td>0.723</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.847</td>
<td>0.839</td>
<td>1.169</td>
<td>0.856</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.919</td>
<td>0.912</td>
<td>1.109</td>
<td>0.902</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>0.765</td>
<td>0.763</td>
<td>1.315</td>
<td>0.760</td>
</tr>
<tr>
<td>United States</td>
<td>0.968</td>
<td>0.972</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Average</td>
<td>0.811</td>
<td>0.807</td>
<td>1.256</td>
<td>0.834</td>
</tr>
</tbody>
</table>

| a | VRSTE scores: Technical efficiency scores under variable returns to scale — output-oriented (BCC model). Efficient countries are defined by a score of 1, while inefficiency is indicated by the values greater than 1. |
| b | Reciprocals of the VRSTE scores shown in column (3). The efficiency scores are now in the interval (0, 1]. Countries achieving a score of one are again efficient. |

Those values exceeded 5.138, so we reject the null hypothesis of no technical inefficiency effects, increasing therefore the credibility of the estimated stochastic frontier models.\(^{16}\)

5.4. Efficiency of OECD countries

SFA yields a prediction for the degree of productive efficiency of each producer. The indices of technical efficiency for each country \(i\) were calculated as\(^{17}\)

\[
TE_i = e^{-u_i}
\]

where \(0 < TE_i \leq 1\). A country or economy will be fully efficient provided that \(TE\) is worth 1; otherwise, the country will be considered as inefficient.

The efficiency scores for each country were shown in Table 3 in columns (1) and (2). Industry efficiency can be viewed as the average of the efficiencies of all the firms in the industry; thus, a natural predictor of industry efficiency is the average of the predicted efficiencies of the firms in the sample (Coelli et al., 2005). In our study, the average efficiency in the OECD was by 81% (last row in Table 3); this finding indicates that OECD countries, as an industry, to operate efficiently should simultaneously expand their output by 30% keeping their inputs fixed.\(^{18}\)

Table 3 also showed the efficiency scores obtained from the DEA method (columns (3) and (4)). We estimated the technical efficiency by an output-oriented BCC model (Banker et al., 1984). We used GDP as output, and CAPITAL and LABOR as inputs.\(^{19}\)

The results showed that the average efficiency is higher with DEA than with SFA: 0.834 vs. 0.811/0.807. The differences were statistically significant (see Annex D). This result is in line with recent efficiency works such as Johnes (2014). The main finding from this study was that the level of average efficiency in the English university sector varied considerably by estimation method, with parametric methods generally providing the lowest estimates of efficiency and non-parametric methods the highest (Johnes, 2014).

6. Alternative methods for evaluating the impact of process/contextual variables on efficiency

The identification of the factors that explain differences in efficiency is essential for improving the economic results of the countries. However, it is important to check the robustness of our results. To this end, we regressed the DEA efficiency

\(^{16}\) In the model estimated in the Annex B, LR = 20.340.
\(^{17}\) Index of technical efficiency in an output-oriented version.
\(^{18}\) To obtain this percentage, we must calculate the inverse of the efficiency scores of the columns (1) and (2), and then calculate the mean. The results were 1,298 and 1,305 respectively.
\(^{19}\) A brief outline of this method was given in Annex C.
Table 4
Estimation of the impact of process/contextual variables using data envelopment analysis efficiency scores.

Method 1 (DEA + OLS)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>-0.2395</td>
<td>0.0549</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MANAGEMENT</td>
<td></td>
<td></td>
<td>0.0139</td>
<td>0.1638</td>
</tr>
<tr>
<td>INNOVATION</td>
<td></td>
<td></td>
<td>-0.1869</td>
<td>0.0682</td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>-0.0593</td>
<td>0.1398</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LABOR_MARKET</td>
<td>-0.0501</td>
<td>0.0537</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FINANCIAL_MARKET</td>
<td>0.0405</td>
<td>0.0731</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.8868</td>
<td>0.8372</td>
<td></td>
<td>1.8164 1.1100</td>
</tr>
</tbody>
</table>

Number of obs. 19 No. of obs. 19
F(4, 14) 5.04 F(5, 13) 2.82
Prob > F 0.0100 Prob > F 0.0615
R-squared 0.5747 R-squared 0.5178

Method 2 (DEA + Censored Tobit regression)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>0.2151**</td>
<td>0.0568</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MANAGEMENT</td>
<td></td>
<td></td>
<td>-0.0150</td>
<td>0.1504</td>
</tr>
<tr>
<td>INNOVATION</td>
<td></td>
<td></td>
<td>0.1692**</td>
<td>0.0525</td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>0.0068</td>
<td>0.1411</td>
<td></td>
<td>0.1556  0.2364</td>
</tr>
<tr>
<td>LABOR_MARKET</td>
<td>0.0865</td>
<td>0.0592</td>
<td></td>
<td>0.0926  0.0630</td>
</tr>
<tr>
<td>FINANCIAL_MARKET</td>
<td>-0.1143</td>
<td>0.0817</td>
<td></td>
<td>-0.1794 0.1041</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.2504</td>
<td>0.5185</td>
<td></td>
<td>-0.1994 0.0905</td>
</tr>
</tbody>
</table>

Number of obs. 19 No. of obs. 19
LR chi2(4) 14.78 LR chi2(5) 13.05
Prob > chi2 0.0052 Prob > chi2 0.0229
Pseudo R2 3.073 Pseudo R2 2.7132
Log likelihood 4.9850105 Log likelihood 4.1197019

Method 3 (DEA + Bootstrapped-truncated regression)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>-0.4133</td>
<td>0.1662</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MANAGEMENT</td>
<td></td>
<td></td>
<td>0.2289</td>
<td>0.4715</td>
</tr>
<tr>
<td>INNOVATION</td>
<td></td>
<td></td>
<td>-0.3932</td>
<td>0.1659</td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>0.1679</td>
<td>0.4930</td>
<td></td>
<td>-0.0634 0.6893</td>
</tr>
<tr>
<td>LABOR_MARKET</td>
<td>0.3039</td>
<td>0.2539</td>
<td></td>
<td>0.2927 0.2877</td>
</tr>
<tr>
<td>FINANCIAL_MARKET</td>
<td>-0.7451</td>
<td>0.4177</td>
<td></td>
<td>-0.9148 0.5119</td>
</tr>
<tr>
<td>Constant</td>
<td>4.8561**</td>
<td>1.4834</td>
<td></td>
<td>5.0851** 1.8557</td>
</tr>
</tbody>
</table>

Number of obs. 19 No. of obs. 19
Number of efficient obs. 5 No. of efficient obs. 5
Number of bootstr. reps. 1000 No. of bootstr. reps. 1000
Wald chi2(4) 11.89 Wald chi2(5) 11.46
Prob > Chi2(4) 0.0175 Prob > Chi2(5) 0.0043

As in Banker and Natarajan (2008), we regressed the logarithm of the DEA efficiency scores shown in column (3) in Table 3 on process/contextual variables using ordinary least squares.

Since the DEA efficiency scores shown in column (4) in Table 3 are over the bounded interval (0, 1], many prior studies have used two limit censored Tobit model to estimate the impact of contextual variables (e.g. Hoff, 2007). More recently, the researchers have also used a truncated regression following Simar and Wilson’s bootstrap approach (2007).

Table 4 showed the results of the estimation of Eq. (7) using those three methods. According to Methods 1 and 2, the estimated coefficients associated with business sophistication (the sophistication of the production processes) and innovation (the capacity for innovation) were statistically significant and with the expected signs. Since the values of the efficiency scores were larger than or equal to one in Method 1, negative (positive) regression’s coefficients would mean that

\[
DEA_i = \alpha + \sum_k \beta_k X_{ik} + \varepsilon_i
\]  

where: \(i\) refers to a single country, \(X_{ik}\) is a matrix of potential determinants of the estimated DEA\(_i\) scores, and \(\varepsilon_i\) is an error term.

To estimate Eq. (7), most of applied studies have used either ordinary least squares (OLS) or Tobit regression (e.g. Hoff, 2007; McDonald, 2009), methods strongly recommended by Banker and Natarajan (2008). More recently, the researchers have also used a truncated regression following Simar and Wilson’s bootstrap approach (2007).
due to the rise of the independent variable, inefficiency decreases (increases). The negative sign indicates that the higher the sophistication of production processes and the capacity for innovation, the lower the inefficiency (or, the higher the efficiency). This same idea was corroborated by Method 2. In this case, the estimated coefficients are positive. Because the efficiency scores varied from zero to one, we can assert that a higher sophistication of the productive processes and a greater capacity for innovation were associated with a greater efficiency of the aggregate production process. Nevertheless, the coefficients estimated following the approach of Simar and Wilson (2007) did not show statistical significance. This result is not surprising according to Banker and Natarajan (2008). They proved that the Simar–Wilson's approach does not yield correct inferences in environments characterized by stochastic frontiers of the type first proposed by Aigner et al. (1977).

7. Conclusion

This paper presents different approaches to evaluate the efficiency of a sample of OECD countries from the production efficiency point of view — their ability to operate close to, or on the boundary of their production set. In this regard, we advocate mainly the use of the stochastic frontier analysis to construct the “best practice” macroeconomic performance frontier for a cross-section data set of 19 OECD countries. Our basic measure of economic performance is the level of output measured by GDP, and use the number of hours to measure labor input and capital services to measure capital input. Simultaneously, we examine the influence of process/contextual variables that explain OECD countries' efficiency differences. We find a positive effect of competitiveness – business sophistication and innovation – on productive efficiency gains.

Increasing efficiency and productivity should be at the core of the policy agendas of governments and international organizations. The proposed methodologies can serve as a useful benchmarking guide to countries attempting to increase their levels of efficiency. Policymakers seeking to identify priority areas for reforms to encourage innovation should bet on public investment in R&D and take into account intellectual property rights and patents, alongside competition policy since a lack of competition reduces the pressure on firms to incorporate better technology. But changes in the organizational behavior of firms are also needed. The introduction of cutting-edge technology, business process changes, and managerial innovation also drives productivity and efficiency gains.

Acknowledgments

I would like to acknowledge the useful comments given to me by the anonymous referees and the help also received by the editor.

Annex A.

Cluster analysis is a statistical method that identifies groups of samples that behave similarly or show similar characteristics (look-alike groups). Data are divided into $k$ partitions or groups with each partition representing a cluster. The process, which is called “$k$-means”, appears to give partitions which are reasonably efficient in the sense of within-class variance. This method was developed by MacQueen (1967) who suggested the name $k$-means for describing an algorithm that assigns each item to the cluster having the nearest centroid (mean). This method was appropriate for our data. The Global Competitiveness Report 2011–2012 included the technological adoption sub-index (availability of latest technologies, firm-level technology absorption, and foreign direct investment and technology transfer). Each country had an average score which ranged from 1 to 7 (the higher, the better). We aimed to partition the sample of OECD countries into similar producers using that indicator. Two clusters were finally identified with 19 countries belonging to cluster 1, and Italy in cluster 2.

Annex B.

Table 5 presented the estimation of the stochastic frontier of production that incorporated as inputs capital, labor, and human capital. However, the estimated coefficient associated with human capital was not statistically significant. It has been verified that there is no correlation between the three inputs. The average efficiency ($= 0.808$) practically did not change compared with the estimates shown in Table 3 (last row of columns (1) and (2)). Therefore, this input was not considered finally in the SFA and DEA analyzes shown in Table 3.

Annex C.

Non-parametric techniques such as DEA use mathematical programming methods to measure relative efficiency of units commonly referred to as decision-making units (DMUs). The form of the production function is taken as unknown. Relative efficiency is measured by comparing observed performance against best-practice performance. In practice, DMUs may produce many outputs from multiple inputs, and so programming techniques are used to identify the piecewise linear
Table 5
SFA estimates with three inputs.

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Frontier production function</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln (CAPITAL)</td>
<td>0.1120*</td>
<td>0.0339</td>
</tr>
<tr>
<td>ln (LABOR)</td>
<td>1.0030*</td>
<td>0.0177</td>
</tr>
<tr>
<td>ln (% adults 25–64 years old who had attained tertiary education, 2011)</td>
<td>-0.1316</td>
<td>0.1867</td>
</tr>
<tr>
<td>Constant</td>
<td>4.4593*</td>
<td>0.6704</td>
</tr>
<tr>
<td><strong>Technical inefficiency function</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PROD_PROCESS_SOPHISTICATION</td>
<td>-0.4109**</td>
<td>0.2036</td>
</tr>
<tr>
<td>GOODS_MARKET</td>
<td>-0.1211</td>
<td>0.4632</td>
</tr>
<tr>
<td>LABOR_MARKET</td>
<td>-0.0666</td>
<td>0.1862</td>
</tr>
<tr>
<td>FINANCIAL_MARKET</td>
<td>0.0350</td>
<td>0.1604</td>
</tr>
<tr>
<td>Constant</td>
<td>3.5130**</td>
<td>1.7158</td>
</tr>
</tbody>
</table>

Number of obs. 19
Wald ch2(3) 3775.89
Prob > chi2 0.0000
Loglikelihood 12.562011

a Output = ln(GDP).
b Due to convergence problems, the estimation also included market size (10th pillar of the GCI 2011–2012) whose estimated coefficient was not statistically significant.
** Represents 5% level of significance.

Table 6
Differences in average technical efficiency with SFA and DEA.

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Mean</th>
<th></th>
<th>Obs</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEA efficiency scores</td>
<td>19</td>
<td>0.834</td>
<td>DEA efficiency scores</td>
<td>19</td>
<td>0.834</td>
</tr>
<tr>
<td>SFA efficiency scores (Model 1)</td>
<td>19</td>
<td>0.811</td>
<td>SFA efficiency scores (Model 2)</td>
<td>19</td>
<td>0.807</td>
</tr>
<tr>
<td>Difference of means (DEA scores — SFA scores)</td>
<td>19</td>
<td>0.023</td>
<td>Difference of means (DEA scores — SFA scores)</td>
<td>19</td>
<td>0.027</td>
</tr>
<tr>
<td>Is the diff. statistically significant at 5%?</td>
<td>Yes</td>
<td></td>
<td>Is the diff. statistically significant at 5%?</td>
<td>Yes</td>
<td></td>
</tr>
</tbody>
</table>

a ttest: Ho: diff. = 0 (degrees of freedom = 18)

\[ t = 2.8494 \]

Pr(T > t) = 0.0053.

b ttest: Ho: diff. = 0 (degrees of freedom = 18)

\[ t = 3.2779 \]

Pr(T > t) = 0.0021.

frontier joining up all efficient DMUs which provide an estimate of the frontier. Under variable returns to scale (VRS) – output-oriented – the following linear programming problem must be solved for each of the n DMUs

maximize \( \phi_k \)

subject to

\[
\sum_{j=1}^{n} \lambda_j y_{rk} - \sum_{j=1}^{s} \lambda_j y_{rj} \leq 0 \quad r = 1, \ldots, s
\]

\[
x_{ik} - \sum_{j=1}^{m} \lambda_j x_{ij} \geq 0 \quad i = 1, \ldots, m
\]

\[
\sum_{j=1}^{n} \lambda_j = 1
\]

\[
\lambda_j \geq 0 \quad \forall j = 1, \ldots, n
\]

where there are \( s \) outputs and \( m \) inputs; \( y_{rk} \) is the amount of output \( r \) produced by DMU \( k \); \( x_{ik} \) is the amount of input \( i \) used by DMU \( k \). Overall technical efficiency of DMU \( k \) is measured by \( \phi_k \) in the output-oriented framework. With \( \phi > 1 \) the decision unit is inside the frontier (i.e. it is inefficient), while \( \phi = 1 \) implies that the decision unit is on the frontier (i.e. it is efficient).

Under output-orientation, efficiency scores correspond to required production expansion to make a producer efficient, keeping input levels fixed. Observe that \( \phi \) will take a value greater than or equal to one for each producer or DMU, and that \( (\phi - 1) \) is the proportional increase in outputs that could be achieved by the \( j \)th producer with input quantities held constant.
constant. Note too that $1/\phi$ defines a technical efficiency score that varies between zero and one — output-orientated scores also reported in our results.

Annex D.

See Table 6.

References


