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Ali Emrouznejad and Francisco Vargas

Data Envelopment Analysis for Performance Measurement in Developing Countries

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EDITORIAL - Data Envelopment Analysis for performance measurement in developing countries

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There has been continuous and rapid growth in the field of Data Envelopment Analysis (DEA) since it was originally been proposed by Charnes et al. (1978) on the basis of the seminal work of Farrell (1957). There is now a considerable amount of theoretical articles (Emrouznejad, Yang 2018) in measuring various notations of efficiency, such as technical efficiency, cost efficiency and revenue efficiency, in both static and over time frameworks, as well as measuring Total Factor Productivity Growth (TFPG). The family of DEA models is also employed routinely in many areas from assessment of public organizations such as health care systems, educational institutions and governmental bodies to private organizations such as banks and service providers.

The articles comprising this special issue of the Central European Review of Economics and Management contribute to the theory and applications of DEA in Developing Countries. As a result of the rigorous refereeing process, 8 articles were accepted for inclusion in this special issue. This set of articles represent only a small fraction of the total number of submitted manuscripts, but can still offer a well-balanced mix of topics of DEA in the Developing Countries.

The first four articles of this issue are related to efficiency measurement in banking and financial institutions in some developing countries.

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This issue start with the first article that deals with economic interpretations of DEA in measuring banking efficiency. Maryam Hasannasab and Dimitris Margaritis focus on evaluation of the banking systems of Central and Eastern Europe (CEE). They employ parametric forms of distance functions to obtain shadow prices of bank inputs and outputs and contrast and compare them with price proxies typically employed in empirical studies. Specially they show how knowledge of one input price can be used to price outputs and how one output price can be used to price inputs along with information on input and output quantities. They use a Shephard-type input/output distance function as the technology constraint for profit maximisation to obtain the input and output ‘crossover’ pricing rules. They find differences between shadow prices and actual prices suggesting that input and/or output mix may not be consistent with cost minimization or revenue and profit maximization. They also report that bank efficiency is highest on average in Estonia, which also boasts the highest bank capitalization rate in the CEE region.

Janet Ganouati and Hédi Essid, the authors of the second article in this issue, evaluate the productivity of Islamic banks in 13 countries over the period 2005-2014 using a Malmquist productivity index. By decomposing the productivity into scale efficiency, technological change and technical efficiency, they identify source of productivity change in Islamic banks. They find that the Islamic banks are productive and efficient over the study period. Further, they also show that subprime crisis had a slightly negative effect on productivity in Islamic banking industry.

On the same topic the third article in this issue examines the impact of global financial crisis in bank efficiency in Saudi Arabia. Md. Golam Solaiman, Abdul Kader, Peter Wanke and Md. Abul Kalam Azad apply DEA during 2006-2014 on eleven commercial banks from Saudi banking sector which covers almost 50% of total banks within the country. Overall, their results show that banks in Saudi Arabi are inefficient in terms of technical and scale efficiency. The results also reveal these banks are not immune to the global financial crisis, though, only one bank has kept their unit efficient positions during the study period. It is also shown that the impact of global crisis on bank efficiency is found visible among other banks. They have also test the robustness of this study.

In the next article, Santa Kar and Joyeeta Deb analysis performance of Microfinance Institutions (MFIs) in India. First, they explain that MFIs emerged as major player in providing microfinance services and therefore such institutions need to be financially sustainable in order to achieve their double bottom-line objective. Therefore, this article proposes a two-stage analysis to measure the performance of Indian MFIs and verify the impact of sustainability on the efficiency of the MFIs. In the first stage non parametric DEA framework is developed to estimate the efficiency of the MFIs and to gauge to what extent the production of the bad output could be minimized. In the second stage, Tobit regression is used to identify the factors that have significant impact on efficiency of the MFI, particularly to answer whether sustainability has any significant impact on the efficiency of the MFIs.

The domain of the next two articles is the evaluation of healthcare systems. Zungu Mathias Mulumba, Lindah Nalubanga, Christine Nankanja, Kwihangana Manasseh and Jonas Månsson, Jimmy Hollén measure the technical efficiency in Ugandan referral hospitals using a Data Envelopment Analysis framework. They decompose long-run technical efficiency of hospitals into short-term technical efficiency, scale efficiency and congestion. Their results reveal that the source of the long-run inefficiency varies over the years. For 2012, more than 50% of the observed inefficiency relates to scale factors. However, in 2013 and 2014 the major contributor to the long-run inefficiency was input congestion.

In the sixth article, Maria Stella de Castro Lobo and Edson Correia Araujo use dynamic network DEA model in period 2008-2013, to depict the relationships that take place between diverse levels of care (primary health care/PHC and secondary-tertiary health care/STC) in Brazil. This study measure the performance of Brazilian state capitals, which implement key health policies and assist patients from smaller surrounding municipalities, especially for STC. They show that projections onto the frontier enable establish own management diagnosis and goals for financing and development.

The next two articles are related to performance comparison in information technology industry and performance benchmarking of Indian states. Prosenjit Das evaluates Total Factor Productivity Growth (TFPG) of Indian IT industry during the period from 2004-05 to 2014-15. The author considered a balanced panel consists of

70 IT firms. Further, the TFPG of Indian IT industry has been decomposed into three components: catch-up, frontier-shift, and scale efficiency change (SEC). Das finds that during the study period, the average TFP and frontier-shift has been improved while catch up effect is found to have been declined. It is also shown that the variables, such as export have positive and statistically significant impact on the catch-up and frontier-shift. Salaries and wages intensity have positive impact on TFPG. Export intensity, Salaries and wages intensity have positive impact on TFPG while age of the firms has positive impact on catch-up and TFPG. On an average, the firms which spent on research and development (R&D) have experienced improvement in TFPG and frontier-shift. This study has also found that the impact of the US subprime crisis has been negative on catch-up, frontier-shift, and TFPG.

Finally, in the last article in this issue, Ram Pratap Sinha constructs an index of fiscal performance of Indian states using four non-parametric approaches: Data Envelopment Analysis (DEA), Free Disposal Hull (FDH), Order-m and Order-alpha. This study uses a two-stage approach, where in the first stage, four non-parametric methods have been used to evaluate the performance of Indian states for five consecutive years. Further, in order to tackle the problem of estimation bias (due to sampling variations) bootstrapped DEA and bootstrapped Order-m methods have been applied. In the second stage, impact of indebtedness on the performance of the states has been assessed using a censored regression framework. The major outcome of this study is the construction of a fiscal performance index based on multiple indicators. Moreover, the second stage results indicate that state performance is significantly influenced by their degree of indebtedness. The proposed approach in this article can be effectively used to benchmark state performance which can serve as a basis for resource transfer from the central government to the states.

To conclude, we are grateful to all the authors and to the many reviewers who made this special issue a success. Although it was not possible to include all submitted manuscripts, the editors of this special issue hope that all authors found the feedback helpful for their future work. We also extend our thanks to Professor Dr. Joost (Johannes) Platje, Editor-in-Chief of the Central European Review of Economics and Management, for giving us the opportunity and for providing full support during preparation of this special issue.

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Pricing inputs and outputs in banking: an application to CEE countries

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Abstract:

Aim: A problem in efficiency and productivity studies in banking is that some of the input and output prices used in the estimation of cost, revenue and profit functions are proxies of questionable quality with obvious impact on the reliability of performance measures. We address this issue focussing on the banking systems of Central and Eastern Europe where arguable this problem may even be more acute.

Design / Research methods: We employ parametric forms of directional distance functions to obtain shadow prices of bank inputs and outputs, and compare them with price proxies typically employed in empirical studies. The key idea here is to exploit cost, revenue and profit maximisation as the optimisation criteria to derive pricing rules, which allow us to find shadow prices for both inputs and outputs. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We also use total cost to shadow price inputs and total revenue to shadow price outputs.

Conclusions / findings: We find differences between shadow prices and actual prices suggesting that input and/or output mix may not be consistent with cost minimisation or revenue and profit maximisation. We also find that bank efficiency is highest on average in Estonia, which also boasts the highest bank capitalisation rate in the CEE region.

Originality / value of the article: The study departs from the traditional literature on efficiency and productivity by focussing on pricing and their implications thereof for input-output mix.

Implications of the research: Prices for problem loans are not observable, hence our approach provides an avenue for computing shadow prices for bad outputs in banking. This is important since it gives us an indication of the loss of good output needed to lower the bad output by one unit.
Key words: directional distance function, bank efficiency, shadow prices, CEE banking
JEL: D24, G21, C61

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1. Introduction

A well-known problem in efficiency and productivity studies in banking is that some of the input and output prices used in the estimation of cost, revenue and profit functions are proxies of questionable quality. The implications of this problem can be wide ranging, not only influencing directly bank performance measures, but may also be affecting, among others, measures of returns to scale, as well as merger and acquisitions decisions, credit risk assessments, and the measurement of financial services with direct links to deposits and loans or other financial products in the national accounts. Arguably, the problem is even more acute in the case of banking systems in developing countries. Our focus are the banking systems of Central and Eastern Europe (CEE).[1] We employ parametric forms of directional distance functions to obtain shadow prices of bank inputs and outputs, and contrast them with price proxies typically employed in empirical studies. We pay particular attention to the modelling of both good and bad outputs recognising the importance of credit risk for banks.

We exploit cost minimisation and revenue maximisation as the optimisation criteria to derive direct pricing rules, which allow us to find shadow prices for both inputs and outputs. We show how knowledge of bank cost can be used to price inputs and knowledge of bank revenue can be used to price outputs along with information on input and output quantities. We also obtain indirect or crossover pricing rules exploiting profit maximisation as the optimisation criterion, which allows us to find shadow prices for both inputs and outputs simultaneously. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We parameterise the directional input distance function using a quadratic functional form. We then proceed to obtain shadow prices for inputs utilising an input directional distance function, shadow prices for outputs

[1] Studies with a focus on CEE banking efficiency and productivity include Fries and Taci (2005), Koutsomanoli-Filippaki et al. (2009a, b), Yildirim and Philippatos (2007).

using an output directional distance, and price inputs and outputs simultaneously utilising a directional distance function with both input and output orientation.

We study seven CEE banking systems, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland and Slovakia. Our focus is the post financial and sovereign crisis period, specifically the four-year period 2013-2016. While different in many respects, the banking systems of the CEE countries are characterised by high market concentration, ranging from well in excess of 70 percent in Estonia and Latvia to a low of around 45% in Poland, and high foreign (mainly Western European) ownership, in particular in the Czech Republic, Estonia, Lithuania and Slovakia. Both high rates of concentration and foreign ownership are the result of market deregulation and economic reform in conjunction with the countries accession to the European Union. The CEE countries and their banking systems attained high growth rates driven by large foreign capital inflows in the period prior to the financial crisis. While not directly involved in the menace of toxic assets, the crises did have adverse effects albeit at varying degrees on CEE bank portfolios with large declines in profitability driven by the very high level of impairment costs (Deloitte, 2012). The Czech, Polish and Slovak banking sectors managed to get through the crisis much more easily than those of the Baltic States and Hungary did.

However, one concern was that many of these countries, especially the three Baltic States expanded far too much in the immediate period preceding the global financial crisis, and hence became very vulnerable to major external shocks recognising that much of the expansion was triggered by foreign capital inflows. The upshot of this was that total bank assets fell quite rapidly in the three Baltic States between 2007 and 2012, with Estonia recording the largest drop in banking assets (in excess of 40 percent) during this period according to figures compiled by Eurostat. In contrast, the Czech Republic and especially Poland recorded large increases in total banking assets during the same period. Banking assets as a percentage of GDP fell by almost half in the case of Estonia, from over 220 percent to about 120 percent, and by about one quarter, from about 100 percent to 70 percent in Lithuania and from about 160 percent to just over 120 percent in Latvia. The Czech Republic recorded a modest increase, with total banking assets rising from about 105 percent of GDP to 115 percent, while in Poland they increased from about

70 percent to 85 percent of GDP. Clearly, Estonia was way overleveraged in the years before the crisis, and the substantial drop in leverage indicates a much needed rationalisation of its banking sector, bringing Estonia and to a lesser extent Latvia more in sync with the other CEE countries.

A second concern was that the development of the banking sectors of the CEE countries following accession to the European Union was driven by asset expansion with very little evidence of relative prices for inputs and outputs adjusting to reflect the opportunities for rationalisation made available through financial market deregulation and more widely through the overall economic reform programme. This is important, especially in view of major developments in the post crisis period associated with stricter regulatory requirements.

The paper is organised as follows. Section 2 describes the methodology used to compute the efficiency measures and shadow prices for inputs and outputs. Section 3 describes the data and presents the empirical results. Section 4 concludes the paper.

2. Methodology

2.1. Parametric method

The parametric method uses a functional form to model empirically the associated distance function, from which the shadow prices of outputs can be calculated. Once the functional form is determined, we use linear programming to estimate the parameters of the model. Aigner and Chu (1968) proposed a deterministic linear programming model for calculating the parameters of the distance function. This model has been widely employed in shadow price estimation. Its objective is to seek a set of parameters that minimises the sum of deviations of the distance function value from the frontier of production technology subject to the underlying technology constraints. The constraint conditions cover the feasibility, monotonicity, disposability, translation properties of the distance function. While desirable inputs and outputs satisfy strong disposability, we assume that undesirable outputs (non-performing loans) and desirable outputs satisfy only joint weak disposability. In addition, we require that the functional form should be flexible, i.e. allow for interaction and second order terms to provide a complete characterisation of technology. Färe and Sung (1986) show that within the class of generalised quadratic functions, the quadratic function is the best choice for the directional distance function, in the sense that provides a second order approximation to the true but unknown production relation, with parameters restrictions to satisfy the translation property.

We assume that we observe inputs, good and bad output data, $(x, y, b) \in \mathbb{R}^N_{\geq} \times \mathbb{R}^M_{\geq} \times \mathbb{R}^J_{\geq}$ and in addition, we assume that both input and output direction vectors $g^x = (g^x_1, \dots, g^x_N), g^y = (g^y_1, \dots, g^y_M), g^b = (g^b_1, \dots, g^b_J)$ have been chosen. We estimate the directional technology distance function $\vec{D}_T((x, y, b; g^x, g^y, g^b)$ using a quadratic functional form. We recall that the direct representation of directional technology distance function is defined as

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = max\,\{\beta : (x - \beta g^x, y + \beta g^y, b - \beta g^b) \in T\}$$

Note that this function satisfies the representation and translation properties, i.e,

$$T = \{(x, y, b): \vec{D}_T(x, y, b; g^x, g^y, g^b) \geq 0\},$$

$$\vec{D}_T(x - \alpha g^x, y + \alpha g^y, b - \beta g^b; g^x, g^y, g^b)$$
$$= \vec{D}_T(x, y, b; g^x, g^y, g^b) - \alpha, \quad \alpha \in \mathbb{R}.$$

To translate the shadow pricing formulas into empirical results we need to parameterize the distance function. We choose the quadratic functional form expressed by:

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \sum_{j=1}^{J} \gamma_j b_j$$
$$+ \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{nn'} x_n x_{n'} + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \gamma_{jj'} b_j b_{j'}$$
$$+ \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} x_n y_m + \sum_{n=1}^{N}\sum_{j=1}^{J} \nu_{nj} x_n b_j + \sum_{m=1}^{M}\sum_{j=1}^{J} \mu_{mj} y_m b_j$$

s.t.

$$\alpha_{nn'} = \alpha_{n'n}, n \neq \acute{n};\ \beta_{mm'} = \beta_{m'm}, m \neq m';\ \gamma_{jj'} = \gamma_{j'j}, j \neq j'.$$

We estimate the quadratic directional distance function using linear programming methods following Aigner and Chu (1968) by solving the following linear programming problem:

$$\min \sum_{k=1}^{n} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b)$$

$s.t.$

$$(1)\ \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, \quad k = 1, \dots, K, \quad (feasibility)$$

$$(2)\ \partial_{y_m} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \leq 0, k = 1, \dots, K, \quad m = 1, \dots, M, \quad (monotonicity)$$

$$(3)\ \partial_{x_n} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, k = 1, \dots, K, \quad n = 1, \dots, N, \quad (monotonicity)$$

$$(4)\ \partial_{b_j} \vec{D}_T(x^k, y^k, b^k; g^x, g^y, g^b) \geq 0, k = 1, \dots, K, \quad j = 1, \dots, J, \quad (monotonicity)$$

$$(5) - \sum_{n=1}^{N} \alpha_n g_n^x + \sum_{m=1}^{M} \beta_m g_m^y - \sum_{j=1}^{J} \gamma_j g_j^b = -1, \quad (translation),$$

$$- \sum_{n=1}^{N} \delta_{nm} g_n^x + \sum_{\acute{m}=1}^{M} \beta_{mm'} g_m^y - \sum_{j=1}^{J} \mu_{mj} g_j^b = 0, \quad \mathrm{m} = 1, \dots, \mathrm{M},$$

$$- \sum_{n=1}^{N} \nu_{nj} g_n^x + \sum_{m=1}^{M} \mu_{mj} g_m^y - \sum_{j=1}^{J} \gamma_{jj} g_j^b = 0, \quad j = 1, \dots, J,$$

$$- \sum_{n'=1}^{N} \alpha_{n\acute{n}} g_n^x + \sum_{\mathrm{m}=1}^{M} \delta_{nm} g_m^y - \sum_{j=1}^{J} \nu_{nj} g_j^b = 0, \quad \mathrm{n} = 1, \dots, \mathrm{N},$$

$$(6)\ \alpha_{nn'} = \alpha_{n'n}, n \neq \acute{n};\ \beta_{mm'} = \beta_{m'm}, m \neq m';\ \gamma_{jj'} = \gamma_{j'j}, j \neq j'. (Symmetry)$$

Noting that

$$\partial_{x_n} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x, y, b)}{\partial x_n} = \alpha_n + \sum_{n'=1}^{N} \alpha_{nn'} x_{n'}^k + \sum_{m=1}^{M} \delta_{nm} y_m^k + \sum_{j=1}^{J} \nu_{nj} b_j^k,$$

$$\partial_{y_m} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x, y, b)}{\partial y_m} = \beta_m + \sum_{m'=1}^{M} \beta_{mm'} y_{m'}^k + \sum_{n=1}^{N} \delta_{nm} x_n^k + \sum_{j=1}^{J} \mu_{mj} b_j^k,$$

$$\partial_{b_j} D_T(x^k, y^k, b^k) = \frac{\partial D_T(x, y, b)}{\partial b_j} = \gamma_j + \sum_{j'=1}^{J} \gamma_{jj'} b_{j'}^k + \sum_{n=1}^{N} \nu_{nj} x_n^k + \sum_{m=1}^{M} \mu_{mj} y_m^k.$$

We use the same functional form for all banks, large and small and across different CEE banking systems, recognising that all banks face fundamentally the same production technology for traditional core banking activities (i.e., taking deposits and making loans). Although the largest banks may rely a lot more on securities trading and off-balance-sheet activities, it is not a priori clear whether this will impact significantly on the empirical results recognising that the CEE region is dominated by banks with largely a traditional focus.[2]

2.2. Pricing models and shadow prices

We follow the approach of Färe et al. (2017) to obtain shadow prices using the estimated distance functions via the Lagrangian method. We use different pricing rules based on different, in terms of their orientation, directional distance functions associated with different optimisation criteria. The pricing rule based on an input directional distance function is associated with cost minimisation as the behavioural

[2] Spierdijka et al. (2017) present a similar argument for the US bank market, characterised by a small number of very large banks and a very large number of smaller banks.

criterion and requires either total cost or one of the input prices to be observed. The pricing rule based on an output directional distance function is associated with revenue maximisation as the behavioural criterion and requires either total revenue or one of the output prices to be known. The pricing rule based on a directional distance function with both input and output orientation is associated with profit maximisation and requires one of the input or output prices to be known. When we require one of the prices to be known, we rely on what we perceive to be the most reliable input or output price proxy to calculate shadow prices for the other inputs and outputs. For robustness purposes, we experiment with alternative choices of the 'known' price. We then compare the shadow prices with actual prices. Since we are also interested in pricing bad outputs (non-performing loans and leases), we obtain shadow prices of the bad output and compare it with the actual and shadow price of the corresponding good output (loans and leases).

We first show how to calculate shadow prices for inputs and outputs using a directional distance function. We rely on profit maximisation as the optimisation criterion, which allows us to construct shadow prices for both inputs and outputs simultaneously. Second, we construct input prices using an input directional distance function. Third, we exploit revenue maximisation as the optimisation criterion to construct shadow prices for outputs, both desirable and undesirable. To do this we use the output directional distance function.

In an environment of low interest rates coupled with important regulatory changes, we would expect that bank revenues from interest-bearing activities be under pressure thereby directly affecting bank profitability (see Spierdijka et al., 2017). Under these conditions, cost management by banks in terms of their ability to use inputs more efficiently, not only in a technical efficiency sense but also in terms of their ability to respond efficiently to changing relative prices is important. To this end, we set out to calculate shadow input and output prices representing the opportunity cost of choosing the observed input or output quantity (i.e. the opportunity cost of money to the bank from the perspective of the next best alternative use). We compare these prices with the actual observed (proxy) prices of inputs and outputs. In particular, we focus on prices for deposits, loans, other earnings assets and loan loss provisions. Since smaller banks may have lesser ability to diversify their activities, we would like to see if there any differences between large and small banks. We also assess performance in relation to a host of indicators related to funding structure, liquidity and asset structure.

We set up the profit maximisation Lagrangian problem as follows

$$\max py - wx - rb - \mu \vec{D}_T(x, y, b; g^x, g^y, g^b)$$

where p, w, r are the prices for desirable outputs y , inputs (x), and undesirable outputs (b), respectively, and μ is the Lagrangian multiplier (e.g. a measure of how much profit would increase if the optimisation constraint was relaxed). The first order conditions associated with the Lagrangian profit maximization problem are as follows:

$$p - \mu \nabla_y \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0,$$
$$-w - \mu \nabla_x \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0$$
$$-r - \mu \nabla_b \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0$$

If one output price, say p_1, is known then we have

$$\mu = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^x, g^y, g^b)}$$

which as shown by Färe et al. (2017) yields the estimation of all other prices, $w_1, \dots, w_m, p_2, \dots, p_s$ as:

$$(w_1, \dots, w_N)$$
$$= -\frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{x_N} \vec{D}_T(x, y, b; g^x, g^y, g^b) \right),$$

$$(p_2, \dots, p_M)$$
$$= \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{y_2} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{y_M} \vec{D}_T(x, y, b; g^x g^y, g^b) \right),$$

$$(r_1, \dots, r_J)$$
$$= \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{b_1} \vec{D}_T(x, y, b; g^x g^y, g^b), \dots, \partial_{b_J} \vec{D}_T(x, y, b; g^x g^y, g^b) \right),$$

Similarly, if one of the input prices, say w_1, is known then
$$\mu = -\frac{w_1}{\partial_{x_1}\vec{D}_T(x,y,b;g^x g^y,g^b)}$$

which yields the estimation of all other prices, $w_1,\dots,w_m,p_2,\dots,p_s$ as:
$$(w_1,\dots,w_N) = \frac{w_1}{\partial_{x_1}\vec{D}_T(x,y,b;g^x g^y,g^b)}\left(\partial_{x_2}\vec{D}_T(x,y,b;g^x g^y,g^b),\dots,\partial_{x_N}\vec{D}_T(x,y,b;g^x g^y,g^b)\right),$$
$$(p_1,\dots,p_M) = -\frac{w_1}{\partial_{x_1}\vec{D}_T(x,y,b;g^x g^y,g^b)}\left(\partial_{y_1}\vec{D}_T(x,y,b;g^x g^y,g^b),\dots,\partial_{y_M}\vec{D}_T(x,y,b;g^x g^y,g^b)\right),$$
$$(r_1,\dots,r_J) = \frac{w_1}{\partial_{x_1}\vec{D}_T(x,y,b;g^x g^y,g^b)}\left(\partial_{b_1}\vec{D}_T(x,y,b;g^x g^y,g^b),\dots,\partial_{b_J}\vec{D}_T(x,y,b;g^x g^y,g^b)\right)$$

From here, by altering the optimisation criterion and rewriting the first order conditions for cost minimization in lieu of profit maximisation, viz.
$$-w-\mu\nabla_x D_I(x,y,b;g^x)=0,$$
we can derive the input pricing rule as
$$(w_1,\dots,w_N) = C\,\frac{\left(\partial_{x_1}D_I(x,y,b;g^x),\dots,\partial_{x_N}D_I(x,y,b;g^x)\right)}{\partial_x D_I(x,y,b;g^x).x},$$
where C is observed total cost. Similarly, applying the first order conditions for revenue maximisation,
$$p-\mu\nabla_y D_O(x,y,b;g^y,g^b)=0 \text{ and } -r-\mu\nabla_b D_O(x,y,b;g^y,g^b)=0,$$
we can obtain pricing rules for desirable and undesirable outputs as:
$$(p_1,\dots,p_M) = R\,\frac{\left(\partial_{y_1}D_O(x,y,b;g^y,g^b),\dots,\partial_{y_M}D_O(x,y,b;g^y,g^b)\right)}{\partial_y D_O(x,y,b;g^y,g^b).y},$$
$$(r_1,\dots,r_J) = R\,\frac{\left(\partial_{b_1}D_O(x,y,b;g^y,g^b),\dots,\partial_{b_J}D_O(x,y,b;g^y,g^b)\right),}{\partial_y D_O(x,y,b;g^y,g^b).y}$$

where R is observed total revenue.

3. Empirical application

We use data obtained from Orbis Bank Focus over the period 2013 to 2016. We follow the intermediation approach (see Sealey and Lindley, 1977). We assume banks use a production technology consisting of three inputs, labour measured by staff costs, capital measured by fixed assets and deposits; two desirable outputs, loans and other earning assets, and one undesirable output (loan loss reserves). We measure the price of deposits as the ratio of interest paid on deposits over total deposits, the price of loans as interest income on loans over total loans, and the price of other earning assets as interest income on other earning assets over other earning assets.

Table 1 presents the descriptive statistics of the data as well as the efficiency measures. Poland is the largest banking sector in the CEE. Funding costs (deposit prices) are on average lowest in the Baltic States while interest rate margins (difference between loan and deposit prices) are largest in Hungary and Poland.

Table 1. Descriptive Statistics

	Variables		CZ	EE	HU	LT	LV	PL	SK
			Mean (Std. Dev)						
Inputs-Outputs	Inputs	SE	59,918	10,541	101,607	21,785	23,209	127,211	48,851
			(92,351)	(12,139)	(167,030)	(16,773)	(19,532)	(152,463)	(46,304)
		CD	5,569,586	737,368	4,663,658	2,214,214	1,813,112	8,411,963	3,700,694
			(7,972,065)	(1,148,849)	(6,479,863)	(2,173,354)	(1,886,960)	(10,693,660)	(3,488,906)
		FA	60,200	3,533	107,099	15,806	25,188	89,099	48,152
			(119,960)	(3,109)	(185,962)	(20,497)	(19,729)	(139,359)	(55,241)
	desired outputs	L	4,837,779	847,501	3,601,175	1,982,595	1,232,896	8,137,381	3,367,852
			(6,184,529)	(1,476,762)	(4,822,613)	(1,962,016)	(1,729,883)	(10,064,639)	(3,368,447)
		OEA	2,597,441	167,928	2,218,984	511,340	736,813	3,081,602	1,260,703
			(4,182,332)	(233,744)	(2,452,269)	(451,863)	(759,078)	(3,559,381)	(1,254,961)
	Undesired output	LLR	162,681	16,596	598,424	45,199	50,546	386,009	135,485
			(202,480)	(20,454)	(939,564)	(46,347)	(49,888)	(458,911)	(120,123)
Prices		P(D)	0.0108	0.0076	0.0188	0.0056	0.0049	0.0185	0.0117
			(0.0101)	(0.0098)	(0.0135)	(0.0049)	(0.0048)	(0.0093)	(0.0072)
		P(L)	0.0491	0.0348	0.0666	0.0392	0.0546	0.0535	0.0509
			(0.0214)	(0.0129)	(0.0215)	(0.0211)	(0.0213)	(0.0217)	(0.0162)
		P(OEA)	0.0226	0.0583	0.0507	0.0202	0.0134	0.0375	0.0269
			(0.0177)	(0.1775)	(0.0273)	(0.0102)	(0.0094)	(0.0217)	(0.0085)
Efficiencies		DI	0.8400	0.9189	0.6852	0.8539	0.8175	0.7450	0.7434
			(0.1706)	(0.0762)	(0.2084)	(0.0125)	(0.1146)	(0.2040)	(0.1740)
		DO	0.8623	0.9276	0.6483	0.8902	0.8813	0.7951	0.8183
			(0.1288)	(0.0393)	(0.82249)	(0.8902)	(0.0742)	(0.1701)	(0.0930)
		DT	0.8981	0.9437	0.7456	0.9046	0.8886	0.8259	0.0.8321
			(0.1139)	(0.0397)	(0.1938)	(0.0819)	(0.0745)	(0.1542)	(0.1113)
	# Observations		90	24	49	20	57	97	45

Notes: SE is staff expenses, CD is customer deposits measured in thousands of Euros, FA is fixed assets measured in thousands of Euros, L is loans measured in thousands of Euros, OEA is other earnings assets measured in thousands of Euros, NPL is reserves for non-performing-loans. DI, DO and DT are the efficiency scores based an input directional distance function, output directional distance function, and a directional distance function with both input and output orientation, respectively. For convenience, efficiency scores are reported in the range of zero to one, by rescaling the distance function (DDF) values as 1/(1+DDF). Figures in brackets denote standard deviations. CZ=Czech Republic, EE= Estonia, HU=Hungary, LT=Lithuania, LV=Latvia, PL=Poland and SK= Slovakia.

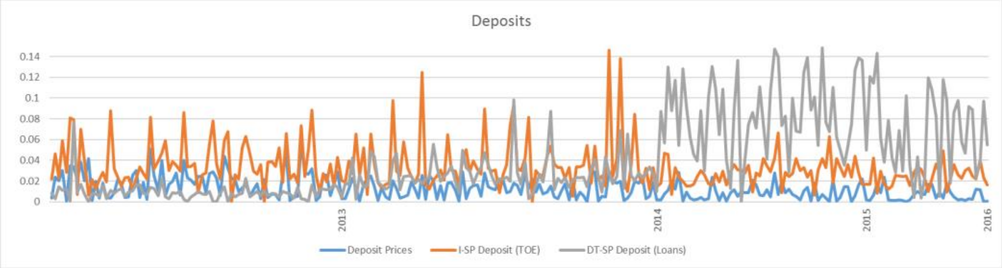
3.1 Empirical results

We estimate directional distance functions by setting the values of the directional vector equal to the data averages. More specifically, we set $g^x = \vec{x}, g^y = 0, g^b = 0$ for the input directional distance function, $g^x = 0, g^y = \vec{y}, g^b = \vec{b}$ for the output directional distance function, and $g^x = \vec{x}, g^y = \vec{y}, g^b = \vec{b}$ for the directional distance function with both input and output orientation. To estimate the constrained optimisation model given by (1)-(6), we first normalise each output and input by its mean value. This has the convenience of ease of interpretation of the parameter estimates of the directional distance function (see Färe et al., 2001 and Cuesta and Zofio, 2005). Using data averages as the direction also has the convenience of estimating the normalised model with direction values equal to unity. However, when we calculate shadow prices, we adjust the gradients to conform to the pricing rules given above.

Table 1 shows efficiency is highest in Estonia where there has been considerable rationalisation of the banking system, and lowest in Hungary where profitability has been under pressure, in part because of government-imposed levies albeit mainly because of the economy's vulnerability to external financial shocks. As to be expected, efficiency scores from the directional distance function (DT) are greater than those obtained by the partial orientation models (DI and DO), since DT allows banks to adjust both inputs and outputs simultaneously.

Figures 1-4 plot actual prices and shadow prices for all banks during the entire sample period 2013-2016. Figure 1 shows the actual price of deposits and the shadow prices calculated from the input directional distance function (DI) using information on total cost (I-SP Deposits) and the directional distance function (DT) using the crossover pricing rule with information on the price of loans (DT-SP Deposits). Our estimates show that the opportunity cost rate of deposits is generally greater than the actual interest rate paid on deposits, and this gap has increased in the latter part of the sample period. In a simplified situation where there is infinite supply of deposits, the shadow price would presumably be zero. Hence, a positive value is indicative of the intrinsic cost to the bank to ramp deposits up or down quickly in order to meet liquidity demands or regulatory requirements.

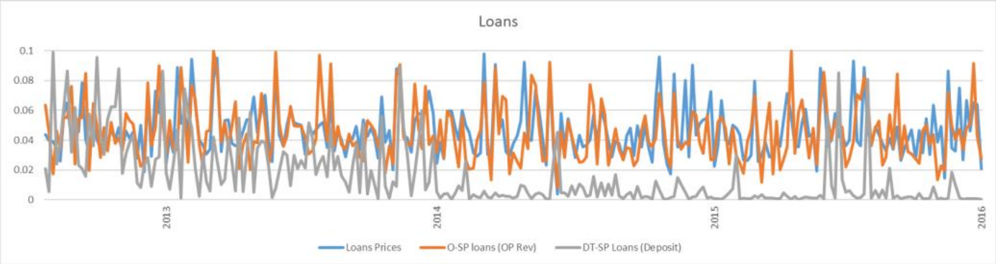
Figure 1. Deposits Prices



Notes: I-SP Deposits (TOE) indicates that the shadow price for deposits is calculated from an input directional distance function with known total expenses (TOE); DT-SP Deposits (Loans) indicates that the shadow price for deposits is calculated from a directional distance function using a crossover pricing rule with known price of loans.

Figure 2 shows the actual and shadow prices of loans calculated from the output directional distance function (DO) using information on total revenue (O-SP Loans) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP Loans). Our estimates show that the opportunity cost rate of loans (O-SP) is generally similar to the actual price of loans while the alternative measure (DT-SP) indicates a lower opportunity cost.

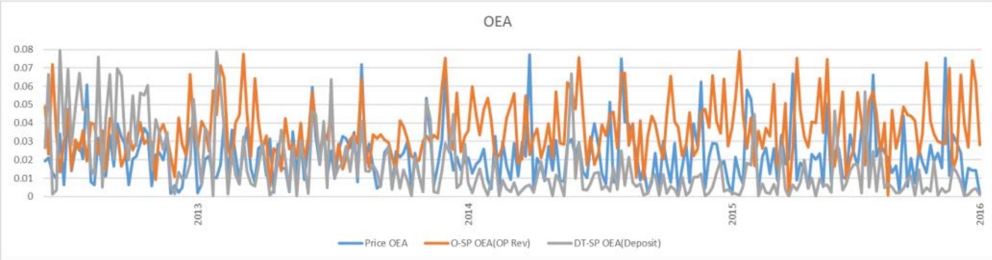
Figure 2. Loan Prices



Notes: O-SP loans (OP Rev) indicates that the shadow price for loans is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP loans (Deposits) indicates that the shadow price for loans is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Figure 3 displays the actual price of other earning assets and its shadow price calculated from the output directional distance function (DO) using information on total revenue (O-SP OEA) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP OEA). Our estimates show that the opportunity cost rate of other earning assets (O-SP OEA) is generally greater than the actual price but lower when calculated from the directional distance function. We ascribe these differences to the differences in the construction of pricing rules (direct versus crossover) and differences in the optimisation criteria (revenue versus profit maximisation).

Figure 3. Other Earning Assets Prices

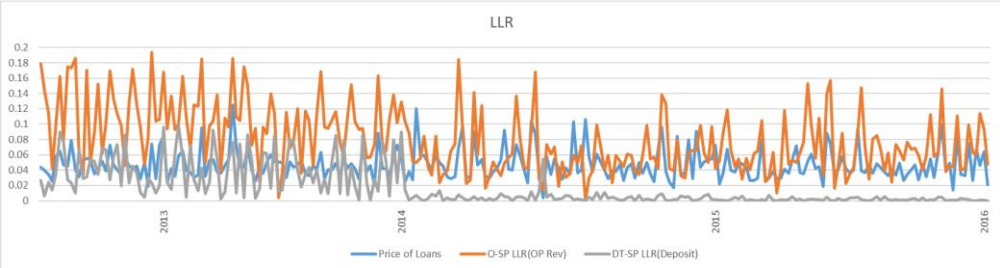


Notes: O-SP OEA (OP Rev) indicates that the shadow price for other earning assets (OEA) is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP (Deposits) indicates that the shadow price for OEA is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Figure 4 shows the actual price of loans and the shadow price of loan loss reserves calculated from the output directional distance function (DO) using information on total revenue (O-SP LLR) and the directional distance function (DT) using the crossover pricing rule with information on the price of deposits (DT-SP LLR). Bad output prices are not observable, hence shadow prices provide useful information in assessing the opportunity cost of reducing the bad output by one unit. Our estimates show that the opportunity cost of loan loss reserves (O-SP LLR) is generally greater than the actual price of loans; however, it is lower when calculated from the directional distance function. Since these opportunity costs relate to loss of revenue (gross income) vis-a-vis loss of profit (net income), such differences may not be entirely surprising.

We turn next to gain more insights on our bank performance measures by relating them to various indicators of size, liquidity, revenue sustainability, asset and funding structure as shown in the tables below. Table 2 displays efficiency averages and price ratio averages across different bank sizes measured by total assets. We find that smaller banks are more efficient whereas larger banks are the least efficient. Concerning price ratios, the most notable patterns arise in relation to the ratio of the shadow price of LLR to the price of loans, and the ratio of shadow prices of loans to deposits.

Figure 4. Loan Loss Reserve Shadow Prices



Notes: O-SP LLR (OP Rev) indicates that the shadow price for loan loss reserves (LLR) is calculated from an output directional distance function with known operating revenue (OP Rev); DT-SP LLR (Deposits) indicates that the shadow price for LLR is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

Table 2. Efficiency and Relative Prices across different bank sizes

TA	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.9450	0.9254	0.9156	0.9922	1.0297	1.0636	1.0430	0.9883	1.0267	0.9981
	(0.0419)	(0.0660)	(0.0421)	(0.0380)	(0.0290)	(0.0622)	(0.0301)	(0.1065)	(0.0616)	(0.0270)
Medium	0.8664	0.8071	0.8228	0.9913	1.0177	1.0406	1.0356	1.0003	1.0330	1.0061
	(0.0972)	(0.1125)	(0.1285)	(0.0183)	(0.0981)	(0.0434)	(0.0962)	(0.0729)	(0.0351)	(0.0202)
Large	0.7520	0.6298	0.7254	1.0074	1.0239	1.0240	1.0343	1.0136	1.0140	1.0148
	(0.1686)	(0.1976)	(0.2011)	(0.0177)	(0.0195)	(0.0475)	(0.0150)	(0.0399)	(0.0162)	(0.0364)

Notes: TA, L, D, OEA, LLR are total assets, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

The loans to deposits ratio (L/D) shows how lending activity is matched to the expansion of the deposits base. Table 3 shows that banks with lower L/D ratios are more efficient. Again no clear patterns arise in relation to most price ratios aside from the actual and shadow price ratios of loans to deposits.

Table 3. Efficiency and Relative Prices across loan to deposits ratio

L/D	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.9105	0.8536	0.8807	0.9971	1.0186	1.0500	1.0514	1.0274	1.0385	1.0118
	(0.1003)	(0.1526)	(0.1108)	(0.0329)	(0.0205)	(0.0630)	(0.0247)	(0.0250)	(0.0286)	(0.0304)
Medium	0.8042	0.7068	0.7653	1.0021	1.0186	1.0287	1.0343	1.0166	1.0164	1.0132
	(0.1493)	(0.1800)	(0.1687)	(0.0166)	(0.0195)	(0.0444)	(0.0142)	(0.0178)	(0.0191)	(0.0218)
Large	0.8480	0.8004	0.8170	0.9919	1.0343	1.0482	1.0264	0.9585	1.0182	0.9942
	(0.1437)	(0.1847)	(0.1722)	(0.0286)	(0.1042)	(0.0500)	(0.1002)	(0.1214)	(0.0627)	(0.0313)

Notes: L, D, OEA, LLR are loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Other earning assets to total assets ratio (OEA/TA) provides information on asset structure, and more generally information on the bank business model, with higher securities to assets ratios being indicative of business model leaning heavier towards investment banking activities. We find that banks with larger OEA/TA are more efficient, which may be the result of being more diversified. In terms of price ratios, we note that larger banks have lower loan to price ratios, both actual and shadow, which may relate to their ability to generate income from non-traditional banking activities.

Liquidity is a critical issue for banks and their regulators. Table 5 shows that more liquids banks are more efficient and have higher loan price to deposits ratios.

Table 4. Efficiency and Relative Prices across other earnings assets to total assets ratio

OEA/TA	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8386	0.7824	0.8122	0.9941	1.0235	1.0527	1.0271	0.9711	1.0136	0.9922
	(0.1384)	(0.1771)	(0.1644)	(0.0306)	(0.1019)	(0.0532)	(0.0996)	(0.1244)	(0.0641)	(0.0319)
Medium	0.8089	0.7289	0.7698	0.9977	1.0226	1.0255	1.0363	1.0095	1.0213	1.0088
	(0.1585)	(0.2032)	(0.1787)	(0.0157)	(0.0205)	(0.0438)	(0.0148)	(0.0217)	(0.0158)	(0.0222)
Large	0.9147	0.8492	0.8805	0.9979	1.0249	1.0491	1.0495	1.0215	1.0386	1.0180
	(0.0923)	(0.1450)	(0.1096)	(0.0291)	(0.0288)	(0.0596)	(0.0249)	(0.0349)	(0.0269)	(0.0274)

Notes: OEA, TA, L, D, LLR are other earning assets, total assets, loans, customer deposits and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Table 5. Efficiency and Relative Prices across liquid assets to total assets ratio

LA/TA	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8387	0.7754	0.8010	0.9930	1.0165	1.0383	1.0266	0.9740	1.0126	1.0012
	(0.1463)	(0.1942)	(0.1711)	(0.0185)	(0.0995)	(0.0482)	(0.0976)	(0.1181)	(0.0488)	(0.0308)
Medium	0.8250	0.7436	0.7882	1.0001	1.0311	1.0407	1.0381	1.0084	1.0257	1.0091
	(0.1583)	(0.1989)	(0.1787)	(0.0301)	(0.0335)	(0.0578)	(0.0238)	(0.0520)	(0.0367)	(0.0327)
Large	0.8987	0.8415	0.8734	0.9980	1.0236	1.0482	1.0478	1.0197	1.0355	1.0087
	(0.0963)	(0.1368)	(0.1086)	(0.0312)	(0.0247)	(0.0551)	(0.0248)	(0.0280)	(0.0368)	(0.0235)

Notes: LA, TA, L, D, OEA, LLR are liquid assets, total assets, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

The cost to income (C/IC) ratio is often used as an indicator for the profitability of a bank in terms of its ability to generate revenue from its expenditures. There is no clear pattern emerging from Table 6 in terms of the relation between the cost to income ratio and bank efficiency. The relationship is positive under input orientation albeit negative under output orientation. The relationship is also negative between the C/IC ratio and the shadow prices of loans to deposits.

Table 6. Efficiency and Relative Prices across cost to income ratio

C/IC	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8645	0.7882	0.8282	0.9942	1.0195	1.0371	1.0432	1.0173	1.0258	1.0100
	(0.1237)	(0.1793)	(0.1453)	(0.0311)	(0.0352)	(0.0545)	(0.0277)	(0.0628)	(0.0339)	(0.0345)
Medium	0.8511	0.7699	0.8371	1.0018	1.0143	1.0416	1.0309	1.0055	1.0226	1.0085
	(0.1388)	(0.1980)	(0.1459)	(0.0227)	(0.0926)	(0.0525)	(0.0953)	(0.0778)	(0.0236)	(0.0277)
Large	0.8472	0.8027	0.7978	0.9949	1.0374	1.0489	1.0395	0.9796	1.0253	1.0006
	(0.1549)	(0.1704)	(0.1839)	(0.0269)	(0.0338)	(0.0543)	(0.0281)	(0.0881)	(0.0612)	(0.0244)

Notes: C, IC, L, D, OEA, LLR are total cost, income, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Greater reliance on deposits is an indicator of more stable source of funding for banks. Table 7 reveals a U-shaped relationship between the deposits to total funds ratio and bank efficiency.

Table 7. Efficiency and Relative Prices across deposits to total funding ratio

D/TF	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.8618	0.8212	0.8238	0.9975	1.0342	1.0460	1.0252	0.9559	1.0148	1.0011
	(0.1449)	(0.1737)	(0.1712)	(0.0194)	(0.1065)	(0.0448)	(0.0999)	(0.1197)	(0.0605)	(0.0338)
Medium	0.8024	0.6919	0.7661	1.0031	1.0216	1.0282	1.0393	1.0190	1.0221	1.0141
	(0.1533)	(0.1980)	(0.1773)	(0.0226)	(0.0202)	(0.0547)	(0.0206)	(0.0225)	(0.0227)	(0.0287)
Large	0.8982	0.8473	0.8727	0.9910	1.0168	1.0520	1.0474	1.0271	1.0360	1.0039
	(0.0980)	(0.1331)	(0.1037)	(0.0351)	(0.0209)	(0.0583)	(0.0263)	(0.0258)	(0.0312)	(0.0234)

Notes: TF, D, L, OEA, LLR are total funds, customer deposits, loans, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Tables 8 and 9 show that banks at the upper tertile of impaired loans to total loans and loan loss reserves to interest margin ratios are less efficient than those in the lower tertile.

Table 8. Efficiency and Relative Prices across Impaired loans to gross loans ratio

IML/GL		eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	Average	0.8848	0.8002	0.8844	1.0010	1.0159	1.0354	1.0301	1.0113	1.0144	1.0089
	Std. Dev	0.1095	0.1754	0.0994	0.0176	0.0242	0.0485	0.0108	0.0429	0.0222	0.0311
Medium	Average	0.8295	0.7414	0.8004	0.9993	1.0246	1.0448	1.0414	1.0055	1.0222	1.0082
	Std. Dev	0.1358	0.1823	0.1439	0.0191	0.0220	0.0467	0.0222	0.0688	0.0509	0.0268
Large	Average	0.8484	0.8191	0.7785	0.9905	1.0305	1.0472	1.0416	0.9855	1.0376	1.0019
	Std. Dev	0.1633	0.1833	0.2003	0.0390	0.1013	0.0647	0.1021	0.1075	0.0451	0.0299

Notes: IML, GL, L, D, OEA, LLR are impaired loans, gross loans, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

Table 9. Efficiency and Relative Prices across loan loss reserves to interest margin ratio

LLR/IM	eff_{DT}	eff_{DI}	eff_{DO}	$\frac{S(L)}{P(L)}$	$\frac{S(D)}{P(D)}$	$\frac{S(LLR)}{P(L)}$	$\frac{P(L)}{P(D)}$	$\frac{S(L)}{S(D)}$	$\frac{P(L)}{P(OEA)}$	$\frac{S(L)}{S(OEA)}$
Small	0.9461	0.9216	0.9258	0.9912	1.0194	1.0607	1.0325	0.9840	1.0244	1.0000
	(0.0469)	(0.0691)	(0.0410)	(0.0339)	(0.0960)	(0.0596)	(0.0991)	(0.1164)	(0.0609)	(0.0256)
Medium	0.8682	0.7895	0.8497	0.9956	1.0190	1.0470	1.0447	1.0127	1.0315	1.0039
	(0.0903)	(0.1281)	(0.0930)	(0.0258)	(0.0227)	(0.0477)	(0.0242)	(0.0516)	(0.0348)	(0.0303)
Large	0.7492	0.6509	0.6885	1.0045	1.0334	1.0188	1.0356	1.0055	1.0174	1.0150
	(0.1686)	(0.2064)	(0.1924)	(0.0178)	(0.0373)	(0.0446)	(0.0164)	(0.0435)	(0.0184)	(0.0301)

Notes: LLR, IM, L, D, OEA, LLR are loan loss reserves, interest margin, loans, customer deposits, other earning assets and loan loss reserves, respectively. P and S stands for price and shadow price, e.g. S(L) is the shadow price for loans.

4. Conclusion

In this paper we have studied the performance of the CEE banking industry by explicitly modelling loan losses as an undesirable by-product of the loan production process. Recognising that bank input and output prices used in empirical studies are of questionable quality, we approached the problem of estimating the opportunity cost of bank inputs and outputs as a shadow price problem. We modelled technology using parametric forms of directional distance functions, and used the estimated parameters of the distance functions and knowledge of cost or revenue to obtain shadow prices for bank inputs and outputs, respectively. We also used crossover pricing rules to obtain shadow prices for inputs and outputs under profit maximisation.

We find that on average bank efficiency is highest in Estonia among the CEE countries. Recognising that Estonia also boasts the highest bank capitalisation in the CEE, we may infer that our findings are consistent with the franchise value hypothesis, i.e. better capitalised banks are also those with better management practices, which are put in place to protect the charter value of the financial institution. Our results also show that shadow prices for bank inputs and outputs differ significantly from observed price proxies typically used in the estimation of bank cost, revenue and profit functions. While this finding is not surprising, its implications deserve due attention among academics and practitioners. For example, differences between shadow and actual price ratios suggest that the output mix, input mix or both may not be consistent with revenue maximisation, cost minimisation, or profit maximisation, respectively.

Prices for problem loans are not observable, hence our approach provides an avenue for computing shadow prices for bad outputs in banking. This is important since it provides us with a quantitative assessment of the loss of good output (loans) needed to lower the bad output (problem loans) by a unit. This is particularly relevant in the current low interest environment where banks are under pressure to raise loans to improve profitability.

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Nakłady i wyniki cenowe w bankowości: zastosowanie w krajach Europy Środkowo-Wschodniej

Streszczenie

Cel: Problemem związanym z badaniami nad wydajnością i produktywnością w bankowości jest to, że niektóre cenowe nakłady i wyniki wykorzystywane do szacowania funkcji kosztów, przychodów i zysków mogą cechować się wątpliwą jakością i tym samym wpływać na wiarygodność mierników kondycji finansowej. Autorzy zwracają uwagę na tę kwestię i koncentrują się na systemach bankowych w Europie Środkowo-Wschodniej, gdzie, dyskusyjnie, problem ten może być nawet bardziej palący.

Metodyka badań: Autorzy zastosowali formy parametryczne funkcji kierunkowych, aby uzyskać ceny cienie bankowych nakładów i wyników i porównali je z aproksymantami cen typowo stosowanymi w badaniach empirycznych. Główną ideą było wykorzystanie kosztu, przychodu i maksymalizacji zysku jako kryteriów optymalizacji w celu wyprowadzenia zasad cenowych, które pozwoliły na znalezienie cen cieni zarówno dla nakładów, jak i wyników. Wykazano, jak wiedza na temat ceny jednego czynnika może być wykorzystana do wyników cenowych, a także, jak wiedza na temat ceny jednego wyniku może być wykorzystana do nakładów cenowych wraz z informacją o ilościach nakładów i wyników. Zastosowano również koszt całkowity do nakładów cen cieni oraz przychód całkowity do wyników cen cieni.

Wnioski: Badania wykazały różnice pomiędzy cenami cieniami a aktualnymi cenami, sugerując, że mix nakładów i / lub wyników może nie być spójny z minimalizacją kosztów bądź maksymalizacją przychodów czy zysków. Stwierdzono także, że najwyższa wydajność banków występuje średnio w Estonii, chlubiącej się też najwyższą stopą kapitalizacji banków w Europie Środkowo-Wschodniej.

Wartość artykułu: Badanie wyraźnie odróżnia się od tradycyjnej literatury dotyczącej wydajności i produktywności poprzez koncentrację na cenach i polityce cenowej i ich oddziaływaniu na nakłady i wyniki.

Ograniczenia: Ceny nie są łatwo zauważalne w odniesieniu do problemów z pożyczkami. Z tego powodu przedstawione w artykule podejście wskazuje na drogę pozwalającą obliczyć ceny cienie w przypadku złych wyników w bankowości. Jest to istotne, ponieważ stanowi oznakę utraty dobrych wyników, aby obniżyć złe wyniki jednostki.

Słowa kluczowe: parametryczne funkcji kierunkowych, wydajność banków, ceny cienie, bankowość w Europie Środkowo-Wschodniej

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The sources of productivity change and efficiency in Islamic banking: Application of Malmquist productivity index

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Abstract:

Aim: This paper aims to explore performance of Islamic banks in 13 countries from the period 2005 to 2014 and investigates sources of productivity change over the time.

Design / Research methods: The present study gather data on the 31 Islamic banks. The productivity is examined using the Data Envelopment Analysis-based Malmquist productivity index. That we decompose into scale efficiency, technological change and technical efficiency. Source of productivity change in Islamic banks is then identified. We use intermediation approach and production approach to select inputs and outputs of banks.

Conclusions / findings: Although the two approaches are different, our empirical implementation shows that they yield very similar results regarding productivity, efficiency and source of productivity change. Islamic banks are productive and efficient over the study period, but they did not show to be scale efficient and they suffer from technological change evolutions. Moreover, we are able to show that Subprime crisis had a slightly negative effect on productivity in Islamic banking industry.

Originality / value of the article: Empirical studies are still rare and findings are controversial on productivity and efficiency of Islamic banks. This study intends to fill the gaps with a specific focus on measuring productivity index using two different intermediation approach and production approach to select input and output variables.

Implications of the research (if applicable) – Islamic banks are scale inefficient and must improve size of their activities, one possible suggestion is meagering small banks.

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Limitations of the research (if applicable) – Further research can use bootstrapping techniques to correct total factor productivity estimates for bias and to assess the uncertainty surrounding such estimates.

Keywords: Islamic banks, Productivity, efficiency, Data Envelopment Analysis, Malmquist index decomposition
JEL: D24, G21

1. Introduction

Islamic banking refers to a system of banking that is consistent with Islamic law *"Sharia'h"* principles and guided by Islamic economics. The main difference between Islamic and conventional banking is that Islamic teaching says that money itself has no intrinsic value, and forbids people from profiting by lending it, without accepting a level of risk. In other words, interest known as *"Ribaa"* cannot be charged. In fact, to make money from money is prohibited. Wealth can only be generated through legitimate trade and investment. Any gain relating to this trading is shared between person providing the capital and person providing the expertise. Institutions offering Islamic financial services constitute a significant and growing share of the financial system in the world. Since the inception of Islamic banking about three decades ago, the number and reach of Islamic financial institutions worldwide has risen from one institution in one country in 1975 to over 300 institutions operating in more than 75 countries. Islamic banks are concentrated in the Middle East and Southeast Asia, but they are also present as niche players in Europe and the United States. Reflecting the increased role of Islamic finance, the literature on Islamic banking has grown. A large part of the literature contains comparisons of instruments used in Islamic and commercial banking, and discusses the regulatory and supervisory challenges related to Islamic banking. Several studies in recent years focused on the efficiency analysis of Islamic banks using simple and advanced methodologies, and testing several interesting hypotheses (see eg. Wanke, Azad, Barros, Kabir Hassan 2016; Wanke, Azad, Barros 2016; Rosman et al. 2014; Said 2013; Onour, Abdallah 2011). Empirical works dealing with productivity are very rare. Literature on existing studies can be classified into two groups. The first group of studies includes performance assessment and determinants of Islamic banks, whereas the second group of studies includes the comparative analysis of performance level between Islamic and conventional banking sectors.

El Moussawi and Obeid (2011) used Data Envelopment Analysis (DEA) model to decompose the productive efficiency into technical efficiency, allocation efficiency, and cost efficiency of Islamic banks. They found an increase of production efficiency of the Islamic banks over the study period. Assaf et al. (2011) analysis technical efficiency of Saudi banks using two-stage DEA approach, following intermediation approach. Saudi banks improved their efficiency since 2004. Following intermediation approach, Bahrini (2015) used the bootstrapped Malmquist index to a sample of Islamic banks operating in 10 MENA countries. He found a decrease in productivity, technical efficiency and technological efficiency. However, scale efficiency found to be a source of productivity amelioration. Johnes et al. (2015) decompose Malmquist index into technical efficiency change and technological change to detect productivity variation source in Islamic banks. Following intermediation approach, they found positive technical efficiency change and negative technology change, which are allowed to differ between groups of banks. Kamarudin et al. (2017) examined the productivity of Islamic banks in Southeast Asian Countries from the period 2006 to 2014. They found that banks have been operating at the wrong scale of operations and world financial crisis have significantly influenced productivity level of Islamic banks.

Bilal et al. (2011) apply intermediation approach to select inputs and outputs and use DEA model to compare efficiency of Islamic banks and conventional banks. He found that scale inefficiency is dominated by the pure technical inefficiency effects in determining Islamic banks' overall or technical inefficiency. Kamarudin et al. (2014) used intermediation approach to assess performance of banks. They found that Islamic banks are more efficient than conventional banks. Mobarek and Kalonov (2014) investigate the performance of Islamic banks versus conventional banks around the recent financial crisis. Their major finding was that overall Islamic banks are less efficient than Conventional banks and this superiority varies depending on bank size and the impact of recent crisis is not visible on both banking sectors.

From a review of studies, it is obvious, that literature suffers from the lack of empirical research focused on productivity analysis and sources of productivity in Islamic banking sector. Moreover, several studies that have been devoted to assess the performance of Islamic banks generally examine the productivity following either the intermediation approach or the production approach. The intermediation approach is the common used approach to assess performance of Islamic banks. In summary, numbers of studies have shown that Islamic banks demonstrate performance and there is still no evidence of the effect of Subprime crisis on Islamic banks productivity. Therewith, there is no evidence of sources of productivity variation in literature.

This paper attempts to fill the gap in the empirical literature in this area by providing an empirical analysis of productivity measurement using the total factor productivity Malmquist index and its decomposition into technological change, scale change and technical efficiency change components. The estimation method is non-parametric relying on DEA. To model an Islamic bank two approaches may be followed: intermediation approach and production approach. The basic difference between these two approaches is that in intermediation approach deposits are treated as input whereas it has output status in production approach. In this paper, we estimate efficiency of Islamic banks using DEA by adopting production approach for a first model and intermediation approach for a second model. We use a non-parametric Kruskal-Wallis test to examine the differences in productivity, efficiency and productivity components derived from the two suggested models. Furthermore, we study the evolution of technical efficiency under variable returns to scale and scale returns to scale. This study has three major contributions to existing literature. Firstly, we show that the approach chosen for the definition of Islamic banking inputs and outputs does not have impact on the level of efficiency and productivity scores. Secondly, while technical efficiency change and technological change present sources of productivity amelioration, the scale efficiency change is a source of productivity deterioration. Finally, we show that Subprime crisis had a slight effect on productivity of Islamic banks following intermediation approach.

The remainder of the paper is organized as follows. Section 2 explains the methodology focusing on the Malmquist productivity index. Data is described in section 3. Results are reported in section 4. Finally, conclusions are formulated in section 5.

2. The Malmquist productivity index

Basing on distance function estimation, non-parametric frontier approaches are used to measure efficiency and productivity of Decision Making Units (DMUs). The total factor productivity Malmquist index has been developed by (Caves et al. 1982) from the notion of "proportional scaling" introduced by (Malmquist 1953). In what follows, we consider the production set S^t which models the transformation of inputs $x^t \in \mathbb{R}_+^N$ into outputs $y^t \in \mathbb{R}_+^M$ at time t :

$$S^t = \left\{ \left(x^t, y^t \right) : x^t \text{ can produce } y^t \right\} \qquad (1)$$

S^t is the set of all feasible output-input vectors in period *t*. It is assumed to be closed, bounded, convex, and to satisfy strong disposability of outputs and inputs.

As provided by Shephard (1970), in an output based approach, the production technology is completely characterized by the output distance function:

$$D_{out}^t \left(x^t, y^t \right) = \min \left\{ \theta : \left(x^t, y^t / \theta \right) \in S^t \right\} \qquad (2)$$

The output distance function is simply the inverse of the Farrell (1957) output-oriented measure of technical efficiency and is less than or equal to one (i.e. $D_{out}^t \left(x^t, y^t \right) \le 1$) if and only if $\left(x^t, y^t \right) \in S^t$. Note that the distance function is equal to the unit (i.e. $D_{out}^t \left(x^t, y^t \right) = 1$) if $\left(x^t, y^t \right)$ belongs to the "frontier" of the production technology set and the DMU is technically efficient.

Computing the Malmquist productivity index between time period's $t_1 < t_2$, requires two additional distance functions to be defined. One measures the maximum proportional change in outputs required to make $\left(x^{t_2}, y^{t_2} \right)$ feasible in relation to the technology at t_1, i.e.:

$$D_{out}^{t_1} \left(x^{t_2}, y^{t_2} \right) = \min \left\{ \theta : \left(x^{t_2}, y^{t_2} / \theta \right) \in S^{t_1} \right\} \qquad (3)$$

The second refers to the maximum proportional change in output required to make $\left(x^{t_1}, y^{t_1}\right)$ feasible in relation to the technology at t_2 :

$$D_{out}^{t_2}\left(x^{t_1}, y^{t_1}\right) = \min\left\{\theta : \left(x^{t_1}, y^{t_1}/\theta\right) \in S^{t_2}\right\} \qquad (4)$$

A Malmquist productivity index between periods t_1 and t_2 where $t_1 < t_2$, can be defined as:

$$M_{out}\left(x^{t_2}, y^{t_2}, x^{t_1}, y^{t_1}\right) = \left[\frac{D_{out}^{t_1}\left(x^{t_2}, y^{t_2}\right)}{D_{out}^{t_1}\left(x^{t_1}, y^{t_1}\right)} \frac{D_{out}^{t_2}\left(x^{t_2}, y^{t_2}\right)}{D_{out}^{t_2}\left(x^{t_1}, y^{t_1}\right)}\right]^{1/2} \qquad (5)$$

It presents the geometric mean of the output-based Malmquist productivity indices for t_1 and t_2 defined by Caves et al. (1982). Several decompositions are developed in the literature, but the most widely used in empirical studies is the decomposition of Ray and Desli (1997) that we use in this paper. It's defined as follows:

$$\begin{aligned}
M_{out}^{t_1/t_2}\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) &= \underbrace{\left[\frac{D_{out}^{t_2}\left(x^{t_2}, y^{t_2} \middle| VRS\right)}{D_{out}^{t_1}\left(x^{t_1}, y^{t_1} \middle| VRS\right)}\right]}_{technical\ \ efficiency\ change(\ TE\Delta)} \\
&\times \underbrace{\left[\frac{D_{out}^{t_1}\left(x^{t_2}, y^{t_2} \middle| VRS\right)}{D_{out}^{t_2}\left(x^{t_2}, y^{t_2} \middle| VRS\right)} \times \frac{D_{out}^{t_1}\left(x^{t_1}, y^{t_1} \middle| VRS\right)}{D_{out}^{t_2}\left(x^{t_1}, y^{t_1} \middle| VRS\right)}\right]^{\frac{1}{2}}}_{technological\ change\ (T\Delta)} \\
&\times \underbrace{\left\{\left[\frac{D_{out}^{t_1}\left(x^{t_2}, y^{t_2} \middle| CRS\right) / D_{out}^{t_1}\left(x^{t_2}, y^{t_2} \middle| VRS\right)}{D_{out}^{t_1}\left(x^{t_1}, y^{t_1} \middle| CRS\right) / D_{out}^{t_1}\left(x^{t_1}, y^{t_1} \middle| VRS\right)}\right] \times \left[\frac{D_{out}^{t_2}\left(x^{t_2}, y^{t_2} \middle| CRS\right) / D_{out}^{t_2}\left(x^{t_2}, y^{t_2} \middle| VRS\right)}{D_{out}^{t_2}\left(x^{t_1}, y^{t_1} \middle| CRS\right) / D_{out}^{t_2}\left(x^{t_1}, y^{t_1} \middle| VRS\right)}\right]\right\}^{\frac{1}{2}}}_{scale\ efficiency\ change\ (SE\Delta)} \\
&= TE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) \times T\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) \times SE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right)
\end{aligned} \qquad (6)$$

Where VRS and CRS in the definitions of the distance functions in equation 6 refer to the type of returns to scale exhibited by the technology, variable return to scale for VRS and constant returns to scale for CRS.

In this decomposition technical efficiency change $TE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right)$ is measured relative to the best practice technologies. The technical change $T\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right)$ is defined on the best practice technologies. The scale change factor $SE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right)$ is the geometric mean of a pair of scale efficiency ratios, one measured on period t_1 technology and the other measured on period t_2 technology.

This decomposition had the intuitive appeal of identifying of sources of productivity growth in terms of the technical efficiency change $TE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) \overset{<}{\underset{>}{=}} 1$ according as total factor productivity change is enhanced, unaffected or retarded. The technical change $T\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) \overset{<}{\underset{>}{=}} 1$ according as total factor productivity change is enhanced, unaffected or retarded and the technical change $SE\Delta\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right) \overset{<}{\underset{>}{=}} 1$ according as total factor productivity change is enhanced, unaffected or retarded.

Now to compute the Malmquist productivity index, we consider a set of L DMUs observed at two different periods t_1 and t_2, $Z = \left\{\left(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}\right);\ t_1 = 1,\ldots,T_1;\ t_2 = 1,\ldots,T_2;\ i = 1,\ldots,L\right\}$.

We use DEA approach to estimate the components of the Malmquist productivity index. These components can be estimated via linear programming techniques. For this, we should consider the following linear programs for each DMU i, $i = 1,\ldots,L$:

The first program, for an arbitrary DMU0 is as follows:

$$
\begin{aligned}
&\left[\hat{D}_{out}^{t_1}\left(x_0^{t_1}, y_0^{t_1} \middle| CRS\right)\right]^{-1} = \max\theta \\
&s.t. \\
&\quad \theta y_{0m}^{t_1} \le \sum_{i=1}^{L} \lambda_i^{t_1} y_{im}^{t_1},\ m = 1,\ldots,M \\
&\quad \sum_{i=1}^{L} \lambda_i^{t_1} x_{in}^{t_1} \le x_{0n}^{t_1},\quad n = 1,\ldots,N \\
&\quad \lambda_i^{t_1} \ge 0,\quad i = 1,\ldots,L
\end{aligned}
\tag{7}
$$

The linear program (7) calculates the distance function $\hat{D}_{out}^{t_1}\left(x_0^{t_1}, y_0^{t_1} \middle| CRS\right)$ under the assumption of CRS, to obtain the distance function $\hat{D}_{out}^{t_1}\left(x_0^{t_1}, y_0^{t_1} \middle| VRS\right)$ under the assumption of VRS, it is sufficient to add the constraint $\sum_i \lambda_i^{t_1} = 1$ in the program (7). Computing the distance function $\hat{D}_{out}^{t_2}\left(x_0^{t_2}, y_0^{t_2}\right)$ is exactly like (7), where t_2 is substituted for t_1.

The second program, for an arbitrary DMU0 is presented as follows:

$$\left[\hat{D}_{out}^{t_1}\left(x_0^{t_2}, y_0^{t_2} \middle| CRS\right)\right]^{-1} = \max\theta$$

$$s.t.$$

$$\theta y_{0m}^{t_2} \le \sum_{i=1}^{L} \lambda_i^{t_1} y_{im}^{t_1},\ m = 1,...,M$$

$$\sum_{i=1}^{L} \lambda_i^{t_1} x_{in}^{t_1} \le x_{0n}^{t_2},\ n = 1,...,N$$

$$\lambda_i^{t_1} \ge 0, i = 1,...,L \qquad (8)$$

The linear program (8) computes the distance function $\hat{D}_{out}^{t_1}\left(x_0^{t_1}, y_0^{t_1} \middle| CRS\right)$ under the assumption of CRS, the distance function $\hat{D}_{out}^{t_1}\left(x_0^{t_1}, y_0^{t_1} \middle| VRS\right)$ under the assumption of VRS is obtained by adding the constraint $\sum_i \lambda_i^{t_1} = 1$ in the program (8). Computing the distance function $\hat{D}_i^{t_2}\left(x_i^{t_1}, \mathrm{y}_i^{t_1}\right)$ is exactly like (8), where t_2 is substituted for t_1 and conversely.

Finally for the sake of simplicity, the distances involved in these linear programs will be noted $\hat{D}_{out}^{t_1/t_1}$, $\hat{D}_{out}^{t_2/t_2}$, $\hat{D}_{out}^{t_2/t_1}$ and $\hat{D}_{out}^{t_1/t_2}$ respectively.

3. Data and input/output specification

We use DEA to estimate the production function of Islamic banks and to assess their efficiency. Despite the increasing interest in studying the banking industry, there is still no coherent definition of inputs and outputs. It is commonly acknowledged that the choice of variables in efficiency studies significantly affects results. Two approaches dominate the banking theory literature: the production and intermediation approaches. According to production approach, banks provide services to customers by administering customers' financial transactions, keeping customer deposits, issuing loans, cashing cheques and managing other financial assets (Berg et al. 1993). Productivity and efficiency can be analyzed by comparing the quantity of services given with the quantity of resources used. Five activities are performed by a bank: supplying demand, facilitating deposit services, short and long-term loan services, brokerage and other services, property management and the provision of safe deposit boxes. They pointed out that a bank incurs positive operating costs in terms of labor, machines, materials, and buildings. However, according to intermediation approach, bank accepts deposits from customers and transforms them into loans to clients. Thus, inputs are labor, materials and deposits, and outputs are loans and other income generating activities such as banking services (Mester 1997). In the intermediation approach, banks performing two major roles of mobilizing and distributing resources efficiently in order to smoothen investment activities in the economy. Following El Moussawi and Obeid (2011), none of the two approaches dominates the others. Therefore, in modeling Islamic bank behavior ensuring the robustness of results, this paper follows two different approaches to measure the efficiency. We present a detailed literature review in Table 1.

Table 1. A survey of DEA research in banks

Paper	Inputs	Outputs	Approach
(Assaf et al. 2011)	Total employees Fixed assets Total deposits	Total customer loans securities Interbank loans	Intermediation approach
(Shahid et al. 2010)	Total deposits Capital Price of capital Price of deposits	Investments Loans & advances	Intermediation approach
(Bilal et al. 2011)	Total assets Total deposits Labor	Total loans Total income	Intermediation approach

Table 1. Continuation

Paper	Inputs	Outputs	Approach
(Johnes et al. 2009)	Deposit and short-term funding Fixed assets General and administrative expenses Equity (used as a proxy for risk)	Total loans Other earning assets	Intermediation approach
(Yaumidin 2007)	Overheads costs Fixed assets Total deposits	Total loans Other income Total earning Assets	Intermediation approach
(Mostafa 2009)	Total assets Equity	Net profit ROA ROE	Intermediation approach
(Kazemi Matin, Azizi 2011)	Total assets Total deposits Equity	Loans ROE	Intermediation approach
(Amirteimoori & Emrouznejad 2011)	IT Budget Fixed assets Number of employees	Deposits Profit earned	Production approach
(Bagherzadeh Valami 2009)	Payable interest Staff Non- performing loans	The total sum of the four main of deposits Other deposits Loans granted Received interest Fee	Production approach
(Chiou 2009)	Staff Fix asset Total deposits Salary expenses	Provision of loans Investment Interest revenue Non-interest revenue	Intermediation approach
(Sufian 2009)	Capital Total of deposits Labor Labor Capital Interest expenses Interest expenses Labor Other operating expenses(-operating expenses)	Loans Investment Deposits Loans investments Interest income Non-interest income	Intermediation approach Value added approach Operating approach
(Isik, Kabir Hassan 2003)	Labor=number of full- time employee Capital Loanable funds	Short-term loans Long-term loans Risk-adjusted off-balance sheet items Other earning assets	Intermediation approach

Table 1. Continuation

Paper	Inputs	Outputs	Approach
(Isik, Kabir Hassan 2002)	Labor Capital Funds	Short-term loans Long-term loans Risk-adjusted off-balance sheet items Other earning assets	Intermediation approach
(Das, Ghosh 2006)	Deposits Labor :number of employees Capital=fixed assets Equity	Loans and advances Investments Other income	Intermediation approach
(Staub et al. 2010)	Operational expenses net of personnel expenses Personnel expenses Interest rates expenses	Total loans net of provision loans Investments Deposits	Production approach
(Kohers et al. 2000)	Labor Physical Capital Time and saving deposits Purchased funds	Demand deposits Time and saving deposits Real estate loans Other loans Net non-interesting income	Intermediation approach
(Havrylchyk 2006)	Deposits Fixed assets Labor	Loans Treasury bonds Off-balance items	Intermediation approach
(Luo 2003)	Profitability efficiency: Employee Total assets Equity Marketability efficiency: Revenue Profit	Profitability efficiency: Revenue Profit Marketability efficiency: Market value Stock price EPS	Production approach
(Assaf et al. 2011)	Deposits Number of FTE Total assets	Loan Securities	Intermediation approach
(Wanke, Azad, Barros 2016)	Personnel expenses Total operating expenses	Total earning assets Total deposits Net interest income	TOPSIS criteria
(Wanke, Azad, Barros, Kabir Hassan 2016)	Equity Provisions Personal expenses Number of employees	Assets Deposits Operational results Banking products	Positive negative criteria
(Said 2013)	Labor cost Fixed assets Total deposits	Total loans Liquid assets Other income	Intermediation approach

Table 1. Continuation

Paper	Inputs	Outputs	Approach
(Onour, Abdallah 2011)	Salaries and wages expenses Total deposits	Total loans Net income	Intermediation approach
(Rosman et al. 2014)	Deposits Short-term funding Fixed assets and Personal expenses	Loans Other earning assets	Intermediation approach
(Johnes et al. 2015)	Deposits and short-term funding Fixed assets General and administrative expenses Equity	Total loans Other earning assets	Intermediation approach
(Kamarudin et al. 2014)	Deposit Labor	Loan Income	Intermediation approach
(Mobarek, Kalonov 2014)	Deposits Equities Personnel expenses Fixed assets	Total loans Other earning assets	Intermediation approach
(Johnes et al. 2014)	Total loans Other earning assets	Short term funding Fixed assets General and administration expenses	Intermediation approach
(Sufian 2009)	Deposits Labor Physical capital.	Loans Investment	Intermediation approach
(Yudistira 2004)	Staff costs Fixed assets Total deposits	Total loans Other income Liquid assets	Intermediation approach

Source: Authors' own elaboration.

In this paper, we use two models, the first one following the production approach, the second the intermediation approach. Data includes input and output variables for 31 Islamic banks operating in 13 countries all over the world for the year 2005 to 2014. The period chosen for the study was to catch the effect of Subprime crisis on efficiency and productivity in Islamic banks. Data is extracted from statements and balance sheets which are made available by the Islamic Banks and Financial Institutions Information (IBIS). Then, basing on the above literature review presented by Table 1, we select the following variables (see Table 2). Indeed, following intermediation approach, labor and capital are used to intermediate deposits into loans and other earning assets (Yudistira 2004). Whereas, following production approach, deposits are considered as outputs since it is assumed that they are proportionate to the output of depositors services provided, following (Staub et al. 2010). Furthermore, loans and other earning assets are important outputs to be considered in the Islamic banking case.

Table 2. Inputs/outputs matrix

	Inputs	**Outputs**
Model 1: Production approach	Employee expenses Fixed assets Equity	Total deposits Total loans
Model 2: Intermediation approach	General and administrative expenses Fixed assets Total deposits	Total loans Other earning assets

Source: Authors' own elaboration.

All input and output variables are converted into US dollars using end of year market value, and deflated by the Consumer Price Index of each country, in order to take account of macroeconomic differences across countries during the study time period.

4. Empirical results

Following Ray and Desli (1997) paper, we decompose Malmquist index (MI) productivity changes to include scale efficiency (SE), technical efficiency change (EC) and technological change (TC) as described above using two approaches. Note that the feature of Malmquist index is the infeasibility of several DMUs programs (Essid et al. 2014). Thus, all results and percentage presented in this section are calculated for feasible DMUs only.

4.1 Production approach results

From Table 3, the last row show that the productivity of Islamic banking sector has increased by an average of 6.73% during the period 2005-2014. It is clear that

Islamic banks show considerable productivity amelioration across sample period. We can identify the source of this productivity gain in the components of the Malmquist index. We observe that efficiency gains and technological gains have been of the order of 2.48% and 10.84% respectively. However, results show a stagnation of scale efficiency during the whole period of study. These results suggest that despite the existence of necessary investments and the improvement of transformation the new resources in outputs, Islamic banks must increase the size of activities by encouraging mergers. It is important to note that average productivity, technical efficiency, technological efficiency and scale efficiency differ substantially across Islamic banks.

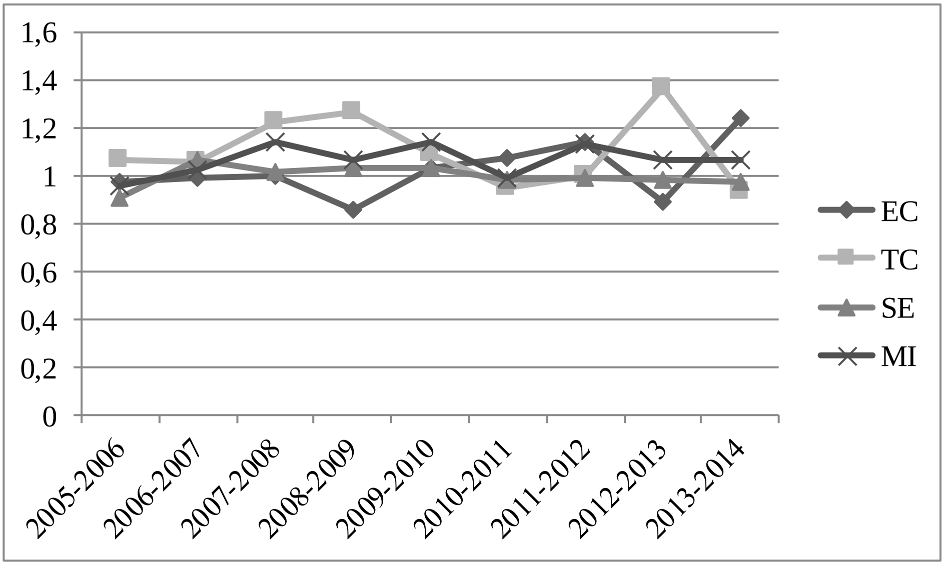
Table 3. Average annual productivity measures and index components of 31 banks (production approach)

Period	Years	EC	TC	SE	MI
1	2005-2006	0.9777	1.0693	0.9095	0.9568
2	2006-2007	0.9948	1.0613	1.0674	1.0274
3	2007-2008	0.9985	1.2287	1.0209	1.1467
4	2008-2009	0.8552	1.2716	1.0318	1.0704
5	2009-2010	1.0375	1.0885	1.0337	1.1464
6	2010-2011	1.0762	0.9490	0.9831	0.9909
7	2011-2012	1.1467	1.0012	0.9941	1.1305
8	2012-2013	0.8959	1.3701	0.9850	1.0682
9	2013-2014	1.2404	0.9363	0.9784	1.0688
	Mean	1.0248	1.1084	1.0004	1.0673

Source: Authors' own elaboration.

Figure 1 shows that Islamic banks have shown productivity gains during the periods 2006-2010 and 2011-2014. However, the period 2005-2006 and 2010-2011 are marked by productivity deterioration. The greatest gain in productivity (15%) is marked during the period 2007-2008. This period is marked by the financial Subprime crisis, then we can link Islamic banks productivity gain by the Subprime crisis consequence. This improvement can be mostly attributed to technical technological improvement ranging around 23%. In fact, this result can be explained by the improvement of Islamic banks know-how to produce services in a critical environment of conventional banks during this crisis period.

Figure 1. Evolution of Malmquist index and its components over the period 2005-2014 (production approach)



Source: Authors' own elaboration.

We perform the Kruskal-Wallis test to assess the difference between Malmquist index and productivity. Based on the P-values presented in Table 4, there is no significant difference between Malmquist index and its components.

Table 4. Kruskal-Wallis test results (productivity vs. index components)

		Efficiency Change	Technological Change	Scale Efficiency
Malmquist Index	Chi-2	8	8	6.313
	P-value	0.4335	0.4335	0.2769

Source: Authors' own elaboration.

Table 5. 2007-2008 banks results following production approach

ID	Bank	Country	EC	TC	SE	MI
BK1	Al Baraka Bank (Pakistan) Limited	Pakistan	0.7176	1.3945	0.9586	0.9592
BK2	Al Baraka Bank (Sudan) Limited	Sudan	0.8701	1.1831	1.0329	1.0633
BK3	Al Baraka Bank Egypt	Egypt	1.1987	1.0324	1.0119	1.2523
BK4	Al Rajhi Bank	Saudi Arabia	1.0000	1.1512	0.9469	1.0901
BK5	Al Shamal Islamic Bank	Sudan	0.8644	1.0925	1.0645	1.0053
BK6	Arab Islamic Bank	Palestine	0.8363	1.2768	0.9543	1.0189
BK7	Bahrain Islamic Bank B.S.C.	Bahrain	0.6590	1.3078	0.6527	0.5625
BK8	Bank Aljazira	Saudi Arabia	1.0691	1.0963	1.2386	1.4517
BK9	Bank Alkhair	Bahrain	1.5325	1.0940	0.5571	0.9339
BK10	Bank Islam Malaysia Berhad	Malaysia	1.0000	0.9933	0.9174	0.9112
BK11	Bank Islami Pakistan Limited	Pakistan	0.6018	1.4808	0.8017	0.7144
BK12	Bank Sepah	Islamic Republic of Iran	1.3326	0.9015	1.0132	1.2172
BK13	Blue Nile Mashreq Bank	Sudan	0.9005	1.0338	0.9852	0.9171
BK14	Boubyan Bank	Kuwait	0.8750	1.4330	1.0444	1.3097
BK15	CIMB Islamic Bank Berhad	Malaysia	1.0000	1.7309	0.9999	1.7307
BK16	Dubai Islamic Bank	United Arab Emirates	1.0000	1.0172	1.0185	1.0361
BK17	Emirates Islamic Bank	United Arab Emirates	1.0370	1.6811	1.0697	1.8648
BK18	Faisal Islamic Bank of Egypt	Egypt	1.0000	0.6446	1.0300	0.6640
BK19	Faysal Bank (Pakistan)	Pakistan	0.9662	1.1565	1.0844	1.2118

Table 5. Continuation

ID	Bank	Country	EC	TC	SE	MI
BK20	Gulf Finance House	Bahrain	2.4997	1.0982	0.7032	1.9303
BK21	International Investment Bank	Bahrain	0.3767	2.6019	0.8590	0.8419
BK22	Investors Bank B.S.C.	Bahrain	0.4664	1.5238	3.1039	2.2057
BK23	Islami Bank Bangladesh Limited	Bangladesh	0.9381	1.0358	0.8650	0.8406
BK24	Jordan Islamic Bank	Jordan	0.8020	1.2735	0.9676	0.9883
BK25	Karafarin Bank	Islamic Republic of Iran	Infeasible	Infeasible	Infeasible	Infeasible
BK26	Kuwait Finance House	Kuwait	1.0000	0.9854	0.9337	0.9201
BK27	Kuwait Finance House Bahrain	Kuwait	1.3508	1.1867	0.9088	1.4567
BK28	Meezan Bank	Pakistan	1.0928	1.0248	0.9935	1.1126
BK29	Qatar Islamic Bank	Qatar	1.0000	1.0987	0.8870	0.9746
BK30	Saman Bank	Islamic Republic of Iran	Infeasible	Infeasible	Infeasible	Infeasible
BK31	Sharjah Islamic Bank	United Arab Emirates	0.9689	1.1023	1.0021	1.0702
MEAN			0.9985	1.2287	1.0209	1.1467
MIN			0.3767	0.6446	0.5571	0.5625
MAX			2.4997	2.6019	3.1039	2.2057
S.D			0.3771	0.3513	0.4232	0.3844

Source: Authors' own elaboration.

In Table 5, we present results[1] of 31 banks during the period 2007-2008. From this table we note that 29 programs have feasible solutions and two programs have unfeasible solutions. 19 banks have shown a productivity improvement and 10 banks have exhibit productivity deterioration. Investors Bank B.S.C. in Bahrain has marked the highest productivity improvement (120.06%). This rise is principally due

[1] Other period's results are available upon request from corresponding author.

to the improvement of scale change of the order of (210.4%). However, Bahrain Islamic Bank B.S.C. in Bahrain has shown the highest productivity recession (43.7%) that is attributed to technical efficiency decrease (34.1%) and scale efficiency decrease (34.7%). Decomposition of Malmquist index values results and its dispersions around the mean show obviously that is difficult to identify a typical behavior shared by all Islamic banks.

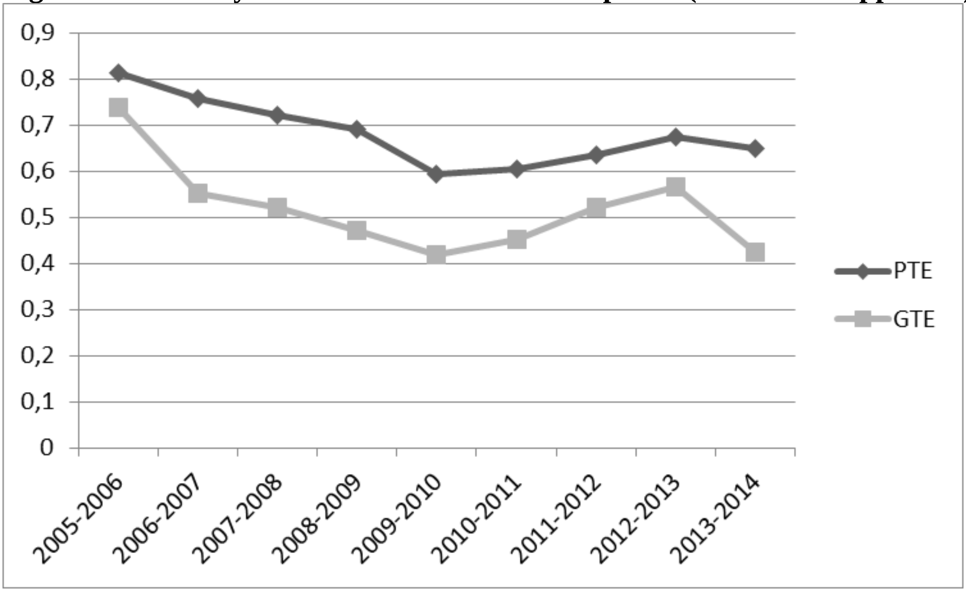
In Table 6, we present measures of technical efficiency calculated under the assumption of constant returns to scale (CRS), called global technical efficiency (GTE), and the assumption of variable returns to scale (VRS), called pure technical efficiency (PTE). A positive difference between GTE and PTE measurements shows that economies of scale do exist in the sector of Islamic banking.

Table 6. Average annual technical efficiency for the period 2005-2014 (Production approach)

		PTE		GTE	
Period	Years	Mean	S.D	Mean	S.D
1	2005-2006	0.8121	0.2406	0.7377	0.2763
2	2006-2007	0.7585	0.2779	0.5529	0.2902
3	2007-2008	0.7224	0.3039	0.5214	0.3167
4	2008-2009	0.6910	0.3127	0.4708	0.2965
5	2009-2010	0.5927	0.3034	0.4184	0.2365
6	2010-2011	0.6060	0.3108	0.4508	0.2596
7	2011-2012	0.6361	0.3053	0.5220	0.2799
8	2012-2013	0.6748	0.2969	0.5663	0.2610
9	2013-2014	0.6495	0.3278	0.4240	0.2505
	Mean	0.6826	0.2977	0.5182	0.2741

Source: Authors' own elaboration.

Figure 2. Efficiency under CRS and VRS assumptions (Production approach)



Source: Authors' own elaboration.

Assuming VRS (CRS), the average technical efficiency has shown the highest level in the period 2005-2006, it was of the order of 81% (74%). then, we can note that Islamic banks in this period have, on average, to increase their production by 19% (26%) to become efficient. However, the period 2009-2010 was marked by the lowest level of technical efficiency. It was of the order of 59% (42%) under VRS (CRS) assumptions. Therefore, Islamic banks have, on average, to increase their production by 41% (58%) to become efficient. Besides, we find that technical efficiency dispersion is relatively stagnant, which means that Islamic banks have used the same technology during the ten years of study period. These results are shown by Figure 2.

Following production approach, Islamic banks were productive during the period 2005-2014. Furthermore, Subprime crisis had a positive effect on productivity of Islamic banking sector. This result contradicts Mobarek and Kalonov (2014) and Kamarudin et al. (2017) findings. Moreover, we find that technical change is the main source of productivity gains, which confirms (Johnes et al. 2015) findings.

4.2 Intermediation approach results

Assuming intermediation approach, we find that the total factor productivity has improved by 54.36% during the period 2005-2014. This productivity increase is due to technological gains of the order of 11.86% and to technical efficiency gains of the order of 36.33%. However, Islamic banks have shown scale efficiency losses of the order of 0.526%. This finding indicates that there are diseconomies of scale for Islamic banks which suggest that mergers should be encouraged to improve size of activities.

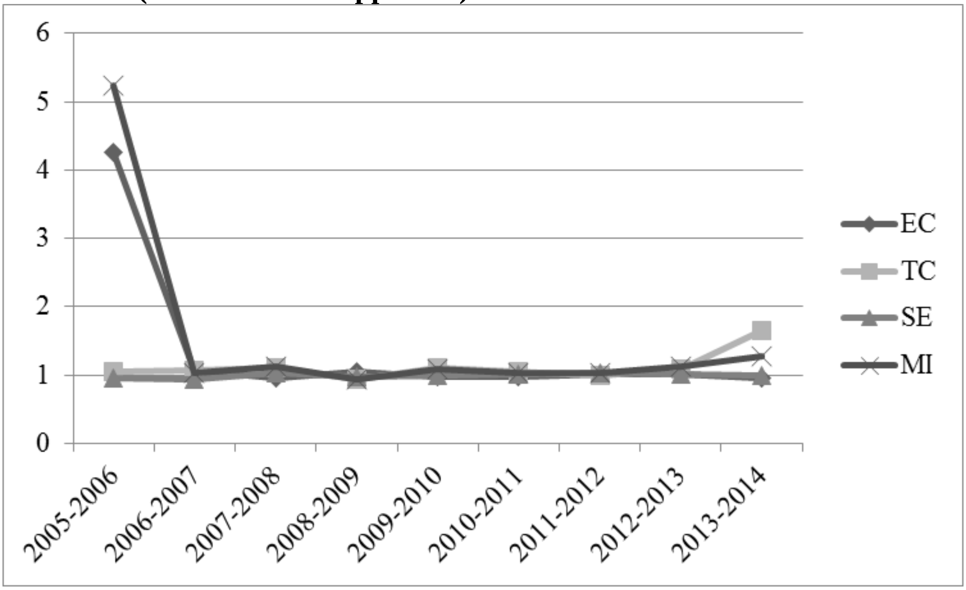
Table7. Average annual productivity measures and index components of 31 banks (intermediation approach)

Period	Years	EC	TC	SE	MI
1	2005-2006	4.2656	1.0529	0.9619	5.2396
2	2006-2007	1.0631	1.0638	0.9343	1.0301
3	2007-2008	0.9633	1.1126	1.0263	1.1293
4	2008-2009	1.0431	0.9439	0.9675	0.9462
5	2009-2010	0.9836	1.1106	0.9925	1.0921
6	2010-2011	0.9726	1.0470	1.0197	1.0292
7	2011-2012	1.0064	0.9976	1.0303	1.0294
8	2012-2013	1.0128	1.0894	1.0205	1.1293
9	2013-2014	0.9589	1.6499	0.9993	1.2669
	Mean	1.3633	1.1186	0.9947	1.5436

Source: Authors' own elaboration.

Moreover, Table 7 shows that Islamic banks are productive during the whole study period except (2008-2009), which is the period post Subprime crisis. In fact, the Malmquist index has taken the worst value (0.9462) during the period (2008-2009). Thus, we can note that Islamic banks were slightly sensitive to crisis just during these two years of crisis (Figure 3). Despite the fact that Islamic banks are productive during the study period, there is a deep fall in productivity since the second period. Thus, Subprime crisis may have noxious consequence on productivity of Islamic banking industry following intermediation approach. However, productivity has shown a rise after 2013. This rise is due to the improvement of technological change of the order of 65%.

Figure 3. Evolution of Malmquist index and its components over the period 2005-2014 (intermediation approach)



Source: Authors' own elaboration.

Using Kruskal-Wallis test, table 8 shows that there is no significant difference between Malmquist index and its components following intermediation approach.

Table 8: Kruskal-Wallis test results (productivity vs. index components)

		Efficiency Change	Technological change	Scale Efficiency
Malmquist Index	Chi-2	8	8	8
	P-value	0.4335	0.4335	0.4335

Source: Authors' own elaboration.

Table 9 presents banks productivity and components results[2] during 2008-2009, post Subprime crisis period. Two programs from 31 have infeasible solutions. 17 banks from 29 have shown productivity gains and 12 have shown productivity losses. A typical behavior about productivity, shared by Islamic banks could not be identified, following intermediation approach.

[2] Other period's results are available upon request from corresponding author

Table 9. 2008-2009 banks results following intermediation approach

ID	Bank	Country	EC	TC	SE	MI
BK1	Al Baraka Bank (Pakistan) Limited	Pakistan	0.7176	1.3945	0.9586	0.9592
BK2	Al Baraka Bank (Sudan) Limited	Sudan	0.8701	1.1831	1.0329	1.0633
BK3	Al Baraka Bank Egypt	Egypt	1.1987	1.0324	1.0119	1.2523
BK4	Al Rajhi Bank	Saudi Arabia	1.0000	1.1512	0.9469	1.0901
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BK26	Kuwait Finance House	Kuwait	1.0000	0.9854	0.9337	0.9201
BK27	Kuwait Finance House Bahrain	Kuwait	1.3508	1.1867	0.9088	1.4567
BK28	Meezan Bank	Pakistan	1.0928	1.0248	0.9935	1.1126
BK29	Qatar Islamic Bank	Qatar	1.0000	1.0987	0.8870	0.9746
BK30	Saman Bank	Islamic Republic of Iran	Infeasible	Infeasible	Infeasible	Infeasible
BK31	Sharjah Islamic Bank	United Arab Emirates	0.9689	1.1023	1.0021	1.0702
MEAN			0.9985	1.2287	1.0209	1.1467
MIN			0.3767	0.6446	0.5571	0.5625
MAX			2.4997	2.6019	3.1039	2.2057
S.D			0.3771	0.3513	0.4232	0.3844

Source: Authors' own elaboration.

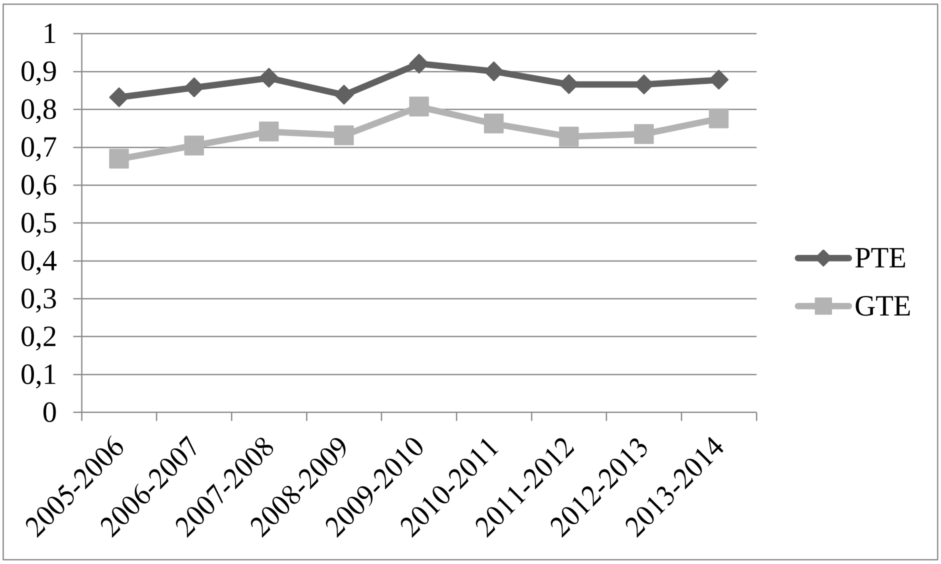
We present technical efficiency levels in Table 10. Assuming VRS (CRS) assumption, the average technical efficiency has shown the highest gains level 92.08% (80.70%) in period 2009-2010. Thus, Islamic banks become more efficient during the period post crisis. This increase may be due to the failure of conventional banking sector. In total, Islamic banks have to increase on average their efficiency by 12.86% (26.05%) to become efficient.

Table 10. Average annual technical efficiency for the period 2005-2014 (intermediation approach)

	PTE		GTE	
	Mean	S.D	Mean	S.D
2005-2006	0.8319	0.2615	0.6696	0.2709
2006-2007	0.8578	0.2052	0.7046	0.2402
2007-2008	0.8833	0.1832	0.7413	0.2572
2008-2009	0.8383	0.1837	0.7315	0.2189
2009-2010	0.9208	0.3448	0.8070	0.3095
2010-2011	0.9003	0.3612	0.7622	0.2769
2011-2012	0.8660	0.3131	0.7280	0.2641
2012-2013	0.8658	0.3040	0.7348	0.2723
2013-2014	0.8781	0.3376	0.7760	0.3101
Mean	0.8714		0.7395	

Source: Authors' own elaboration.

Figure 4. Efficiency under CRS and VRS assumptions (Intermediation approach)



Source: Authors' own elaboration.

The efficiency dispersion is not stagnant, which means that Islamic banks have used different technologies during the 10 years. Average technical efficiencies under CRS and VRS assumptions are presented in Figure 4.

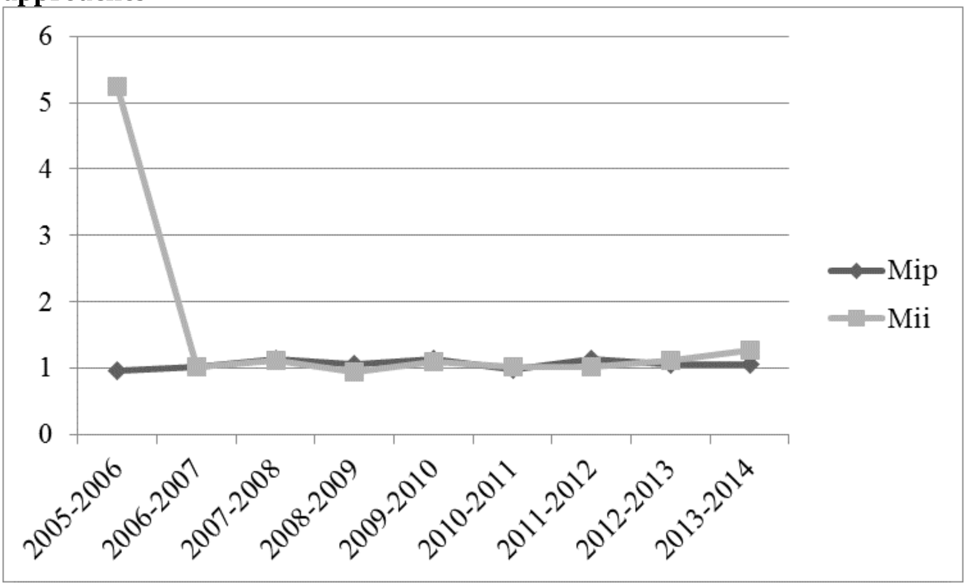
Following intermediation approach, Islamic banks have seen productivity rise during the study period. However, the period post subprime crisis was marked by a decrease in productivity. In addition, we find that Islamic banks were operating at the wrong scale of operations. These results are in line with Kamarudin et al. (2017) findings.

4.3 The Malmquist index decomposition: intermediation vs. Production approaches

Since the definition of outputs and inputs in Islamic banking studies is controversial, this paper uses two different approaches. In this section, we try to identify if the banking profession could have an effect on the measure of its performance. Let ECp, TCp, Sep, MIp and PTEp be the measurements of technical efficiency change, technological change, scale efficiency change, Malmquist index and pure technical efficiency respectively obtained using the production approach.

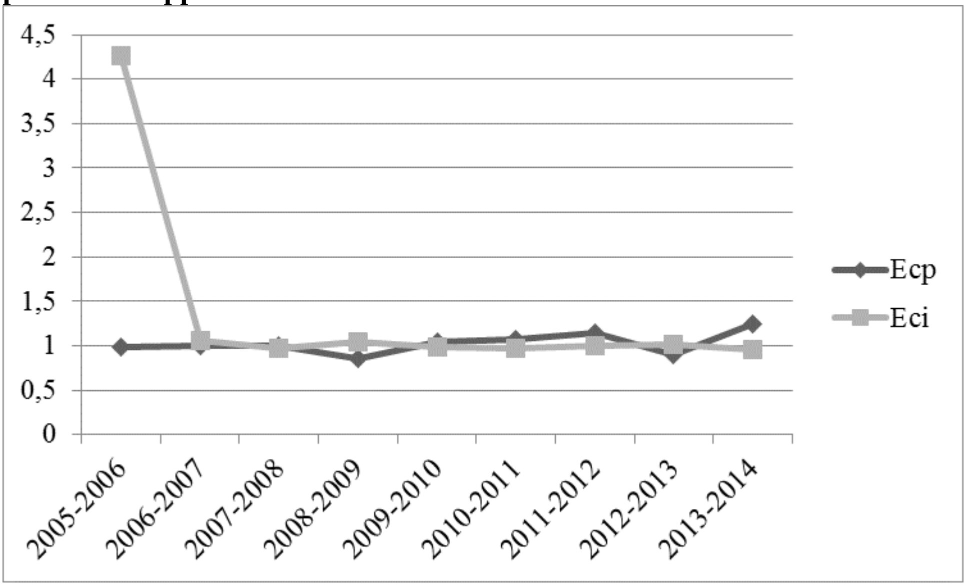
Similarly, ECi, TCi, SEi, MIi and PTEi are measures of technical efficiency change, technological change, scale efficiency change, Malmquist index and technical efficiency respectively obtained using the intermediation approach. Whatever the choice of inputs and outputs, we find that Islamic banks are productive and efficient for most of the study period. More specifically, using intermediation approach, the productivity drops during the period 2008-2009 while it keeps a stable pace assuming the production approach (Figure 5). Similarly, using production approach, evolution of efficiency change does not much change compared to the case when we assume intermediation approach during the period 2007-2014 (Figure 6). In the other hand, the two models give different results about technological change and scale efficiency change (Figure 7 and Figure 8). Figure 9 shows that Islamic banks were more efficient following intermediation approach, (PTEi average scores are greater than 80%), than following production approach (PTEi average scores are less than 80%).

Figure 5. Evolution of the Malmquist index: intermediation vs. production approaches



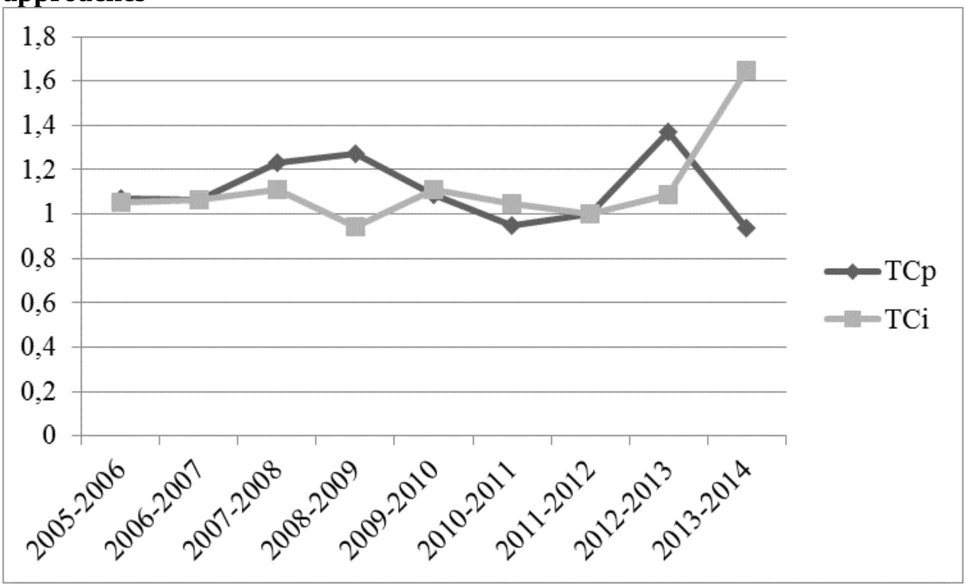
Source: Authors' own elaboration.

Figure 6. Evolution of the technical efficiency change: intermediation vs. production approaches



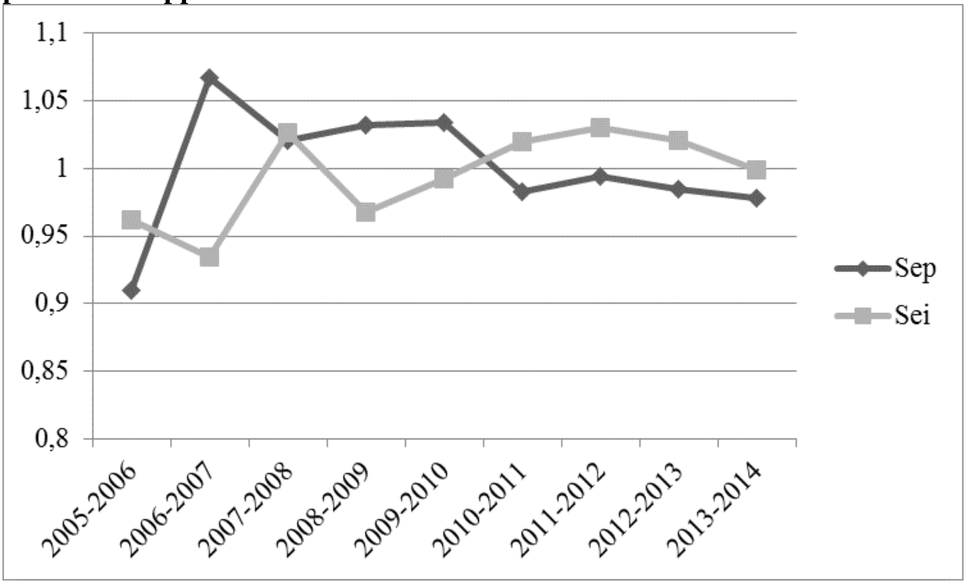
Source: Authors' own elaboration.

Figure 7. Evolution of the technological change: intermediation vs. production approaches



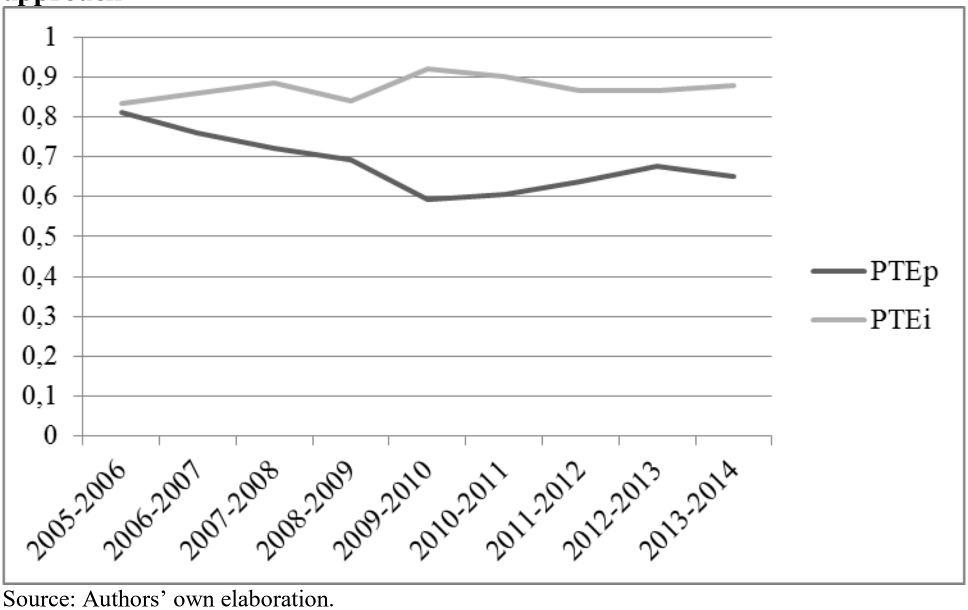
Source: Authors' own elaboration.

Figure 8. Evolution of the scale efficiency change: intermediation vs. production approaches



Source: Authors' own elaboration.

Figure 9. Evolution of pure technical efficiency: Intermediation vs. production approach



Source: Authors' own elaboration.

Table 11. Kruskal-Wallis test P-values

	P-values									
	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	Mean
MI	0.414	0.4159	0.4896	0.4395	0.4268	0.4069	0.3797	0.4208	0.4113	0.4335
TC	0.3918	0.3852	0.5776	0.4615	0.4793	0.5052	0.4896	0.4822	0.5879	0.4335
EC	0.5889	0.3138	0.3885	0.3288	0.2283	0.4553	0.2635	0.282	0.4672	0.4335
SE	0.5658	0.4484	0.4258	0.4692	0.4177	0.4069	0.3656	0.4312	0.4974	0.4335
PTE	0.2045	0.3432	0.7442	0.6356	0.6318	0.8083	0.8078	0.8821	0.7599	0.4373

Source: Authors' own elaboration.

To ensure that the choice of banks profession does not matter for performance measurement, we use the Kruskal-Wallis test. We try to assess the difference between results given by different approaches (intermediation and production approaches). The null hypothesis test is Performance scores (MI, EC, TC, SE and PTE) found following both approaches are identical populations. It states that the population medians are all equal. To determine whether any of the differences between the medians are statistically significant, we compare the P-value to significance level (1%, 5% and 10%) to assess the null hypothesis. Table 11 does not confirm the statistical significance of difference of the attained results. Indeed, basing on the P-values, we don't reject the null hypothesis implying that performance scores given from both approach are identical populations. Thus, production approach and intermediation approach give similar results and Islamic bank profession does not significantly matter in its performance measurement.

5. Conclusion

In this paper, we decompose Malmquist productivity index into three components, namely technical efficiency change, technological change and scale efficiency change; which may determine the sources of improvement or deterioration of Islamic banks productivity. We analyzed productivity of Islamic banks using two approaches: intermediation and production approaches. Findings of two models are very close in terms of productivity and efficiency. However, there are different results concerning sources of productivity change. In fact, Islamic banks have shown gains of productivity during the whole period of study except 2008-2009 using intermediation approach, this can be explained by the sensitivity of Islamic banks to subprime crisis. In addition, technical efficiency improvement and technological change are the principal sources of productivity improvement under both approaches. Besides, we find that Islamic banks industry suffer from insufficient size of activities. These results can then be used to improve size of banks activities by encouraging mergers. In fact, scale efficiency presents a source of productivity losses assuming the both approaches. Moreover, we do not find a significant difference between evolutions of Malmquist index components under intermediation and production approaches. However, technological change and scale efficiency analysis may be sensible to the function of Islamic bank. Our results collaborate with the findings by, among others, Kamarudin et al. (2017). Finally, it would be a great interest to use a bootstrapped Malmquist index to know whether the indicated changes in productivity, technical efficiency; technological change and scale efficiency are significant in a statistical sense.

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Źródła zmiany produktywności i wydajności w islamskiej bankowości: zastosowanie indeksu produktywności Malmquista

Streszczenie

Cel: Niniejszy artykuł ma na celu zbadanie kondycji islamskich banków w 13 krajach w okresie 2005-2014 oraz określenie źródeł zmian produktywności w czasie.

Metodyka badań: Dla celów niniejszego artykułu zebrano dane dla 31 banków islamskich. Produktywność sprawdzono w oparciu o indeks produktywności Malmquista, bazujący na metodzie obwiedni danych (ang.: Data Envelopment Analysis (DEA)). Indeks zdekomponowano na takie elementy, jak wydajność skali, zmianę technologiczną oraz wydajność technologiczną. Następnie zidentyfikowano źródła zmian produktywności w islamskich bankach. Wykorzystano podejście pośrednictwa oraz produkcyjne, aby wyodrębnić nakłady i wyniki banków.

Wnioski: Mimo że obydwa wykorzystane podejścia różnią się od siebie, implementacja empiryczna autorów wskazuje, że prowadzą do bardzo podobnych wyników dotyczących produktywności, wydajności oraz źródeł zmian produktywności. Banki islamskie były w analizowanym okresie produktywne i wydajne, ale nie charakteryzowała ich wydajność skali i cierpiały na ewolucji zmian technologicznych. Co więcej, autorzy są w stanie wykazać, że kryzys dotyczący kredytów hipotecznych typu subprime w niewielkim stopniu negatywnie wpłynął na produktywność w islamskim sektorze bankowości.

Wartość artykułu: Studia empiryczne nadal są rzadkie, a ich wyniki są kontrowersyjne z punktu widzenia produktywności i wydajności islamskich banków. Niniejsze badania mają na celu wypełnienie tej luki ze szczególną uwagą skupioną na pomiarze indeksu produktywności, używając dwóch różnych podejść – pośrednictwa oraz produktywności – aby wyróżnić zmienne nakładów i wyników.

Implikacje: Banki islamskie cechuje niewydajność skali, muszą więc zwiększyć skalę działalności, a jedną z możliwych sugestii jest łączenie małych banków.

Ograniczenia: Dalsze badania mogą wykorzystać samoczynne techniki, aby skorygować szacunki dotyczące całkowitej produktywności czynników z punktu widzenia błędów, a także aby ocenić niepewność związaną z takimi szacunkami.

Słowa kluczowe: banki islamskie, produktywność, wydajność, metoda obwiedni danych, zastosowanie indeksu produktywności Malmquista
JEL: D24, G21

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Bank efficiency in Saudi Arabia: examining the impact of the global financial crisis

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Abstract:

Aim: The global financial crisis in 2008 has obstructed almost every bank around the world. This study examines the impact of global financial crisis on bank efficiency in Saudi Arabia.

Design / Research methods: This study examines the impact of global financial crisis in bank efficiency applying the data envelopment analysis (DEA) during 2006-2014. Eleven commercial banks were examined from Saudi banking sector which covers almost half of total banks of Saudi Arabia. Scale efficiency, technical efficiency and productivity of banks have been examined for assessing the impact of financial crisis overtime.

Conclusions / findings: Results reveal that banks in Saudi Arabia are inefficient in terms of technical and scale efficiency. The results also reveal these banks are not immune to the global financial crisis. Though only one bank has kept their unit efficient positions during the study period, the impact of global crisis on bank efficiency is found visible among other banks. The robustness of this study is also tested.

Originality / value of the article: The importance of this study is twofold. First, examining bank efficiency with special attention to financial crisis. Second, Saudi Arabia needs sustainable growth to be ensured. Hence, examination of impact of financial crisis on bank efficiency of Saudi Arabia will surely help the policy makers for future planning.

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Implications of the research: The findings of this study will assist the policy makers in Saudi Arabia for taking corrective measure in advance in case of such future financial crisis. Moreover, the results will be used by the managers of the respective banks for decision making and problem solving.

Keywords: slack based model, data envelopment analysis, efficiency, Saudi Arabia

JEL: C23; G21; L2

1. Introduction

Bank is the critical part of a financial system which plays an important role to economic development. If banking industry cannot execute well, the economy cannot perform as well. Thus, examining bank efficiency ensures economic growth by providing relevant and comparative performance index. There are a number of tools available for examining bank efficiency. Some studies have examined bank efficiency using financial ratios only. They only showed the relative numerical evaluation. The unique criticism of using these ratio analysis is that it provides biased results because of variable selection. Some studies have also used regression analysis. The criticism of using regression analysis is that it examines the central representativeness of a sample. Thus, examination of a lowest performer comparing to the highest performer is impossible in regression method. In recent days, a vast area of literature has used non-parametric frontier approaches for examining bank efficiency. The prime benefit of using frontier method is that it helps all other banks to compare from the unit (the highest) performer. The frontier approach is mostly two types- DEA (Charnes, Cooper 1959; Emrouznejad et al. 2008) and stochastic frontier approach (SFA) (Wanke, Barros et al. 2016). This study applies the most used DEA technique for examining bank efficiency in Saudi Arabia (Wanke, Azad et al. 2016).

The banking sector of Saudi Arabia is one of the fastest growing markets in the world. Many banks in Saudi Arabia have been conducting their activities as a competitor with each other. The growing interest of academics on this banking sector reflects the importance of studying bank efficiency (Emrouznejad, Anouze, 2009). The main objectives of this study are to identify bank efficiency among the selected Saudi banks using DEA and to measure the impact of global crisis on banking sectors in Saudi Arabia. This study takes 11 banks' data out of 24 banks in Saudi Arabia representing almost half of the total banking sector. Data was collected from the bankscope[1] database. This study includes one output[2] and three inputs[3].Here most of the banks are conventional banks. Net interest margin is used as output. For calculation of efficiency, traditional DEA has applied.

The findings of this study make contributions in twofold: contributions to the management decision makings, and examine efficiency levels before and after financial crisis. The results also reveal that Saudi banks are not immune to the global financial crisis (GFC). Though only one bank has kept its unit efficient positions, the impact of global crisis was visible among the efficiency scores for other banks. This study assists to the decision makers for setting financial strategies, managerial plans and also helps to increase bank efficiency positions on banking fields.

This study consists of another five sections. Section two shows the banking sectors overview and Section three presents a brief literature review. Next Section explains methodology. In methodology chapter, the evolution of DEA and its application in banking sector is described. Afterward, Section five critically examines the results and analysis of this study. Finally, Section six discusses conclusion.

2. Overview of banking sector in Saudi Arabia

Saudi banking sector is one of the world largest and fastest banking markets in the world where 24 commercial banks, of which 12 domestic banks & 11 foreign banks are operated currently. Many banks in Saudi Arabia have been facing healthy competition. In 2008, global financial crisis was created a negative impact in Saudi Arabia banking sectors as a result, many banks failing their efficiency position. But

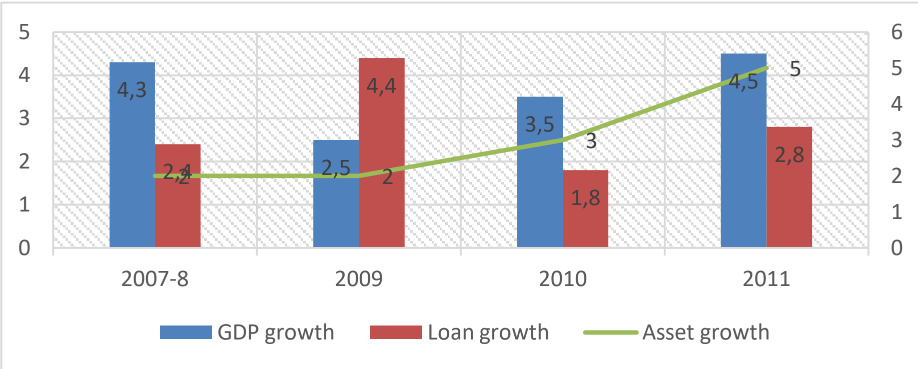
[1] Bank-scope is a comprehensive, global database of banks' financial statements, ratings and intelligence. Its coverage of banks is unique. Bank scope has information on 32,000 banks and is the definitive tool for bank research and analysis

[2] Net interest margin

[3] Loans, equity and total assets

Saudi banking industry registered impressive positive growth in these periods. Because of their strong financial policies and government reserves, Saudi banking sector could recover its position. Earlier study reveals that Saudi banking sector's growth rate reached 13.6 percent where loan growth rate expanding to 12.2 percent during 2007-10. Saudi banks' performance and GDP growth continued ups and downs and their real GDP growth during 2007-10 (2.7%), 2009 (.6%), 2010 (3.8%), 2014 (3.6%) but Saudi Arabia is most benefited of its high oil prices which protects global economic distress. The overall banking and economic growth in Saudi Arabia is shown below.

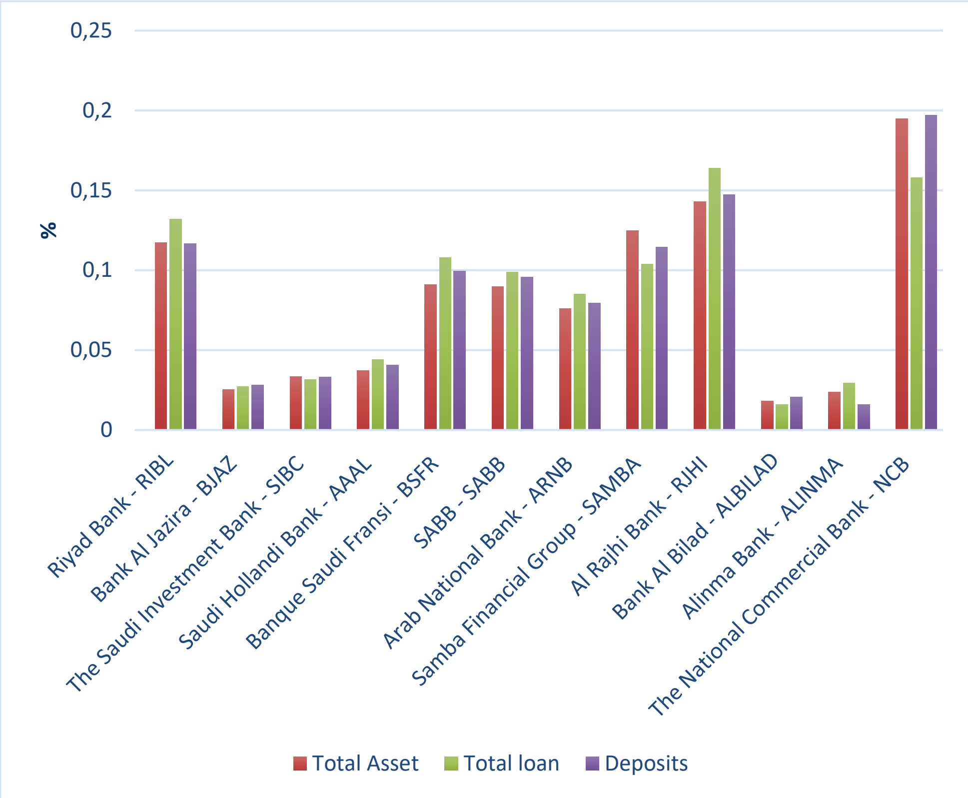
Figure 1: Saudi Arabia banking sectors and economic growth



Source: Ministry of economics and finance, Saudi Arabia

Figure **1** shows that Saudi Arabia banking industry and economic condition had ups and downs during the study period. In this sector, GDP growth was different during the study period 2007 to 2011. Banking loan ratio was fluctuating for GFC where ratio was 2.4 to 4.4 to 1.8 to 2.8 noticed that in 2010 the banking industry sectors were very weak position for GFC where loan ratio was only 1.8, that is less than the ratio of previous year but they were improving their condition.

Figure 2: Individual performance of banks in Saudi Arabia (SAR-Billion)



Source: Authors' calculation based on Annual Report SAMA 2012 in Saudi Arabia

Figure 2 shows that shows that total asset ratio was 97.47 percent of total bank assets, total loans conducting was 99.80 percent of total amount and they gains 98.94 deposits holders of banking industry sectors where average banking performance was good during the study periods. Literature also reveals that banks in Saudi Arabia have strong capitalization according to international standards, and they maintains the average Basal capital law or ratio like as 16% in 2008 (15.9% in September 2009). It is remarkable that all Saudi banks follow Tier 1 capital ratio under BASLE criteria. In addition, the performance and quality of Saudi Banks are very strong by their asset conditions where non- performing loans amount were 1.4 % of total loans at end-2008, while 153% was provisions coverage .NPL remained below 3% at September 2009. Banks maintained their highly liquid capacity where liquid assets representing an average ratio of 34% of total customers deposits in 2008. The healthy situation prevailing at end-September 2009 has continued unabated, with a liquidity ratio at over 30%.

3. Literature review

This study drew the sample banks from Saudi Arabia over the period 2006-2014. The empirical results from static and dynamic panel regression indicate that there is a positive relation between economic growth and institutional quality of institutions in Saudi Arabia has a positive effect of banking concentration on economic growth (Al-Khathlan, Malik 2010). Almumani (2013) found that Saudi banks are more efficient than others banks in this region and he also said that commercial banks are developing their new technology and providing more services. A research by Srairi (2013) examined the efficiency of Islamic banking sector in Saudi Arabia. The results from data envelopment analysis (DEA) indicate that Saudi Arabia Islamic banks have showed a higher mean technical efficiency relative to Asian Islamic banks. Moreover, they showed that Islamic banks from this region are dominating the efficiency frontier. Another study also said that Saudi Arabia banks were in an efficient position by their management of financial resources (Al-Khathlan, Malik 2010).The findings suggest that capital variables (equity to assets and equity to liabilities), net profit revenue on average assets, and loan to total assets have positive influences on Islamic bank profitability. On the other hand, loan loss provision and cost to total income have a negative impact on Islamic bank profitability (Sufian, Mohamad Noor 2009). The findings suggest that domestic banks had better performance relative to the foreign banks during the crisis. This study also found that the liquidity ratio has a negative effect on profitability but size was found to be insignificant determinant of profitability. Moreover, net interest revenue had a positive effect, and GDP is also found to be positively affecting the profitability of domestic banks (Mongid 2016). He examined whether the profitability of Islamic banks is affected by the same factors that affect the conventional banks, using data of 6 Islamic Banks from Saudi Arabia during the period of 1994 to 2012. The findings suggests that capital variables (equity to assets and equity to liabilities), net profit revenue on average assets, and loan to total assets have positive influences on Islamic bank profitability.

On the other hand, loan loss provision and cost to total income have a negative impact on Islamic bank profitability (Sufian, Mohamad Noor 2009). They have investigated the relationship between cost efficiency and competition in the banking industry of 10 MENA countries (i.e. Lebanon, Bahrain, Algeria, Egypt, Israel, Jordan, Morocco, Oman, Saudi Arabia and UAE) over the period 1997-2011. Level of competition was measured through the structural indicator popularly known as H-statistics. And the bank efficiency is estimated through Data Envelopment Analysis (DEA) and the Bootstrap Data Envelopment Analysis (BDEA). This study found that efficiency granger-causes the competition. This cause is found to be negative, implying that progress in terms of cost efficiency lowers the competition. The empirical findings also showed that average cost efficiency in the MENA banking region was relatively high (77.6%). This implies that MENA banks need to improve only by 22.4, to reach the cost efficiency frontier (Rahman, Rosman 2013).

4. Methodology and data

Nowadays, many studies on efficiency use many methods for their research tasks. Data envelopment analysis (DEA) is one of them. It is a data oriented approach for evaluating performance of decision making units (DMU) with multiple inputs and outputs. DEA is founded by Farrell (1957) and is developed by Charnes, Cooper, and Rhodes (1978). DEA proves an uncovering relationship that's hidden from others methodologies. This means one is the efficiency score particularly according to DEA methods where applied a mathematical programing model to observational data that provides a new way of empirical estimation of relations like as production function or efficient function possibility surfaces. DEA is a statistical approach that compares each DMU with the best DMU. DEA usually use for both production and cost data and utilizing the selection variables with unit cost and outputs. Farrell (1957) established the beginning of measuring efficiency through his study "the measurement of productive efficiency". In his study, a firm consists of technical efficiency and allocative efficiency where technical efficiency measures outputs from a certain amount of inputs of a firm. And allocative efficiency measures the ability to utilize inputs by best possible mixture. Technical efficiency can be separated into part of scale efficiency and pure technical efficiency where technical efficiency helps the management implement effective plans–converting inputs into outputs.

Figure 3-a. Technical and allocative efficiencies: case of two inputs, normalized by single output

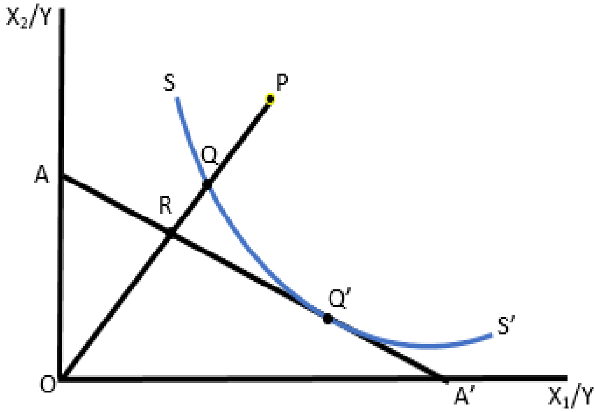
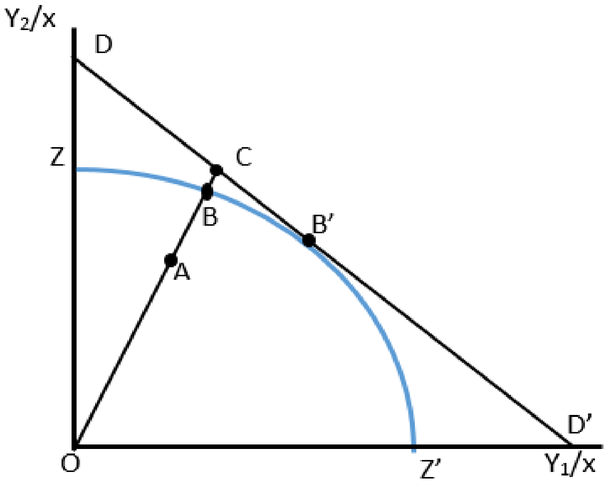


Figure 3-b. Technical and allocative efficiencies: case of two outputs,



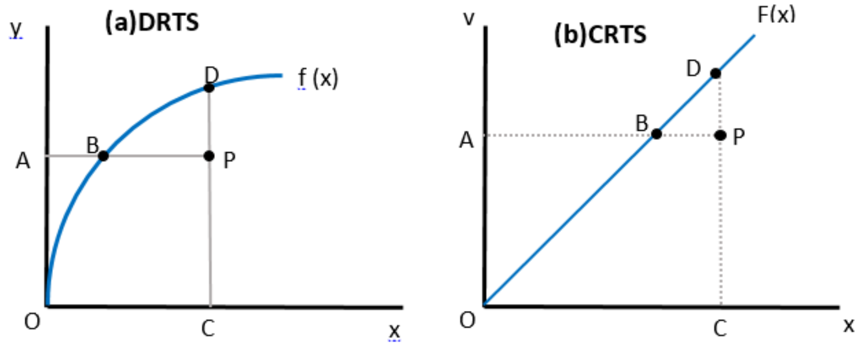
normalized by single input"

If a firm represents only two inputs (X1 and X2) and one output (Y) under the constant returns to scale (CRS) assumption according to figure 3 (both a and b). The SS' curve represents that the firm is fully efficient by technical efficiency. But a firm is operating at the TE point P that we assume an inefficient firm. TE can be measured by TE = OQ/OP =1-QP. And point p measure the allocative efficiency which means: AE = OR/OQ (according to figure 3a). At the point Q indicates the technical efficiency where production cost of a firm decrease by RQ and the firm overall efficiency is measured by: OE=OR/OP. Overall efficiency of a firm means: TE × AE = OQ OP × OR OQ ≡ OR OP = OE.

Output-Oriented Measures

Figure 4(a) indicates the decreasing return to scale by f(x) and at the point p represent the inefficient position of a firm. Prof. Farrel input-oriented measured by TE that's equal to AB/AP ratio and output-oriented measurement point is CP/CD. And output-oriented measures will provide technical efficiency of equivalent measure where CRS exist (Färe, Lovell 1978) Figure 4(b) shows that CRS is censured where AB/AP=CP/CD for any inefficient point P. One can consider only output-oriented measures by considering the case where production involves two outputs (y1 and y2) and one input (x1).

Figure 4: Technical efficiency measures and returns to scale: Case of single input-single output



Here, AB represent the distance of TE. Where output-oriented TE ratio is TE=OA/OB. By price information we can draw the ISO revenue line and define the allocative efficiency to be AE = 0B/0C[4] according to the figure 3b. The Banker, Chames and Cooper model (BBC) allows a flexible construct for the DMUs and presents with piecewise linear function. Similar to CCR model, the BCC model reduces multiple input-output using a virtual input and a virtual output; as shown in equation below.

$$Maximize\ \theta_{BCC} = \frac{\sum_{r=1}^{s} u_r Y_{r0} - \widetilde{u_0}}{\sum_{i=1}^{m} v_i X_{i0}}$$

$$Subject\ to: \frac{\sum_{r=1}^{s} u_r Y_{rj} - \widetilde{u_0}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1; j = 1, \dots, n$$

$$\theta_{BCC} = efficiency\ estimation\ under\ BCC\ model$$

$X_{ij} \geq 0$; i^{th} input to unit j

$v_i \geq 0$; Corresponding weight to i^{th} input

$Y_{rj} \geq 0$; r^{th} output to unit j

$u_r \geq 0$; corresponding weight to r^{th} input

$\widetilde{u_0}: unrestricted$

The new variable $\widetilde{u_0}$is included in order to estimate economics of scale. Where,

$\widetilde{u_0} = 0$, means θ_{BCC} is equivalent to the CCR model

$\widetilde{u_0} > 0$, means the DMU is operating under IRS

$\widetilde{u_0} < 0$, means the DMU is operating under DRSs

[4] Efficiency: Efficiency means the getting maximum output with minimum input. And we also say that efficiency is the ratio of output with input of any system.
Resources process to output to efficiency target.
Technical Efficiency: reflects the ability of a firm to obtain maximal output from a given set of inputs. TE=OQ/OP which is equal to one. It will be take value between 0 and 1.
Allocative Efficiency: reflects the ability of a firm to use the input in optimal proportions given their respective prices.
Economic efficiency =OR/OP and overall economic efficiency = TE+AE
Scale efficiency means the properly uses of input ratio by which gets optimal proportions a firm
VRS: when more relation occurred.
CRS: 1 to 1 relation

5. Results and Analysis

The results obtained from the DEA and Malmquist DEA calculations are presented in Table 1.

Table 1. Table of efficiency of banks in Saudi Arabia (2006 to 2014)

	2006	2007	2008	2009	2010	2011	2012	2013	2014
Al Rajhi Bank	1	1	1	1	1	1	1	1	0.872
Arab National Bank	1	0.83	0.882	0.756	0.857	0.693	0.765	0.745	1
Bank AlBilad	1	1	1	1	1	1	1	1	1
Bank AlJazira JSC	1	1	1	1	0.676	0.672	1	1	0.798
Banque Saudi Fransi JSC	0.671	0.639	0.668	0.623	0.646	0.612	0.63	1	0.77
National Commercial Bank	0.666	0.663	0.812	0.932	1	1	0.957	0.678	1
Riyad Bank	0.749	0.753	0.481	0.471	0.455	0.534	0.628	0.719	0.871
Samba Financial Group	0.862	0.82	0.767	0.761	0.721	0.629	0.664	0.752	0.808
Saudi British Bank JSC	0.941	1	1	0.963	1	0.752	0.721	0.765	0.869
Saudi Hollandi Bank	1	1	1	1	1	0.652	0.748	0.661	0.846
Saudi Investment Bank	0.854	0.703	0.732	0.572	0.694	0.68	0.668	0.952	0.656
Mean value	0.895	0.867	0.862	0.84	0.837	0.769	0.815	0.856	0.874

Source: Authors’ own elaboration.

Table 1 compares the efficiency of banking industry in Saudi Arabia between the years 2006 and 2014. The period was divided into two parts of banking performance one is 2006 to 2009 and another is 2009 to 2014. It can be clearly seen that the efficiency of banking industry is gradually increasing and decreasing among banks in Saudi Arabia like as Al Rahim Bank Public Joint Stock Company, Arab National Bank, Public Joint Stock Company, Bank AlBilad, Bank AlJazira JSC, Saudi Hollandi Bank were efficient in 2006 where banks efficient ratio is 1. But others banks like as Banque Saudi Fransi JSC (0.671), National Commercial Bank (.666), Riyad Bank (0.749), Samba Financial Group (0.862), Saudi British Bank JSC (0.941) and Saudi Investment Bank (0.854) showed weak performance in this period. Which means inefficient score of the banking sectors in Saudi Arabia. After three years, the graph shows that Al Rajhi Bank Public Joint Stock Company, Bank AlBilad, Bank AlJazira JSCand Saudi Hollandi Bank were in an efficient position for their strong bank assets, liquidity.

However, Arab National Bank lost its position gradually form 1 to 0.83 from 0.882 to 0.756 because of a failure in their operational tools as decreasing loans (66811 million), gross loans (68268.4) ,net interest rate and interest margin (2.996), ROAA (2.044), ROAE (17.434),interbank ratio, net loans total assets (60.574), total deposits (72.716) etc. Unfortunately, Saudi Investment Bank, Riyad Bank and Samba Financial Group reduced their efficient ratio gradually because of their poor environment as loans, assets, and interest. Another cause was the global financial crisis in this region in 2008. For this cause banks were negative affected of their core function. And for this causes Saudi British Bank JSC lost their efficient position because this bank was 94% efficient ratio and next year the bank~~s~~ was increasing their ratio and achieved the efficient position in the banking sectors but after 2008 the bank lost their efficient level again. This study shows that overall banking performance and efficiency level were gradually weakened like as from 0.895 to 0.867 to 0.862 to 0.84 during the financial crisis period~~.~~

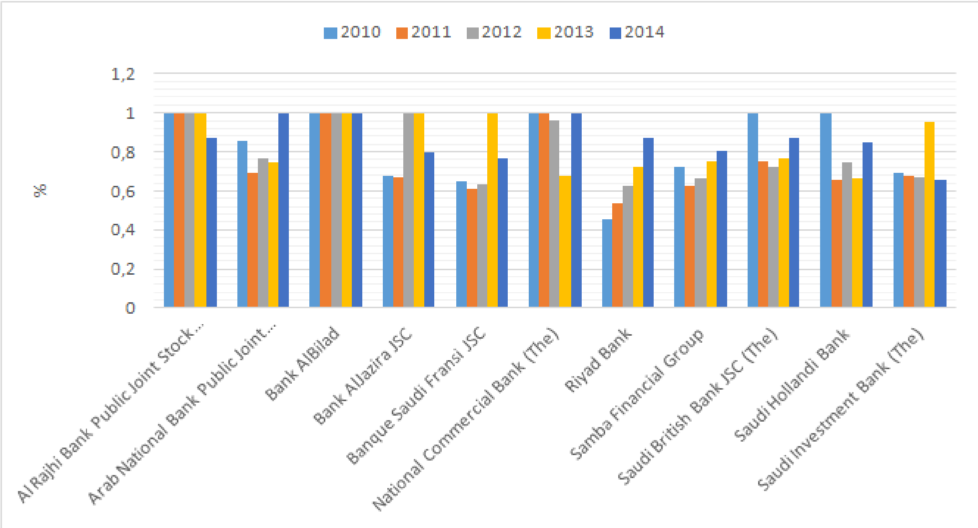
After the financial crisis, banks of Saudi Arabia were improving gradually. And their financial operation sectors were expanded. This means their efficiency score were increasing in most of banks in this region like as Arab National Bank Public Joint Stock Company 0.756(2009), 1(2014); National Commercial Bank 0.932(2009), 1(2014); Riyad Bank 0.471(2009), 0.871(2014); Samba Financial Group 0.76(2009), 0.808(2014); and Saudi British Bank JSC 0.963(2009), 0.869(2014). And many banks were moved to the efficient position because of their positive environment for banking operation by expanding their loans, gross loans, ROAA, ROAE, net loans, total assets and total deposits, etc. On the other hand, many banks diminished were declined from their efficient position. Many banks could not keep their efficient position for individuals, government laws and environmental conditions like as Saudi Investment Bank, Banque Saudi Fransi JSC, Bank AlJazira JSC, Al Rajhi Bank Public Joint Stock Company. Inefficient ratios were 29%, 23%, 21% and 13%. Bank AlBilad was in an efficient position, though their bank asset and loans ratio observed ups and downs, this bank kept their efficient scores from 2006 to 2014 as a result their managerial and operational quality.

Figure 5 shows the efficiency scores for the sample banks from 2006 to 2009. In those years the global financial crisis is included. Global Financial crisis brought about less efficient position than other periods in the banking industry in Saudi Arabia. But, many banks were in an inefficient position before global financial crisis in 2008. As Banque Saudi Fransi JSC, National Commercial Bank, Riyad Bank,Samba Financial Group, Saudi Investment Bank were inefficient from 2006 to 2007 where their loans, gross loans, total earnings assets, total customer deposits, total equity and liabilities were increasing but their net interest margin and net loans were decreasing at this period as a result they become gradually inefficient.

However, global financial crisis widely affected the Saudi Arabia banking sectors. Because many banks are foreign banks in Saudi Arabia so it is a worldwide problem have a negative impact on banking sector efficiency gradually where duration was much longer from 2007 to 2009. Like as Arab National Bank Public Joint Stock Company is from 1 (2006) and 0.756 (2009). Banque Saudi Fransi JSC from 0.671 (2006) and 0.623 (2009). Riyad Bank from 0.749 (2006) and 0.471 (2009). Saudi Investment Bank from 0.854 (2006) and 0.572 (2009).

Finally, many banks were inefficient during the financial crisis period in Saudi Arabia. In this period, many banks lost their efficient score because of a failure in their loans, gross loans, total earning assets and interest margin, etc. As a result, most of the banks were gradually losing efficiency according to the table 1 (0.895 to 0.867 to 0.862 to 0.84) from 2006 to 2009.

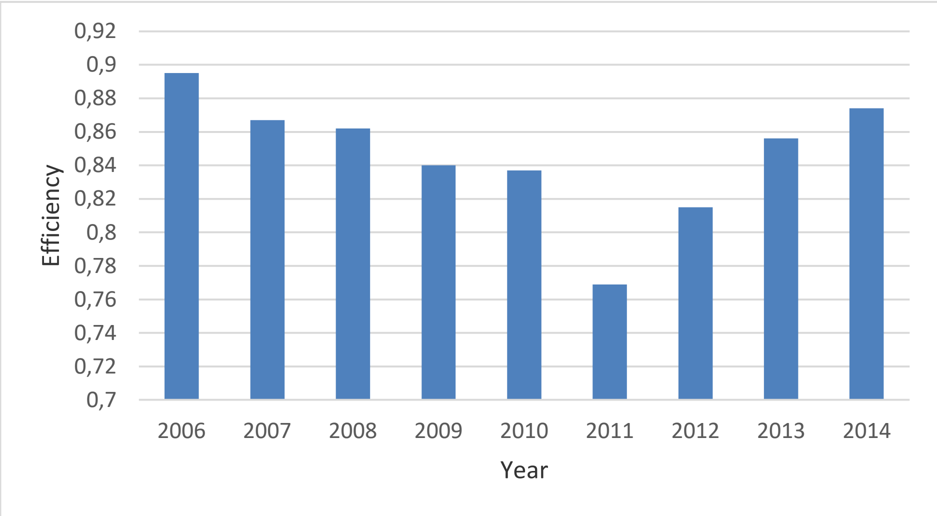
Figure 5. VRS efficiency levels after GFC in Saudi Arabia banking sector



Source: Authors' own elaboration.

Figure 5 shows that banking efficiency level after GFC from 2010 to 2014. Figure 5 shows banks efficiency levels after global financial crisis in Saudi Arabia banking industry during the coverage period from 2010 to 2014. Though, financial crisis is a vital problem all over the world and it is a long term process for recovering that's why it is impossible to achieve an efficient position for any financial institutions rapidly. However, most of banks in this region tried to move from their bad position as possible as fast. That shows above VRS mean in table 1 where overall banks performance is better than GFC period. Like as Arab National Bank Public Joint Stock Company (0.857-0.693-0.765-0.745-1), Banque Saudi Fransi JSC (0.646-0.612-0.63-1-0.77) here after GFC banks became into an efficient position, but they lost their position because of changing net interest margin (2.33-2.422). Riyad Bank (0.455 to 0.534 to 0.628 to 0.719 and 0.871), Samba Financial Group (0.721 to 0.629 to 0.664 to 0.752 to 0.808); but many banks could not achieve an efficient level such banks are increasing their efficient scores. Finally, note that, only one bank kept their efficient position and market position from 2006 to 2014. Bank AlBilad is a private bank. This bank kept its efficient position in the global and local market from 2006 to 2014. That is loans, gross loans total earning assets, total equity and total customer deposits were decreasing ~~a~~ in the period of global financial crisis but this ~~banks~~ kept their efficiency position because of their strong managerial policies. At this time, largely increased recurring earning power, ROAE, ROAA, net interest margin and equity of the Bank AlBilad; that is why it kept their efficiency level because in this bank loans, gross loans and total earning assets, total equity, and total customer deposits were expanding after GFC from 2006 to 2014. Figure 6 shows that Saudi Arabia banks were inefficient during period from 2006 to 2014. Where inefficient score was 0.895 in 2006 and 0.874 in 2014.

Figure 6. Average efficiency score from VRS mean in Saudi Arabia banking sector annually



Source: Authors' own elaboration.

We now test the robustness of the derived results from DEA calculation from the two different independent sample groups (before and after financial crisis). Coakes and Steed (2003) demonstrated that with an even sample distribution, the Mann-Whitney test is the most relevant test.

In table 2, the parametric t-test results reveal that bank efficiency after economic crisis has scored higher with a value of 0.782 whereas local banks are marked with 0.467. In terms of bank efficiency, after crisis efficiency scored 0.782 which is higher than before crisis score. Similar result is observed in both the Mann-Whitney test and Kruskall-Wallis test as shown in table 2. All results are significant at either the 1% or 5% level.

Table 2. Summary of robustness of test results

	Test groups					
	Parametric test		Non-parametric tests			
	t-test		Mann-Whitney test		Kruskall-Wallis test	
Test statistics	t(Prb>t)		z(Prb>z)		X^2(prb> $X^{2)}$	
	Mean	t	Mean rank	z	Mean rank	X^2
Bank Efficiency						
Before Crisis	0.467	-1.561***	43.21	-2.245**	53.17	6.001**
After Crisis	0.782		58.05		59.35	

Note: ** and *** indicate significance level at the 5% and 1% levels respectively.

6. Conclusions

This paper investigates efficiency of banks in Saudi Arabia with special consideration of global financial crisis in 2008. The findings reveal that majority of Saudi banks were found inefficient during the study period. The average efficiency in the year 2006 was 0.985 and 2014 was 0.874 (c.f. Table 1). This particular finding implies that these banks have been facing negative productivity during the crisis period. However, only one bank (Bank Al-Bilad) kept its efficiency score as unit efficient during the study period. The banks in Saudi Arabia got rid of global financial negative effects by providing sound management tools, credit and deposit facilities, foreign exchange services, strong trade securities, investment banking, expanding branches & ATMs service, and government finance etc. Thus, Bank Al-Bilad should be benchmarked with other Saudi banks since this bank was found to be efficient. This paper verified that the global financial crisis had significant impact on banking sector of Saudi Arabia.

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Wydajność banków w Arabii Saudyjskiej: ocena wpływu globalnego kryzysu finansowego

Streszczenie

Cel: Globalny kryzys finansowy z 2008 roku utrudnił funkcjonowanie niemal każdego banku na świecie. Niniejszy artykuł ma na celu ocenę wpływu globalnego kryzysu finansowego na wydajność banków w Arabii Saudyjskiej.

Metodyka badań: Artykuł określa wpływ globalnego kryzysu finansowego na wydajność banków poprzez zastosowanie metody obwiedni danych (ang. data envelopment analysis (DEA)) dla danych z lat 2006-2014. Przebadano 11 komercyjnych banków należących do saudyjskiego sektora bankowego, co stanowiło niemal połowę wszystkich banków w Arabii Saudyjskiej. Aby ocenić wpływ kryzysu finansowego w czasie, uwzględniono wydajność skali, wydajność techniczną oraz produktywność banków.

Wnioski: Na podstawie wyników można stwierdzić, że banki w Arabii Saudyjskiej są niewydajne pod względem wydajności technicznej oraz skali. Ponadto banki te są nieodporne na globalne kryzysy finansowe. Chociaż tylko jeden bank utrzymał swoją pozycję w ramach wydajności jednostkowej, wpływ globalnego kryzysu na wydajność banków jest widoczna w odniesieniu do pozostałych przeanalizowanych banków. Przetestowano także solidność przeprowadzonego badania.

Wartość artykułu: Niniejsze badanie ma podwójne znaczenie. Po pierwsze, przeanalizowano wydajność banków ze szczególnym uwzględnieniem kryzysu finansowego. Po drugie, w Arabii Saudyjskiej należy zapewnić zrównoważony wzrost. Z tego względu określenie wpływu kryzysu finansowego na wydajność banków w Arabii Saudyjskiej z pewnością wesprze decydentów politycznych w przyszłym planowaniu.

Implikacje badań: Wyniki badań zaprezentowane w artykule będą służyć politykom w Arabii Saudyjskiej podczas podejmowania zawczasu odpowiednich kroków w przypadku przyszłego kryzysu finansowego. Co więcej, wyniki będą wykorzystane przez kierowników banków w podejmowaniu decyzji oraz rozwiązywaniu problemów.

Słowa kluczowe: Slack based model, metoda obwiedni danych, Arabia Saudyjska
JEL: C23; G21; L2

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Efficiency determinants of microfinance Institutions in India: two stage DEA analysis

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Abstract:

Aim: In India, Microfinance Institutions (MFIs) emerged as major player in providing microfinance services and therefore such institutions need to be financially sustainable in order to achieve their double bottom-line objective. Besides, Indian MFIs cannot protect themselves from the curse of loan non-repayment. Therefore, this study aims to measure performance of the Indian MFIs and examine whether sustainability has any significant impact on the efficiency of the MFIs.

Design / Research methods: In order to gauge the performance of the Indian MFIs, non parametric Data Envelopment Analysis (DEA) is adopted. Two models of DEA (BCC Model-input oriented and Undesirable Measure Model-output oriented) are applied used for better analysis. Further, to examine the factors influencing efficiency of the MFIs and particularly to answer whether Sustainability has any significant impact on efficiency, Tobit regression is applied in the study. Data of thirty-one Indian MFIs for seven years (2009-2015) are collected from MiX Market for the study.

Conclusions / findings: Result of the study shows that average technical efficiency of the MFIs is estimated to be 79 percent under BCC model and 98 percent under Undesirable Measure Model. Indian MFIs can attain production frontier if they can trim their bad output (proxied by Portfolio at Risk 30) to an extent of around 14 percent. Further, the study validates that sustainability (proxied by Operational Self Sufficiency) has positive impact on efficiency.

Originality / value of the article: Studies made so far on Indian MFIs have not addressed how the MFIs could become efficient by reducing their undesirable/bad output. Besides, no study so far has analysed the impact of sustainability on efficiency of the Indian MFIs. Therefore, this research tries to fill the existing research gap.

Implications of the research: The result of the study can be useful to the Indian Microfinance Industry in improving their performance. The result can further be used by Reserve Bank of India (RBI) to frame yardstick for the clients of the MFIs in connection with borrowing loans from MFIs.

Keywords: Microfinance Institutions, Sustainability, Data Envelopment Analysis

JEL: G21, C67, C33

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1. Introduction

Microfinance is considered to be an imperative tool for sustainable growth in a developing nation. Initially Microfinance Institutions (MFIs) originated with a social mission which is poverty reduction. However, last two decades witnessed a shift in the operation of the MFIs from being social oriented to commercialization (Sriram, 2010; Rauf, Mahamood 2009). MFI's major objective is to provide banking services to the financially excluded people, particularly to provide small credits to the borrowers (Mersland, Strom 2009). Therefore, MFIs should be sustainable in order to continue their services. For attaining sustainability MFIs charges high interest rates, which is even higher than the interest charged by commercial banks (Ahmed, 2002; Diop et al. 2007; Obaidullah 2008). Tulchin (2003) & Hartarska (2005) stated that MFIs face unique challenge because of their double bottom line objective of outreach and sustainability. In the process of attaining self-sufficiency, the MFIs started to become commercial institutions. Crabb & Keller (2006) stated that like commercial banks and other lending institutions, MFIs must manage their repayment risk. Interestingly, MFIN Report (2017) highlights that Indian MFIs suffers from repayment issue as average Portfolio at Risk more than 30 days (PAR30) is estimated to be 7.46 percent which implies that the Indian MFIs cannot guard themselves from the curse of non-repayment.

The drift of the MFIs from their prime objective to commercialization deemed the traditional technique of gauging the performance of the MFIs unfit. Considering the importance of cost trimming in the sector vital, there is felt a need to add fresh dimension of performance measurement incorporating both social and commercial aspect.

The present study proposes relative efficiency as a technique to measure social and financial aspect of MFI performance (Ferdousi 2013). The study proposes to use a non-parametric DEA approach to estimate efficiency. Besides, the study proposes to address the bad output produced by the MFIs in the form of PAR30 by using Undesirable Measure Model. Thereafter, the study tries to answer whether sustainability of MFIs has any significant impact on efficiency of MFIs.

The rest of the paper is organized as: Background of microfinance vis-a-vis genesis of Indian microfinance is explained in the second section followed by Sustainability and its measures in the third section. Technique for estimating efficiency, particularly DEA, is discussed in the fourth section. The fifth section focuses on reviewing of other related studies in and around the area. The sixth section highlights the research design as well as specification of model to be used in the study followed by the result of efficiency estimation in the seventh section and result of Tobit regression in the eighth section. Finally the summary of findings, scope for future research and conclusion of the study is mentioned in the ninth section.

2. Microfinance

Microfinance refers to the provision of small loans without collateral security, to the poor and low-income households, whose access to the commercial bank is limited. Microfinance, thus bridges the gap between the financially excluded group of people and their financial crisis. According to Robinson (2001), microfinance refers to ‘small-scale financial services–primarily credit and savings–provided to people who farm or fish or herd; who operate small enterprises or microenterprises where goods are produced, recycled, repaired, or sold; who provide services; who work for wages or commissions; who gain income from renting out small amounts of land, vehicles, draft animals, or machinery and tools; and to other individuals and groups at the local levels of developing countries, both rural and urban’. Besides granting credit, Microfinance provides other services such as savings, insurance, pension and payment services (Oikocredit 2005). In India microfinance started through loaning miniaturized scale credit amid the 60s' picked up force amid the 90s when Government intervention was made and banks began connecting up with SHG programs. Micro Finance Institutions (MFIs), some private foundations, came forward, whose prior goal was to give microfinance services, such as providing advances, protection of clients’ interest and currency exchange. Despite the fact that these MFIs experiences absence of benefactor steadiness that brings up the issue of their manageability, however such organizations are as yet perceived as effective apparatus for battling neediness and equipping comprehensive development. Following paragraphs depicts brief picture of the evolution of microfinance.

2.1 History of microfinance

Microfinance initiated under the plan of budgetary consideration which expected to bring poor people and denied area of the populace under the scope of money related administrations. Notwithstanding, microfinance commenced hundreds of years prior when casual investment funds and credit bunches began working for poor people. The evolution of microfinance as narrated by Robinson (2001), the incorporation of the “susus” of Ghana, “chit funds” in India, “tandas” in Mexico, “arisan” in Indonesia, “cheetu” in Sri Lanka, “tontines” in West Africa and “pasanaku” in Bolivia started the voyage of microfinance. In 1700s, the Irish creator Jonathan Swift started the most punctual type of present day MFIs: the Irish credit subsidize framework. The Irish credit support framework was intended to give little uncollateralized advances to country poor. Scholar Lysander Spooner composed over the advantages from little credits to the business visionaries and agriculturists as a wellspring of inspiring the job of the poor amid the 1800s and different other formal organizations started to rise in Europe in the types of individuals' banks, credit unions and reserve funds and credit co agents. Of these, the credit unions created by Friedrich Wilhelm, Raiffeisen increased wide recognition in Europe and other North American States, in mitigating the rustic poor from the grip of usurious moneylenders. In 1895 individuals' banks ended up plainly prevalent in Indonesia, and in 1900 the thought spread to Latin America. By the year 1901 the bank achieved two million provincial ranchers. Between the period 1900 to 1906 the caisse populaire development grounded by Alphone and Dormene Desjardians in Quebec established the principal caisse, they passed a law representing them in the Quebec get together. However the unrest in the zone of microfinance occurred in 1970s when Professor Mohammad Yunus helped by his understudy Akhtar Hameed Khan spearheaded the Grameen Bank Model in Bangladesh. Close by Shorebank was framed in 1974 which was the principal microfinance and group improvement bank established in Chicago. Going to the 21st century, the year 2005 was broadcasted as the global year of microcredit by the Economic and Social Council of the United Nations in a require the money related and assembling division to “fuel” the solid entrepreneurial soul of the needy individuals around the globe. In the year 2006 Professor Mohammad Yunus, the organizer of Grameen Bank was granted the Nobel Prize for his endeavours. Regardless of the possibilities of microfinance, think about made by Deutsch Bank in 2007 featured that as indicated by a few gauges just 1-2 percent of all Microfinance Institutions on the planet are fiscally maintainable, which means in this manner a large portion of the Microfinance Institutions need to rely upon outside endowments.

2.2 History of microfinance in India

In India the journey of Microfinance began with the starting of a NGO named Mysore Rehabilitation and Development Agency (MYRADA) in Karnataka, 1968 to encourage a procedure of continuous change for the country poor. Later amid 1984-85 MYRADA accomplished its goals, that is, to help the poor to help themselves by framing Self Help Groups (SHGs) and through association with NGOs and different associations. Close by, in 1974 Shri Mahila SEWA (Self Employed Women's Association) Sahakari Bank was shaped for giving saving money administrations to the poor ladies utilized in the disorderly segment in Ahmadabad, Gujrat. Be that as it may, the microfinance development in India picked up energy with the impedance of NABARD (National Bank for Rural Development) in 1992. It was amid the late 1990s' and mid 2000s' few studies were made with respect to the credit accessibility got by the denied area which featured the possibilities of the miniaturized scale credit which brought about the ascending of different pinnacle establishments like NABARD, SIDBI and Rashtriya Mahila Kosh (RMK) for giving microfinance benefit, Commercial Banks, Regional Rural Banks and Cooperatives likewise give microfinance administrations. Private Institutions named Microfinance Institutions (MFIs) were built up that embraced microfinance benefits as their primary action. Moreover, couple of NGOs began giving direct credit to the borrowers, for example, SHARE in Hyderabad, ASA in Trichy, RDO LOYALAM Bank in Manipur (Tiwari 2004). Once more, couple of NGOs like MYRADA in Bangalore, SEWA in

Ahmadabad, PRADHAN in Tamil Nadu and Bihar, ADITHI in Patna, SAARC in Mumbai are a portion of the NGOs that help the SHGs.

Assocham Report, 2016 categorised the evolution of Microfinance sector into four periods: Initial Period, Change Period, Growth and Crisis and Consolidation and Maturity.

Commencement of Sewa Bank in 1974 and linking of NABARD with SHGs in 1984 was clustered as "Initial Period". Beginning of SHG Loans on par with secured Loans on 2002, MFI lending treated as Public Sector Lending on 2004 and the Krishna crisis in Andhra Pradesh on 2006 was tagged as "Change Period". Entry of Private Equity in Microfinance Industry in 2007, introduction to MicroFinance Institution Network in 2009 and starting of SKS Microfinance offering IPO, Andhra Crisis in the year 2010 was clubbed as "Growth and Crisis Period". Finally, Malegam Committee Report and RBI guidelines on the regulation of MFIs in 2011, grant of banking license to Bandhan in 2014 and launching of MUDRA bank and 8 MFIs granted SFB license in 2015 was grouped as "Consolidation and Maturity Period".

The year 2011 marked an important phase in the Indian microfinance history. Gradual materialization of the MFIs leads to bulk indebtedness among the poor farmers of Andhra Pradesh. However, Beginning of the Andhra Pradesh Microfinance emergency can be followed back in the year March, 2006 when Krishna region government shutdown 57 branches of two biggest MFIs (SHARE and Spandana) and in addition those of couple of littler MFIs. Choice to shut down of these MFIs came in view of the affirmations of dishonest accumulations, unlawful operational practices, (for example, taking reserve funds), poor administration, usurious loan costs, and profiteering (CGAP 2010). There was even an affirmation that 10 borrowers of MFIs in Krishna region conferred suicide since they were not able reimburse the credits taken from MFIs (Shylendra 2006). Quick extension of bank credit as encouraged by activities like ICICI organization model and accessibility of shabby credit in type of "Pavala Vaddi" plot, spurred by political thought, heightened the crisis. As analyzed by Shylendra (2006) clash between States bolstered SHGs and Civil society activities in type of MFIs as the significant purpose for the emission of emergency.

3. Sustainability of MFIs

According to Pissarides et al. (2004), MFI can be proclaimed to be self-sustainable if resources can profitably provide finance to poor on an acceptable scale without using of subsidies, grants or other concession. Sustainable MFIs have repeatable operations and they are able to serve their target clients regularly. Notably, self sufficient MFIs might be financially sustainable but they cannot be claimed to be self financially sustainable unless they are privately profitable. Committee of Donor Agencies (CDA) explains sustainability of MFIs into two degrees: Operational Self Sufficiency and Financial Self Sufficiency. McGuire & Ors (1998) define Operational Self Sufficiency as "require MFIs to cover all administrative costs and loan losses from operating income". Financial Self Sufficiency is defined as the capacity of MFIs to cover all administrative costs as well as loan losses from operating income, after adjusting inflation and subsidies and treating all funding as it had a commercial cost (McGuire, Ors 1998). However, it is believed that small credits are costly and the operation of MFIs cannot generate sufficient income to ensure profitable business. Studies of Brau & Woller (2004) highlighted that unlike formal financial institutions, MFIs cannot be financially sustainable and therefore, they have to rely upon donor subsidies. However, there has been observed a gradual shift in the microfinance industry from subsidized credit delivery program to self sufficient financial institution through which the MFIs can achieve social outreach and financially sustainability without any sort of subsidy-requirement (Robinson 2001).

Marakkath (2014) stated that financial sustainability is denoted by three major metrics: Operational Self Sustainability Ratio, Financial Self Sustainability Ratio and Subsidy Dependence Index. Amongst these the most basic measure of financial sustainability of an MFI is Operational Self Sustainability (OSS). MFI with higher OSS ratio is likely to earn adequate revenue to cover its financing and operating costs as well as loan loss provision and gradually attain the status of FSS without any kind of subsidy-dependence (Meyer 2002; Ledgerwood 1999; Rosenberg 2009). Subsidy Dependence Index indicates the percentage increase required in on-lending interest rates to completely eliminate all subsidies received by an MFI (Yaron 1992).

Another commonly used indicator for estimating institutional scale is Adjusted Return on Assets (Zerai, Rani 2011). Sustainability is also measured by Return on Assets (ROA) and Returns on Equity (ROE) (Olivares 2005). ROA is indicative of a MFI's ability to generate returns using the institution's total assets.

In the present study Operational Self Sustainability (OSS) is taken as an indicator of sustainability of the MFIs. OSS measures how efficiently the MFI can manage its costs with the help of operating income and therefore is considered to be a superior measure of sustainability. Hartarska (2004) has also used Return on Assets (ROA) and Operational Self Sustainability (OSS) in his study to measure sustainability of MFIs. OSS is believed to be a better measure because the value of donation, subsidies and inflation is not recorded in ROA (Hartarska 2004).

The mathematical explanation of Operational Self Sustainability as defined by MIX Market is:

$$OSS = \frac{\text{Operating Income (Loans + Investment)}}{\text{Operating Costs + Loan Loss Provisions + Financing Costs}}$$

4. Techniques for estimating performance of MFIs

Traditional financial ratios are not adequate to evaluate microfinance performance because of its social mission, functioning of MFI is not only constrained to profit-earning but its capacity "to work in long haul without risk of liquidation" (Nanayakkara 2012). Some MFIs purposely concentrate on profit-making to achieve sustainability (e.g. bank-MFI). There exist different MFIs where profitability is not a prior concentration and such MFIs have to sustain by means of donations and grants from donors, e.g. non-governmental organization based MFI (NGO-MFI). Using traditional ratio approach to gauge MFI performance can be vague: an MFI can excel in one aspect however fail in others, consequently causing problem in general benchmarking (Bogetoft, Otto 2011).

Efficiency is therefore proposed in this study to gauge the performance of the MFIs because of its ability to cover both diverse aspects of microfinance and to be connected to both business and not-revenue driven MFIs (Balkenhol 2007).

Efficiency relates utilization of inputs to create output (Cooper et al. 2000). Subsequently, efficiency approach which is capable of estimating efficiency taking multiple inputs and multiple outputs in order to benchmark the performance of MFIs is Data Envelopment Analysis (DEA), explained below.

DEA was first propounded by Charnes, Cooper & Rhodes (1978), broadly known as the CCR, as an extension of single input-output productive efficiency model proposed by Farrell (1957). Using linear programming, it frames a "drifting" piecewise linear production frontier on top of all data as best-practice benchmark set against which each DMU is evaluated, thus it is called "envelopment" (Cook, Zhu 2005; Emrouznejad, Anouze 2010; Fluckiger, Vassiliev 2007). Technical Efficiency is calculated as distance of DMU to reference set, making relative productivity measure for all Decision Making Units (DMUs) (Cook, Zhu 2005; Cooper et al. 2004; Emrouznejad, Anouze 2009). Since its inception, DEA has been widely applied in efficiency estimation of various financial and non-financial organisations.

Two essential DEA models are CCR model of Charnes et al. (1978) and BCC model of Banker et al. (1984). CCR demonstrate technical efficiency under Constant Return to Scale (CRS) condition and states that multiple inputs and outputs for a given DMU are linearly aggregated into single 'virtual' input and output (Widiarto, Emrouznejad 2015). On the other hand, BCC model in Banker et al. (1984) modifies CCR model by applying a more realistic assumption of Variable Returns to Scale (VRS) wherein each DMU is allowed to exhibit different returns to scale due to different environment, hence named VRS model (Widiarto, Emrouznejad 2015).

Two approaches in basic DEA models are input-oriented and output-oriented. In input oriented model, the input reduction is proportionally maximized, keeping output constant while in output-oriented model, the output is proportionally maximized holding inputs constant, the following equation 1 and equation 2 explains input-oriented and output-oriented models respectively.

$\Theta = \text{Min } \Theta$ Subject to $\sum_{j=1}^{n} \lambda_j y_{ri} \geq y_{r0}$, r=1,2,...,s; $\sum_{j=1}^{n} \lambda_j x_{ij} \leq \Theta x_{i0}$, i=1,2,...,m; $\sum_{j=1}^{n} \lambda_j = 1$ (eq 1) $\lambda_j \geq 0$, j=1,2,...,n.	$\varnothing = \text{Max } \varnothing$ Subject to $\sum_{j=1}^{n} \lambda_j y_{ri} \geq \varnothing\, y_{r0}$, r=1,2,...,s; $\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}$, i=1,2,...,m; $\sum_{j=1}^{n} \lambda_j = 1$ (eq 2) $\lambda_j \geq 0$, j=1,2,...,n.

Banker added $\sum_{j=1}^{n} \lambda_j$ =1 in the constraint set to represent convexity constraint for λk in VRS condition; ensuring a DMU to be compared only to similarly-sized DMUs with similar return to scale. Pure technical efficiency scores from BCC model is thereby greater or equal to global technical efficiency scores from CCR model as DMU is measured relative to smaller number of DMUs (Thanassoulis 2001).

Most of the industries, besides producing desirable outputs, produce certain undesirable outputs too. Pollution produced in manufacturing industry, NPA in banking industry are example of undesirable output. Koopmans (1951) suggested the ADD approach where f (U) = -U through which the undesirable output or input could be transformed to desirable output or input. However, Liu & Sharp (1999) stated that one may regard an undesirable input as a desirable output and an undesirable output as a desirable input. This approach signifies that efficient DMUs wish to maximise desirable output and undesirable inputs. Fare et al. (1989) developed a non linear program for treating undesirable outputs: Max Θ, subject to $\Theta\, y_g \leq Y_G$, $\Theta^{-1} y_b = Y_B$ and $x \geq X$, Technical Efficiency = 1/Θ.

5. Review of literature

Microfinance Institutions are the budding financial institutions in developing nations, and are considered as an important area of research. Good number of studies is conducted across the globe in different aspects of Microfinance Institutions; however, here we are concentrating only on those studies which are related to estimation of the efficiency of the Microfinance Institutions. Ratio Analysis is considered to be traditional technique of gauging financial performance; however, Thanassoulis et al. (1996) made a study to compare the traditional ratio analysis technique with Data Envelopment Analysis in assessing the performance of District Health Authorities of England. Result highlighted that though both the methods agree reasonably on the performance of the unit as a whole but ratio analysis, unlike DEA is not found to be suitable for setting targets. Again, for estimating efficiency of financial institutions Stochastic Frontier Approach (SFA) has been widely used, to cite a few: Worthington (1998) used SFA to estimate the efficiency of Credit Unions in Australia. Study was made over 150 Australian credit unions and later used limited variable regression technique to relate credit unions' efficiency scores to structural and institutional consideration. Result of the study implies noncore commercial activities are not a significant influence on the level of cost inefficiency. Quayes (2012) used SFA to present an empirical analysis of the cost efficiency of MFIs in Bangladesh and his results shows that larger MFIs are more efficient with some evidence of a trade-off between efficiency and outreach.

Considering the present study, comprehensive review of the studies relating to the use of Data Envelopment Analysis in gauging the efficiency of financial institutions and more particularly that of Micro Finance Institutions across the globe is made which is presented in the following paragraph.

Soterou & Zenios (1997) and Canhoto & Dermine (2003) both conducted an empirical study to measure efficiency of banking industry, the former took 144 branches of major commercial banks in Cyprus as samples and the later took 20 banking institutions including new and old commercial banks in old Portugal. Efficiency of the samples in both the studies was measured through Data Envelop Analysis model. The major findings of the former study were: superior insights can be obtained by analyzing simultaneously operations, service quality and profitability whereas the later findings implies improvement in efficiency for the overall samples and the new banks dominate the old ones in terms of efficiency. Good number of studies has been made so far on estimating the efficiency of MFIs using Data Envelopment Analysis, to cite a few: Conhoto & Dermine (2002), Neito et al. (2005), Haq et al. (2010), Neito et al. (2009), Kripesha (2013) studied the estimation of efficiency of MFIs using Data Envelopment Analysis. Neito et al. (2005) made a study in order to measure the efficiency of MFIs. Secondary data were collected for 30 Latin American MFIs (Bolivia, Colombia, Dominican Republic, Ecuador, Mexico, Nicaragua, Peru and Salvador) for one year. Result of the study implies that there are country effects on efficiency; and effects that depend on non-governmental organization (NGO)/non-NGO status of the MFI but Haq et al. (2010) made a study to examine the cost efficiency of 39 MFIs across Africa, Asia and Latin America. Data Envelopment Analysis was used for the said study and findings of the study shows that non government MFIs were the most efficient; under intermediation approach, bank MFIs also outperform in the measure of efficiency. Neito et al., (2009) made a study to estimate the efficiency of MFIs in relation to financial and social outputs. Impact on women and poverty reach index has been taken as social performance indicators. The study was made on 89 MFIs and results reveal the importance of social efficiency index. Kripesha (2013) studied the technical efficiency of Microfinance Institutions operating in Tanzania, 29 MFIs were selected for the study and relevant data were collected during the period 2009-2012 through secondary sources and were evaluated using Data Envelop Analysis model. The major findings of the study were: Higher average technical efficiency was observed under production efficiency and most of inefficiency in MFIs was result of inappropriate scale. In India, Singh (2014) conducted a study to examine the efficiency of Indian MFIs over thirty MFIs and a modified form of Data Envelopment Analysis was used, results of the study indicated the inefficiencies of the microfinance sector.

Few studies on estimating performance of MFIs extended to identification of the determinants of efficiency, to cite a few: Nghiem et al. (2006) investigated the efficiency of the microfinance industry in Vietnam. The study was conducted with 46 schemes in the north and central regions. DEA was used to gauge the efficiency of the schemes and later used Tobit regression was used to identify the determinants of efficiency. Result of the study shows that average technical efficiency of the schemes is estimated to be 80 percent and age and location of the schemes are found to be significantly influencing the efficiency. Nawaz (2010) measured the financial efficiency and productivity of the MFIs worldwide considering the subsidies received by the MFIs using DEA. A three stage analysis was adopted for the study where firstly the efficiency of the MFIs is estimated followed by analysing the productivity changes using Malmquist indices and lastly tobit regression is used to identify the determinants of efficiency. Result of the study highlighted substitution between outreach to the poor and financial efficiency, lending to women is efficient only in the presence of subsidies and MFIs in South Asia and Middle East and North Africa tend to be less efficient than others. Abayieet et al. (2011) investigated the economic efficiency of MFIs in Ghana using parametric Stochastic Frontier Approach followed by the use of Tobit regression to identify the determinants of efficiency. The study was conducted on 135 MFIs over a period of four years. Result of the study presented the overall average economic efficiency to the extent of 56.29 percent; age, savings and cost per borrowers were the significant determinants of efficiency. Singh et al. (2013) estimated efficiency of 41 MFIs in India using non parametric DEA where both input oriented and output oriented approaches were used. Later the study used Tobit regression to identify the determinants of efficiency. The findings of the study highlighted that output of the MFIs could be increased to the extent of 59.4 percent; 25 MFIs experienced economies of scale under input oriented approach and 10 MFIs under output oriented approach and MFIs operating in southern part of India are found more efficient. Wijesiri et al. (2015) examined the technical efficiency of 36 MFIs in Sri Lanka using two-stage DEA approach. Bootstrap DEA was used to estimate efficiency followed by the use of double bootstrap truncated regression approach. Result of the study highlighted that most of the MFIs in Sri Lanka were financially and socially inefficient and age and capital-to-asset ratio were crucial determinants of efficiency.

Reviewing the aforementioned studies exhibit that scanty of studies are made to estimate the efficiency of Indian MFIs. Moreover, no study till date has been made to estimate the efficiency of the Indian MFIs to address the bad output, which is an important aspect of the microfinance industry. Besides, the researcher has not come across any study that verifies whether sustainability has any impact over efficiency. Therefore the present study tries to fill this research gap by framing the following objectives of the study:

- Estimate efficiency of the selected MFIs using BCC model and Undesirable Output Model.
- Identify determinants of efficiency, specifically to check whether sustainability has any impact on efficiency.

6. Research design and model specification

Sample Size and Data Source: Secondary data is collected for thirty-one Indian MFIs for six years (2009-2015) from MixMarket.

Selection of Models for Efficiency Estimation and Selection of Inputs and Outputs: The study used production approach to access the performance of MFIs considering the fact that most of the Indian MFIs do not collect deposit (Fluckiger, Vassiliev 2007; Neito et al. 2009; Neito et al. 2007; Haq et al. 2010; Kripesha 2012). The study employs input oriented-BCC model to estimate technical efficiency. Since the MFIs differ in their operational size, therefore such difference in their operational size is likely to affect efficiency. Hence BCC model using VRS assumption is naturally more appropriate in estimating the performance of MFIs (Emrouznejad, Widiarto 2015). Beside BCC model, the study also computes the efficiency of the MFIs using output oriented-Undesirable Measure Model (UMM). The study uses UMM considering the fact that the Microfinance industry produces certain undesirable outputs which cannot be ignored. The selection of inputs and outputs used in the study is on the basis of their repetition in the studies relating to efficiency of Microfinance Industry. Table 1 exhibits the definition of selected inputs and outputs along with their use in other studies.

Table 1. Details of Inputs and Outputs used in the study

Specification (Model)	Variable	Definition	Usage in literature	Unit	MFI Objective Represented
Input (BCC & UMM)	Operating Expenses	Operating expense as a percentage of gross loan portfolio	Gonzoalex (2008), Neito et al. (2005), Tahir, Tahrim (2013), Gebremichael, Rani (2012), Ferdousi (2013)	₹	Financial Efficiency
Input (BCC & UMM)	Employees	The number of individuals who are actively employed by an entity. This number includes contract employees or advisors who dedicate a substantial portion of their time to the entity, even if they are not on the entity's employee’s roster.	Gonzoalex (2008), Neito et al. (2005), Tahir, Tahrim (2013), Gebremichael, Rani (2012), Ferdousi (2013)	Number	Social Efficiency
Output (BCC & UMM)	Gross Loan Portfolio	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off.	Nawaz (2010), Gonzalez (2008), Singh et al. (2013), Tahir, Tahrim (2013), Ferdousi (2013)	₹	Financial Efficiency

Table 1. Continuation

Specification (Model)	Variable	Definition	Usage in literature	Unit	MFI Objective Represented
Output (BCC & UMM)	Number of Active Borrowers	The numbers of individuals or entities who currently have an outstanding loan balance with the MFI or are primarily responsible for repaying any portion of the Loan Portfolio, Gross.	Annim (2012), Gonzalez (2008), Tahir, Tahrim (2013), Ferdousi (2013)	Number	Social Efficiency
Output (UMM)	Portfolio at Risk more than 30days (PAR30)	Represents the portion of loans greater than 30 days past due, including the value of all renegotiated loans (restructured, rescheduled, refinanced and any other revised loans) compared to gross loan portfolio. The most accepted measure of a financial institution's portfolio quality.	Not been used as output in any DEA-microfinance literature	Percentage	

Source: Literature Survey
NB: Description of the variables as per MIX Glossary

The study follows the widely used practice by the micro economic researchers on efficiency. The estimated efficiency score of the BCC Model and Undesirable Measure Model is to be regressed on sustainability, other control and firm-specific variables in order to identify the factors that influence efficiency. Identification of such factors will help the new and existing MFIs to increase their efficiency level

(Elyasiani, Mehdian 1990; Casu, Molyneux 2000; Isik, Hassan 2003; Masood, Ahmad 2010). Equation I and equation II presents the two regression models using the efficiency scores of BCC and UMM respectively.

Y_{BCC} = f (GLP, DE, ROA, ROE, NAB, OSS, S) ....(I)

Y_{UMM} = f (GLP, DE, ROA, ROE, NAB, OSS, S) ....(II)

Y_{BCC} and Y_{UMM} represents the efficiency scores of BCC and UMM respectively. GLP (Gross Loan Portfolio) represents all outstanding principle due for all outstanding client loans. DE (Debt-Equity Ratio) represents total liabilities of the firm compared to equity. ROA (Return on Asset) represent net operating income (less taxes) compared to average assets. NAB (Number of Active Borrowers) represents the number of individuals or entities who have an outstanding loan balance with the firm. OSS (Operational Self Sufficiency) measures the firm's ability to cover its cost through operating incomes. S (Scale) signifies the proportion of Gross Loan Portfolio sanctioned by the firms. The detailed description of the explanatory variables is highlighted in table 2.

Table 2. Explanation of the independent variables

Variables	Computation	Expected Sign
GLP	Total Loans of MFIs	+
DE	Debt/Equity	-
ROA	Net Profit/Total Asset	+
ROE	Net Profit/Share Capital	+
NAB	The total active borrowers of MFIs	+
OSS	Operating Income/(Operating Cost + Financing Cost + Loan Loss Provision)	+
S	Proportion of Gross Loan Portfolio sanctioned by MFIs (Large = GLP more than ₹52.31 crore, Medium = ₹13.07 crore to ₹52.31 crore and Small= GLP less than ₹13.07 crore) (Vector of Dummy Variable) 1=Small, 2= Medium, 3= Large	+

Source: Literature Survey
NB: Classification of the variable "Scale" as per MIX Glossary

7. Result of first-stage DEA

Table 3 highlights the Overall Technical Efficiency of the sample MFIs over the study period, i.e., from 2009 to 2015 and also shows the decomposition of the overall technical efficiency into Pure Technical Efficiency and Scale Efficiency. From the table it can be stated that for the average technical inefficiency of 20 percent (1-0.80) is explained by Pure Technical Inefficiency estimates of 23 percent (1-0.77), that is due to managerial inefficiency in miss utilization of resources resulting into wastages and the rest explained by Scale Inefficiency to the extent of 11 percent (1-0.89) due to the MFIs' operating at sub optimal scale of operation.

Table 3 also presents the technical efficiency scores of the MFIs under both BCC Model-Input oriented as well Undesirable Measure Model-Output oriented; the table shows average TE score under BCC model is 0.79 which implies Technical Inefficiency to the extent of (1-0.79) 21 percent. This indicates that the sample MFIs can reduce cost to the extent of 21 percent and still produce the same output whereas, the average TE score under UMM is estimated to be 0.98, implying the Technical Inefficiency to the extent of (1-0.984) 2 percent which implies that with reducing cost to the extent of just 2 percent the sample MFIs can produce the same output.. The average TE scores range between 0.70 and 0.87 in case of BCC Model and between 0.98 and around 1.00 in case of Undesirable Measure Model. Overall, the MFIs exhibit a consistent trend in the TE scores in case of both the models as evident by a lower standard deviation.

Table 4 represents how the relatively inefficient MFIs can reach the production frontier by altering their bad output. The result of the study highlights that during the study period, 2010 was marked to be the year when the average efficiency score of the MFIs was lowest. However, few MFIs, such as Asirvad, Belghoria, BSS, Chaitanya, Mahasemam, Sanghamithra, SKDRDP, SKS, Smile, Sonata and Spandana, remained efficient throughout the study period. The table also natters that on average, the MFIs require to trim their bad output (PAR30) to an extent of 14 percent. Table 4 exhibit in details the quantity of PAR30 the inefficient MFIs need to trim in order to become efficient.

Table 3. Technical efficiency scores under BCC and UM model (2009-2015)

YEAR	TE and Decomposition under BCC Model			Technical Efficiency Scores under Undesirable Measure Model (Output oriented)
	Overall Efficiency	Pure Technical Efficiency	Scale Technical Efficiency	
2009 (N=31)	0.819	0.819	0.933	0.988
2010(N=31)	0.868	0.868	0.964	0.987
2011(N=31)	0.855	0.855	0.935	0.976
2012(N=31)	0.740	0.740	0.925	0.986
2013(N=31)	0.770	0.770	0.888	0.991
2014(N=31)	0.781	0.781	0.875	0.991
2015(N=30)	0.699	0.537	0.699	0.986
$\bar{X}$	0.790	0.767	0.889	0.986
STDEV	0.061	0.111	0.089	0.005
MAX	0.868	0.868	0.964	0.991
MIN	0.699	0.537	0.6994	0.976

Source: Own calculation using DEA Frontier and DEAP
Note: STDEV= Standard Deviation
MAX= Maximum
MIN= Minimum

Figure 1 exhibits the distribution of MFIs in Efficiency Range estimated through BCC model-Input oriented model. Result highlights that under Input oriented-BCC Model, most of the MFIs' efficiency score ranges between 0.71 and 0.99, indicating that on an average the sample MFIs display cost savings potentiality to the extent of 1percent to 29 percent. The figure also portrays that two MFIs (Sanghamithra and Spandana) under BCC- input oriented model were highly efficient.

However, in Output oriented-Undesirable Measure Model most of the MFIs efficiency score ranges between 0.9 and 1.00 meaning thereby on an average the MFIs have potentiality of around 1 percent to reduce the undesirable output and reach efficiency frontier.

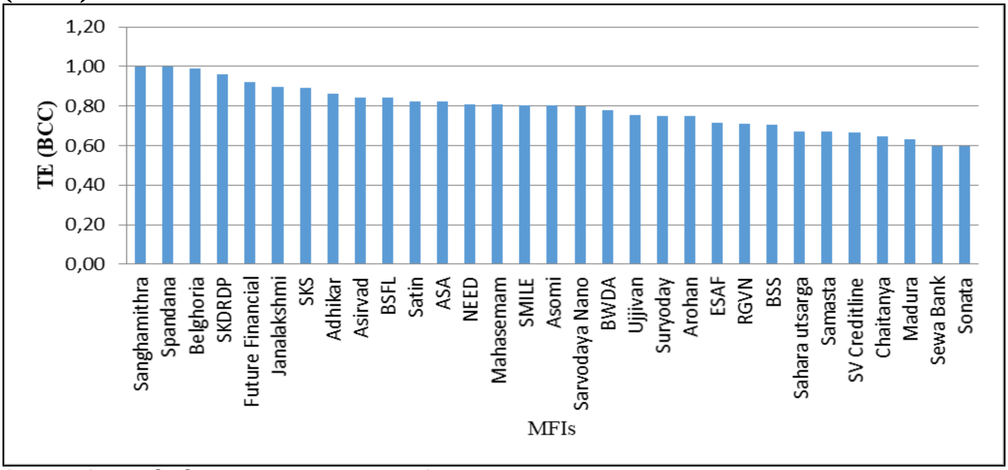
Table 4. Volume of PAR30 inefficient MFIs need to Adjust

MFIs	2010	2011	2012	2013	2014	2015	$\bar{X}$
Adhikar						0.072	0.072
Arohan		0.719					0.719
ASA	1.885						1.885
Asomi	2.289	1.339					1.814
BSFL	37.761		66.681		20.569		41.670
BWDA	5.936	373.171					189.554
ESAF		1.229					1.229
Future Financial		21.344	18.404	8.918	4.539		13.301
Janalakshmi	1.628						1.628
Madura	2.088						2.088
NEED	0.749						0.749
RGVN	3.579						3.579
Sahara utsarga	2.537				1.354	1.377	1.756
Samasta	1.309					0.214	0.762
Sarvodaya Nano	8.622				2.309	0.507	3.813
Satin			0.799				0.799
Sewa Bank	12.802	11.412	21.706		12.369	12.353	14.128
Suryoday	5.019						5.019
SV Creditline	0.669					0.246	0.458
Ujjivan		1.199	0.199				0.699
$\bar{X}$	6.205	58.630	21.558	8.918	8.228	2.461	

Source: Own calculation using DEA Frontier
N.B: Volume of PAR30 to be adjusted = Actual Output- Targeted Output

Table 5 exhibits the ranking of MFIs under both BCC and Undesirable Measure Models as per their technical efficiency, to estimate the correlation between the ranks obtained under the two models Spearman's Rank Correlation is estimated, which shows a value of 0.43 indicating a high positive correlation between ranks of both the models. This is also evident from the fact that Sanghamithra and Spandana are the MFIs which are ranked first under both the Models.

Figure 1. Distribution of MFIs in efficiency range (BCC Model-Input oriented) (N=31)



Source: Own calculation using Frontier DEA

Table 5. Spearman's Rank Correlation of the MFIs between their Efficiency scores calculated under BCC Model and Undesirable Measure Model (n=31)

DMU	BCC	UMM	DMU	BCC	UMM
Adhikar	8	19	NEED	13	16
Arohan	21	17	RGVN	23	26
ASA	12	23	Sahara utsarga	25	25
Asirvad	9	7	Samasta	26	15
Asomi	16	11	Sanghamithra	1	1
Belghoria	3	1	Sarvodaya Nano	17	27
BSFL	10	30	Satin	11	21
BSS	24	13	Sewa Bank	30	31
BWDA	18	29	SKDRDP	4	1
Chaitanya	28	8	SKS	7	12
ESAF	22	22	SMILE	15	5
Future Financial	5	28	Sonata	31	20
Janalakshmi	6	9	Spandana	1	1
Madura	29	24	Suryoday	20	18
Mahasemam	14	6	SV Creditline	27	14
			Ujjivan	19	10
Spearman's Rank Correlation			0.434		

Source: Own calculation using MS Excel

8. Result of second-stage: Tobit Regression

Table 6 exhibits the result of the Tobit regression under both BCC and Undesirable Measure Model. Result of Tobit regression reflect that in case of BCC model the coefficient of Operational Self Sufficiency (OSS), showed positive impact on efficiency, which is as per the researcher's expected sign, however, the result showed coefficient value of OSS 0.001 unit, Singh et al. (2015), Masood and Ahmad (2010) and Gonzalez (2007) also support the finding. The coefficient of Gross Loan Portfolio showed positive impact upon the efficiency of the MFIs which is as per the expectation of the study. Meaning thereby that with one unit increase in GLP, efficiency will increase to the extent of 1.30 units and the finding is supported by Masood and Ahmad (2010). Debt Equity Ratio and Return on Asset accounted to be significantly insignificant.

Table 6. Results of Tobit Regression (Model 1 and Model 2)

E		Coef.		P>|t|		[95% Conf. Interval]			
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 1	Model 2	Model 2
GLP		1.30	7.31	0.023	0.645	1.83	2.43	-2.39	3.85
DE		-0.00	-0.00	0.89	0.64	-0.00	0.00	-0.00	0.00
ROA		-0.01	0.001	0.300	0.68	-0.023	0.01	-0.00	0.01
ROE		-0.001	-0.00	0.04	0.44	-0.00	-0.00	-0.00	-0.00
NAB		4.08	3.23	0.004	0.41	1.31	6.85	-4.46	1.90
OSS		0.001	0.00	0.002	0.70	-0.001	-0.00	-0.00	0.00
S		0.06	0.01	0.01	0.12	0.02	0.10	-0.002	0.02
-cons		0.70	0.97	0.00	0.00	0.64	0.76	0.96	0.99
/sigma		0.16	0.04			0.14	0.17	0.90	0.49

Source: Own calculation using STRATA11

Coefficient of Return on Equity also upholds the researcher's expected sign against this variable indicating one unit increase in Return on Equity will reduce the efficiency by 0.001 unit, the finding is supported by the studies of Singh, et al. (2015) and Masood and Ahmad (2010). The coefficient of Debt Equity ratio is negative which is as per the expectation of the study and is in line with other studies made by Singh et al. (2015), Masood and Ahmad (2010) and Gonzalez (2007). The coefficient of Number of Active borrowers showed positive effect upon efficiency which is as per our assumption, reflecting that one unit of increase in number of active borrowers will increase efficiency to the extent of 3.23 units. Size of the MFIs measured in terms of Scale of operation showed positive impact on the efficiency of the MFI to the extent of 5.7 percent.

Tobit result in case of Undesirable Measure model shows insignificant result in case of all the variables.

9. Conclusion and direction for future research

The present study made an attempt to estimate the Technical Efficiency of selected Indian MFIs over seven years (2009-2015) and thereafter to identify the determinants of efficiency and more particularly to answer whether Sustainability has significant impact on Technical Efficiency. The study used non parametric DEA technique and efficiency is estimated under two models: BCC Model and Undesirable Measure Model, result shows that average TE score under both the models lies between 0.71 and 0.99 implying Technical Inefficiency to the extent of 29 to 1 percent Thereafter the MFIs are ranked as per their Efficiency scores under the two models (BCC and UMM) which shows that Sanghamitra and Spandana are the MFIs which are ranked first under both the Models; when Spearman's Rank Correlation is estimated, result highlights a value of 0.43 indicating a positive correlation between ranks of both the models. Subsequently determinants of Technical Efficiency (under both the models) is identified where it is found that sustainability measured in terms of OSS ratio is found to be having a significant positive impact on TE under BCC model. Besides, it has also been found that in case of Model 1 (BCC Model) Gross Loan Portfolio, Return on Equity, Number of Active Borrowers and Scale of Operation of the MFI are statistically significant at 5 percent level of significance.

As the empirical results indicate that there exist cost savings potentialities on the part of sample MFIs under both the models, therefore there is a need for cost trimming following the best practice. The managers should devote their attention in optimizing the output and reducing the cost. Special care should be taken to vigil timely loan repayment so that rate of PAR30 could be pulled back. At the same time, since sustainability is found to be having a positive significant impact on technical efficiency, therefore, the MFIs should target on maximizing their revenues so as to absorb the costs sufficiently, as it can be comprehended from the analysis that a sustainable MFI is an efficient MFI.

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Determinanty wydajności instytucji mikrofinansowych w Indiach: dwuetapowa analiza DEA

Streszczenie

Cel: Instytucje mikrofinansowe (ang.: *Microfinance Institutions* (MFIs)) wyłoniły się w Indiach jako główny gracz z punktu widzenia świadczenia usług mikrofinansowych. Z tego względu instytucje te muszą być stabilne finansowo, aby osiągnąć założony cel w postaci podwójnych zysków (ang.: *double bottom-line*). Poza tym, indyjskie MFIs nie mogą się ochronić przed klątwą niespłacania pożyczek. Dlatego też celem niniejszego artykuły jest pomiar kondycji indyjskich MFIs oraz określenie, czy podtrzymywalność ma znaczący wpływ na wydajność MFIs.

Metodyka badań: Aby zdiagnozować kondycję indyjskich MFIs, wykorzystano nieparametryczną metodę obwiedni danych (ang. Data Envelopment Analysis (DEA)). Dla bardziej dogłębnej analizy zastosowano dwa modele DEA (zorientowany na nakłady model BCC oraz zorientowany na wyniki Undesirable Measure Model). Następnie użyto w badaniach regresji Tobita w celu określenia czynników oddziałujących na wydajność MFIs, a w szczególności w celu odpowiedzi na pytanie, czy podtrzymywalność ma znaczący wpływ na wydajność. W badaniach wykorzystano uzyskane z MiX Market dane dotyczące 31 indyjskich MFIs w latach 2009-2015.

Wnioski: Wyniki badań wskazują, że techniczną wydajność MFIs można oszacować na poziomie 79% w modelu BCC oraz 98% w *Undesirable Measure Model*. Indyjskie MFIs mogą osiągnąć granicę produkcji, jeśli zdołają obniżyć złe wyniki (określone przy portfelu ryzyka 30) do poziomu około 14%. Ponadto badania potwierdziły, że podtrzymywalność (określona przez samowystarczalność operacyjną) ma pozytywny wpływ na wydajność.

Wartość artykułu: Dotychczasowe badania indyjskich MFIs nie koncentrowały się na tym, jak MFIs mogą stać się wydajne poprzez redukcję niepożądanych / złych wyników. Ponadto żadne dotychczasowe badanie nie analizowało wpływu podtrzymywalności na wydajność indyjskich MFIs. Z tego względu niniejszy artykuł stara się wypełnić istniejącą lukę badawczą.

Implikacje: Wyniki badań mogą być przydatne dla indyjskiego przemysłu mikrofinansowego w celu poprawy jego wydajności. Wyniki mogą być też wykorzystane przez Indyjski Bank rezerw (ang. *Reserve Bank of India*, aby stworzyć wspólną miarę dla klientów MFIs w połączeniu z zaciąganiem pożyczek w MFIs.

Słowa kluczowe: instytucje mikrofinansowe, podtrzymywalność, metoda obwiedni danych (DEA)

JEL: G21, C67, C33

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Technical efficiency decomposed – The case of Ugandan referral hospitals

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Abstract:

Aim: In an audit report provided to the Ugandan Parliament by the Office of the Audit General, Uganda, technical efficiency in Ugandan referral hospitals was measured and analysed. The audit report pointed out that there was a relatively low level of technical inefficiency, at least in comparison with other African countries. The purpose of this study is to look further into the issue of why there is inefficiency.

Design / Research methods: We use a Data Envelopment Analysis framework and decompose long-run technical efficiency into short-term technical efficiency, scale efficiency and congestion.

Conclusions / findings: Our results reveal that the source of the long-run inefficiency varies over the years. For 2012, more than 50% of the observed inefficiency relates to scale factors. However, in 2013 and 2014 the major contributor to the long-run inefficiency was input congestion.

Originality / value of the article: Even though there are a substantial amount of research on efficiency in African hospitals, no other study have investigated existence of congestion. In that respect our research contributes to the existing research.

Implications of the research: We recommend that inefficient hospitals should use efficient hospitals as benchmarks for improving their own efficiency. Further, since a large part of the technical inefficiency relates to congestion we recommend further investigation to identify factors in the production, or organisation that could be related to congestion.

Key words: technical efficiency, scale efficiency, congestion, Uganda, hospitals

JEL: D2, H4, I2.

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1. Introduction

In sub-Saharan Africa, poor health among the population is generally a reality, and Uganda is no exception here. One cause could be that the health care systems are inadequate to meet the needs of the ever-growing population. This suspicion has raised concerns among policy makers and planners about whether health services are being delivered efficiently by hospitals. This study is a development of the work presented in the Uganda Office of the Audit General (2016). In that study long run technical efficiency was investigated and the result was that, compared to other studies targeting African hospitals, the inefficiency was relatively low. However, in secondary analysis performed there were indications that not only internal factors contributed to the inefficiency. The report reported for example bed occupancy rates above 100 per cent which indicates congestion. The development in this paper consists of analysing factors that are not directly related to the overuse of inputs, but relates to different parts of the production. This includes the concept of scale efficiency as well as congestion.

The outline of the study is as follows. Section 2 will give a brief overview of the health care sector in Uganda. In section 3 we will make a comprehensive survey of previous studies targeting technical efficiency in hospital services production in African countries. The main finding is that, even if there are similarities between the country-specific studies in terms of how production is defined, there is a large variation in technical efficiency. This suggests that countries can learn from each other. Further, we have not found any study that explicitly studies the influence of congestion on long run technical efficiency. In section 4 we present the model, definitions and data used for this study. In this section we also discuss the inputs and outputs selected for our study, and we introduce the concept of input congestion. The inputs and outputs have been chosen after considering previous studies and in discussion with the stakeholders. In section 5 our results are presented. Overall, we find relatively small amount of inefficiency, especially when compared to other African countries. Our results also reveal that the source of long-run inefficiency varies between years. For 2012 more than 50% of the observed inefficiency related to scale factors. However, in 2013 and 2014 the major contributor to long-run inefficiency relates to congestion.

2. The health sector in Uganda – a short description

In Uganda, hospital services are provided under a four-tier health care system (primary, secondary, tertiary and quaternary care), with regional referral hospitals (RRHs) being major contributors to essential clinical care because of their provision of specialist clinical services. This study covers thirteen out of the fourteen RRHs in Uganda.

The state has a duty to guarantee the right to health care to all its citizens. In addition, a number of international treaties oblige the Government of Uganda to commit sufficient resources and establish a comprehensive health care framework that meets the health needs of its citizens.[1] In order to deliver the health services required, the Government of Uganda has endeavoured to put in place a regulatory framework in line with the 1995 Constitution of the Republic of Uganda (as amended). The regulatory framework spells out the responsibilities of hospitals at different levels, including RRHs, to provide for the health care needs of the population. Over the past three financial years (2011/12, 2012/13 and 2013/14), there has been an 18% increment in the funding of RRHs, which has risen from UGX 53.86 billion to UGX 63.56 billion (Ministry of Finance, Planning and Economic Development 2011, 2013). Despite the increase in the funding of RRHs over the years there has been a declining quality of health services in the country. This decline in quality is mainly attributed to the lack of drugs and other stocks, the shortage of health workers, delays in accessing health care services in every RRH, mismanagement of hospital infrastructures, and the overcrowding of hospital facilities. This has raised concerns as to whether these hospitals are operating efficiently with the resources available to them. There is a need for the efficient

[1] We refer here to international treaties such as the International Covenant on Economic, Social and Cultural Rights (ICESCR), the Universal Declaration of Human Rights (UDHR) and the Convention on the Rights of the Child, and a number of other non-binding declarations such as the Alma Ata Declaration, the Millennium Declaration and the Abuja Declaration, among others.

provision of clinical and non-clinical services to produce a healthy population as an input for economic development. The inefficiency in the RRHs is an issue that needs to be addressed if Uganda is to reap significant savings from all the activities carried out by RRHs and to meet its Millennium Development Goals related to health.

Uganda has fourteen autonomous RRHs that are responsible for delivering a complementary, integrated, and continuous package of health care to achieve a common national goal. RRHs offer specialised services such as psychiatry, Ear, Nose and Throat (ENT) services, radiology, pathology, ophthalmology, and higher level surgical and medical services, including teaching and research. This is in addition to the services offered at general hospitals. RRHs are required to provide this more specialised care for a population of 2,000,000 people, to have a bed capacity of 500, to employ an average of 349 members of staff and to maintain all the relevant health equipment prescribed by the Ministry of Health. The Ugandan hospital policy provides that RRHs are part of the system for delivering health services in Uganda. RRHs derive their vision and mission from the vision of the health sector, which is: “A healthy and productive population that contributes to social-economic growth and national development” (Ministry of Health 2010: 38). The stated mission for the sector is: “To provide the highest possible level of health services to all people in Uganda through delivery of promotive, preventive, curative, palliative and rehabilitative health services at all levels.” (Ministry of Health 2010: 38). The organisational structure of RRHs includes a Management Board as the highest authority; this provides oversight for the activities of the hospital. The executive function is headed by the Hospital Director. The Government of Uganda’s budget allocation to the thirteen (out of the existing fourteen) RRHs under review for the financial years 2011/12 to 2013/14 amounted to an average of UGX 59 billion, while the money spent amounted to an average of UGX 57.8 billion.

3. Previous studies of hospital efficiency in African countries

Data Envelopment Analysis (DEA) has been widely used across the world to analyse the efficiency in general but also of hospitals.[2] O'Neill et al. (2008) present a survey of efficiency studies on hospitals that spans the time period 1994 to 2004. One of their general findings is that the majority of studies used an input-oriented DEA model. Furthermore, they show that about half of the studies used a long run perspective, i.e. a constant return to scale (CRS) model. The other half used either a short run, i.e. a variable return to scale (VRS) model, or both a VRS and a CRS model. When it comes to quality measures, O'Neill et al. (2008) identify only six studies that included a quality measure such as risk-adjusted in-hospital mortality. The majority of studies have been conducted in the USA and in Europe, however recently several studies on technical efficiency have been conducted in African countries. Studies in countries like Algeria, Angola, Botswana, Burkina Faso, Ghana, Kenya, Namibia, South Africa, Uganda and Zambia have all used DEA to evaluate hospital efficiency. However, none of the studies investigate existence of congestion. We therefore use previous research to determine model and to get a reference for the computed long run efficiency scores. Table 1 summarises the findings of the previous studies in African countries. The presentation is divided into two parts according to the number of studies in each country. First, countries with more than one study are reported, and, thereafter, countries with only one study.

[2] See e.g. Emrouznejad, Yang (2018) for a recent survey of the use of DEA.

Table 1. Studies of technical efficiency in hospitals on the African continent

Author	Country	Units	Data year	No. of inputs	No. of outputs	Method	No. of efficient units	Average technical inefficiency
Multiple country studies								
Marschall & Flessa (2009)	Burkina Faso	20	2004	4	4	DEA	14	29%
Marschall & Flessa (2011)	Burkina Faso	25	2005	4	4	DEA (two stage)	11	13.8% (CRS)
Ramanathan et al. (2003)	Botswana	13	1997	5	14	DEA (SFA per output)	12	1%
Tlotlego et al. (2010)	Botswana	21	2006 – 2008	2	2	DEA	3 (CRS) 8 (VRS)	53%-38%
Akazili et al. (2008a)	Ghana	89	2004	4	5	DEA	30	28%
Akazili et al. (2008b)	Ghana	113	2003/2004	4	5	DEA (two stage)	25	Not reported
Osei et al. (2005)	Ghana (hospitals)	17	2000	4	4	DEA	9	18.5%
	(health centres)	17	2000	2	4	DEA	15	9%
Kirigia et al. (2001)	South Africa	115	1996	2	8	DEA	47	26%
Zere et al. (2001)	South Africa	86	1992/93 – 1996/97	2	2	DEA	11 (total)	35% - 47%
Kibambe & Koch (2007)	South Africa (Gauteng)	14	2004	3	4	DEA	Uses each output separately and several models	30.7% - 1.1%
Linden (2013)	South Africa	52	2007 – 2009	3	4	DEA	7 for all years	10.6%; 9.5%; 9.4%
Masiye (2007)	Zambia	30	2006	6	4	DEA	12	33%
Masiye et al. (2006)	Zambia	40		3	1	DEA	5	38%

Table 1. Continuation

Author	Country	Units	Data year	No. of inputs	No. of outputs	Method	No. of efficient units	Average technical inefficiency
Single country studies								
Djema & Djerdjouri (2012)	Algeria	174	2008	4	5	DEA (two stage)	60	25%;19% ; 23%
Kirigia et al. (2008)	Angola	28	2000 – 2002	3	2	DEA, Malmquist index	11,12,10 (yearly)	33.8%; 34.2%; 32.5%
San Sebastian & Lemma (2010)	Ethiopia	60	2000	2	8	DEA	15 (CRS), 31 (VRS)	43%; 5%
Kirigia et al. (2002)	Kenya	54	1998	11	8	DEA	40	16%
Zere et al. (2006)	Namibia	30	1997/98 – 2000/01	3	2	DEA	3-5	37.3-25.7%
Ichoku et al. (2011)	Nigeria	200	2009	11	4	DEA	48 (CRS) 87 (VRS)	48%; 28%
Kirigia et al. (2007)	Seychelles	17	2001 – 2004	2	9	DEA and Malmquist	5-7 (yearly)	7% (average over years)
Renner et al. (2005)	Sierra Leone	37	2000	2	6	DEA	15	37%
Mujasi et al. (2016)	Uganda	14	2013/14	2	2	DEA	4 (CRS) 9 (VRS)	20% 9%
Yawe (2010)	Uganda	25	1999 – 2003	4	4	DEA (super efficient)	NA	Allows efficiency scores above 100%

Marschall and Flessa (2009, 2011) study technical efficiency in health centres and in primary care in Burkina Faso. Both studies use the same specification of inputs and outputs. The inputs are: personnel costs in 2005 [US$], building area [$m^2$], depreciation of CSPS equipment in 2005 [US$] and vaccination costs in 2005 [US$]. As outputs, general numbers of consultations and nursing care, numbers of deliveries, numbers of immunisations, special services such as number of consultations for family planning, and numbers of prenatal and postnatal consultations, are used. For the health centres an average inefficiency of 29% is reported and for primary care the average inefficiency is 13.8%.

Ramanathan et al. (2003) and Tlotlego et al. (2010) study efficiency in Botswana. A novelty with Ramanathan et al. (2003) is that the study, besides using DEA, uses a stochastic frontier approach while, however, analysing each of the fourteen selected outputs separately. An obvious problem with this study is dimensionality. The authors use fourteen outputs and five inputs and only have access to thirteen observations. The specification in Tlotlego et al. (2010) is different. In this study there are two inputs and two outputs, and 21 units for the analysis. The inputs in this study are the number of clinical staff and the number of hospital beds. The outputs are the number of outpatient visits and the number of inpatient days. The average inefficiency ranges from 53 per cent to 38 per cent, depending on scale assumptions.

There have been three studies on technical efficiency in Ghana. Osei et al. (2005) use DEA to investigate technical efficiency in Ghana in the year 2000. Their data cover seventeen hospitals and seventeen health centres. The inputs used in the analysis are: number of medical officers; number of technical officers; number of support or subordinate staff; and number of hospital beds. The outputs are the number treatments relating to maternity and child care, the number of babies delivered and the number of patients discharged (not including deaths). The average inefficiency for Ghana in this study is 18.5%. Akazili et al. (2008a, 2008b) also use DEA, but in contrast to other studies Akazili et al. (2008b) also cover allocative and long run efficiency. The inefficiency in Akazili et al. (2008a) is 28%; inefficiency is not reported in Akazili et al. (2008b).

Health care in South Africa has been studied by Kirigia et al. (2001), Zere et al. (2001), Kibambe and Koch (2007) and Linden (2013). Kirigia et al. (2001) study technical efficiency in the Kwazulu-Natal province, where the inefficiency was below ten percent. Numbers of nurses and of general staff (administrative and subordinate staff) are used as inputs, and numbers of antenatal care visits, deliveries/births, child health care visits, dental care visits, family planning visits, psychiatric visits, sexually transmitted disease related care visits, and tuberculosis related care visits are used as outputs. In Zere et al. (2001) level I, II and III hospitals in three different provinces in South Africa are in focus. The authors compute measures of CRS, VRS, technical efficiency and scale efficiency. The result was an average technical inefficiency between 32 and 26 per cent if CRS technology is assumed and between 18 and 17.2 per cent if VRS technology is assumed. The study uses two inputs (recurrent expenditure and beds) and two outputs (outpatient visits and inpatient days). Kibambe and Koch (2007) use data for 2004 and the DEA framework, and apply a number of different specifications, among other things taking each output separately. The inefficiency scores are in the range of 1.1% to 30.7%. The inputs in this study are the numbers of physicians (doctors and specialists), nurses, and active beds. The outputs are: total admissions, inpatient visits, outpatient days and total surgeries. Linden (2013) find an average inefficiency of 10.6 percent. The study uses numbers of medical doctors, specialists, active beds, staffed beds, and non-nursing medical and dental staff, cost of drugs, and capital charges as inputs, and numbers of out-patient department attendances, births, surgeries, emergency room visits, admissions and acute discharges as outputs. Masiye et al. (2006) and Masiye (2007) conduct studies of the Zambian hospital sector. In Masiye et al. (2006) roughly 23 per cent of the hospitals are reported to be inefficient. Furthermore, the sample was divided into private and public hospitals. The average technical inefficiency was 30 per cent for the private and 44 per cent for the public hospitals. The inputs used are number of clinical officers, number of nurses and number of other staff. As outputs, outreach services, number of visits and immunisations are used. Masiye (2007) uses a slightly different specification and expands the number of both inputs and outputs. The inputs in the study are non-labour expenditure, number of medical doctors, sum cost for nurses, laboratory technicians, radiographers and pharmacists and finally, administrative and other staff. As outputs the author uses number of ambulatory care visits, inpatient days, maternal and child health, and the sum of the number of lab tests, X-rays and theatre operations. The average inefficiency in the study was 33%.

There are also countries where single studies have been performed. Djema and Djerdjouri (2012) investigate efficiency in Algeria, applying the DEA method. In their study hospitals are divided into three groups according to size, and the analysis is performed on each group. Average technical inefficiency for the small, medium and large hospitals is reported to be 25%, 19% and 23% respectively. The study uses four inputs: numbers of paramedical staff, medical staff, administrative staff and beds. The outputs used are the number of admissions, days of hospitalisation, average duration of the stay and finally, hospital mortality.

In Kirigia et al. (2008), DEA and the DEA-based Malmquist index are used to study hospital production in Angola. The technical inefficiency for the three years was 34, 34 and 32 per cent respectively. Using the Malmquist index the study concludes that the productivity increase was 4.5 per cent for the period, and was due to improvements in efficiency rather than innovation. The study uses the sum of the numbers of doctors and nurses, the amounts spent on drugs and maintenance, and the number of beds as inputs. The outputs used are the numbers of outpatient visits and inpatient admissions.

San Sebastian and Lemma (2010) study technical efficiency in Ethiopia. The results reveal that 15 out of the 60 hospitals were efficient and that the average inefficiency was 43%. The study uses a model consisting of two inputs and eight outputs. The two inputs are: number of health extension workers and number of voluntary health workers (traditional birth attendants and community health workers). The outputs for the model are the number of health education sessions; the number of completed (three) antenatal care visits; the number of babies delivered; the number of people that repeatedly visited the family planning service; the number of cases of diarrhoea treated in children under five; the number of visits carried out by community health workers; the number of totally new patients attending hospital; and finally, the number of malaria cases treated.

Kirigia et al. (2002) and Kirigia et al. (2004) investigate the situation in Kenya. Kirigia et al. (2002) concludes that 56 per cent of the public health centres and 26 per cent of the public hospitals were technically inefficient. The study uses the number of medical officers/pharmacists/dentists, clinic officers, nurses (including enrolled, registered, and community nurses), administrative staff, technicians/technologists, other staff, subordinate staff, pharmaceuticals, non-pharmaceutical supplies, maintenance of equipment, vehicles, and buildings, and food and rations a as inputs. The used outputs are; outpatient Department casualty visits, special clinic visits, MCH/FP visits, dental care visits, general medical admissions, paediatric admissions, maternity admissions, and amenity ward admissions. In a follow up, Kirigia et al. (2004), a slightly specification is used for the public health centres. In the study the authors find that around 56 per cent where technical efficient. Inputs are defined as: clinical officers + nurses, physiotherapist + occupational therapist + public health officer + dental technologist, laboratory technician+ laboratory technologist, administrative staff, nonwage expenditures and number of beds. As outputs the author uses: diarrhoeal + malaria + sexually transmitted infection + urinary tract infections + intestinal worms + respiratory disease visits, antenatal + family planning visits, immunization and finally, other general outpatient visits

Zere et al. (2006) study hospital efficiency in Namibia. In Namibia 30 hospitals were studied, and between three and five were technically efficient between the years 1997 and 2001. The average technical inefficiency was more than 25 per cent. In the study, recurrent expenditure and numbers of beds and nursing staff are inputs, and numbers of outpatient visits and inpatient days are outputs.

Kirigia et al. (2007) investigate both technical efficiency and productivity development in seventeen primary health centres in the Seychelles between 2001 and 2004. The inputs used in the model are the total numbers of hours worked by doctors and nurses. The study uses nine outputs (numbers of patients dressed, domiciliary cases treated, school health sessions, MCH visits, antenatal visits, postnatal visits, immunisations, pap smear visits, and family planning clinic visits). The inefficiency reported was an average over the years of 7 per cent.

Ichoku et al. (2011) study hospital efficiency in 200 Nigerian hospitals in 2009. The method used is DEA. The study uses eleven inputs and four outputs. Depending on the scale assumption, the average inefficiency ranges from 48% (CRS) to 28% (VRS).

Renner et al. (2005) investigate technical efficiency in Sierra Leone. The data cover 37 hospitals in one district. The results reveal an average inefficiency of 37%. Out of the 37 hospitals, 22 were considered to be efficient. The model used has two inputs and six outputs. The inputs are the numbers of technical staff (community health nurses, vaccinators and maternal and child health aides) and subordinate staff (including traditional birth attendants, porters and watchmen). As for the outputs, these are the numbers of antenatal plus postnatal visits, babies delivered, nutritional/child growth monitoring visits, family planning visits, children under the age of five years immunised plus pregnant women immunised with tetanus toxoid (TT), and health education sessions conducted through home visits, public meetings, school lectures and the outpatient department.

Yawe (2010) uses a super efficiency DEA model to analyse hospitals in Uganda between 1999 and 2003. In the study 25 out of 38 district referral hospitals are analysed, using four input and four output variables, as can be seen in Table A1 in Appendix A. The reasons for using a super efficiency DEA model were that the standard DEA model failed to rank the set of efficient hospitals. Using a super efficiency model, the hospitals can be ranked into four groups: strongly super efficient, super efficient, efficient and inefficient. The study estimates five different models and all of them have a feasible solution under constant returns to scale technology. The conclusion is that not adjusting one of the output variables (admissions) would understate the efficiency scores. Furthermore, the results are sensitive for lumping human resources into one variable: this reduces the efficiency score and reduces the number of hospitals on the production possibilities frontier. The focus of the study is on methodology rather than the result. Finally, Mujasi et al. (2016) investigate referral hospitals in Uganda. The authors found a long run efficiency (CRS) of almost 80% and a short run technical efficiency (VRS) of more than 91%. The model consisted of two inputs, beds and medical staff and two outputs; outpatient visits and inpatient admissions.

In summary, the previous research on hospital and health centre performance reveals varying, but overall high, levels of inefficiency. There are a variety of inputs and outputs used, but numbers of staff and beds are used as inputs in the majority of studies. Also, the previous studies generally use inpatient and outpatient measures as outputs. All, with the exception of one study, use the DEA approach to assess efficiency.

4. The data, the definitions and the model

The dataset includes 13 RRHs for the three (3) fiscal years 2011/2012, 2012/2013 and 2013/2014. It was sourced from the Health Management Information System (DHIS-2) which is produced by the Ministry of Health. The Health Management Information System data was used because its reliability makes it the recommended data source for the health sector. The study also obtained data from the RRHs. For each hospital, the dataset included the numbers of health workers, beds, diagnostic equipment, diagnostic tests, outpatient attendances, admissions, deliveries, mortality, stillbirths, live births, immunisation data, antenatal visits, Standard Units of Output (see below), drug expenditure and other operating costs. The input and output variables were chosen following discussions with the Ministry of Health and RRHs and in the light of the hospital production process and the variables commonly used in previous similar research studies on the efficiency of hospitals, as explained above.[3]

The input variables

<u>Health workers</u>: These were chosen because they are directly involved in the provision of health services to patients. Furthermore, for RRHs the wage bill constitutes about two thirds of the total operating costs. The health worker category includes medical professionals (medical officers, specialists and consultants), nursing staff, midwifery staff, dental professionals, and allied health professionals.

<u>Beds</u>: This is commonly chosen in hospital studies as a proxy for capital investment and hospital size.[4]

<u>Drug expenditure</u>: This represents the treatment given to both inpatients and outpatients. It constitutes the actual expenditure on essential medicines and health supplies. Drug expenditure can also act as a proxy for the alternative of admitting patients.

[3] Several specifications have been tested. The results concerning sensitivity analysis is presented in Appendix B, Table B1.
[4] O'Neill et al. (2008)

Output variables

We use the Standard Unit of Output (SUO) proposed by the Ministry of Health in their Annual Health Sector Performance reports, and convert all the outputs of the RRH into outpatient equivalents. The SUO enables a uniform and fair comparison of outputs across hospitals that have varying capacities, and is based on an earlier work of cost comparisons. The SUO is defined as = [(Inpatients x 15) + (Outpatients x 1) + (Deliveries x 5) + (Immunisations x 0.2) + (ANC/MCH/FP x 0.5)].[5] Furthermore, the SUO captures the different types of patient care services provided by the RRHs, such as outpatient services, inpatient services, maternity services, and prevention and rehabilitation services.

Table 2. Summary statistics for inputs and outputs per financial year

2011/12	**Output**	**Inputs**			**Quality indicator**
	SUO	Health Workers	Beds	Drugs (UGX mil)	Mortality
Mean	412,385	172	278	851	241
SD	127,873	43	95	317	135
Minimum	188,681	97	120	329	90
Maximum	609,384	251	429	1356	578
2012/13					
Mean	503,599	172	319	1057	249
SD	176,885	43	92	276	257
Minimum	225,951	97	150	556	56
Maximum	858,116	251	447	1591	962
2013/14					
Mean	524,750	186	321	895	209
SD	158,569	58	88	226	212
Minimum	206,090	69	170	379	62
Maximum	885,840	310	447	1254	893

Source: OAG Analysis of data from RRHs

[5] ANC = 1st and 4th Antenatal Care visits; MCH = Maternal and Child Health contacts; FP = Family Planning visits.

Mortality is used as a rough measure of the quality of the health care provided by the RRHs. It is assumed that the higher the mortality a hospital reports, the lower the quality of its services. This same parameter was, as discussed earlier, used in previous studies as a quality measure. Since the objective is to minimise mortality, this variable is transformed by taking its inverse. The descriptive statistics are presented in Table 2.

The quantity of each input and output generally varies amongst the RRHs and from one year to another. The only exceptions are the numbers of health workers and beds, which remain fairly constant on a year-on-year basis. The aforementioned variation meant that the efficiency analysis had to be carried out for each year separately in order to obtain unbiased results.

The model

In the study we use the DEA framework that first was used by Farrell (1957) and was later extended for use with multiple inputs and outputs by Charnes et al. (1978). From previous research, the dominant model used when measuring technical efficiency is a model that sets the objective as minimising input for a given output level, i.e. an input-based model. First, the concept of technical efficiency needs to be defined. Let *k*, *k* = 1,..,*K* represent the *K* different hospitals, $x_n, n = 1,..,N$ represent the *N* different inputs and $y_m, m = 1,..,M$ represent the *M* different outputs. The production technology, or input requirement set, is defined as $T = \{(x; y) | x \text{ can produce } y\}$. Input-based technical efficiency can then be defined as: If $(x, y) \in T$ but $(\lambda x, y) \notin T$ for $0 < \lambda < 1$ (that is, if the inputs are reduced it will not be possible to produce the observed level of outputs). Technical inefficiency, on the other hand, is a situation where $(\lambda x, y) \in T$ for $\lambda \in (0,1)$ (that is, it is possible to reduce the inputs and still be able to produce the observed output levels). In micro economic theory, long-run technical efficiency requires that the efficiency is evaluated against constant return to scale (*CRS*) technology, here denoted $TE(CRS)$. In the short run, however, it is possible to allow for different types of scales of operation. Therefore, technical efficiency is also evaluated against a variable return to scale (*VRS*) frontier [$TE(VRS)$]. How much of the long run technical efficiency that is explained by the scale of operation is computed and referred to as scale efficiency.

The focus of this study is congestion, and we will follow the framework suggested in Färe and Svensson (1980) and applied in, for example, Grosskopf et al. (2001), Ferriet et al. (2006), Clement et al. (2008), Valdmanis et al. (2008), Simões and Marques (2011).[6] Input congestion refers to a situation where an increase in one or more inputs will cause a reduction in the output produced. To define congestion, the concept of disposability is required. A technology is congestion-free if it is free to dispose of inputs that are not used. This is referred to as the strong disposability of inputs. However, if this is not the case, we refer to the weak disposability of inputs. Technical efficiency for hospital 'o' (λ_o) is computed as follows:

[1] $Max\ \lambda_o$

$s.t.$

[2a] $\sum_{n=1}^{N} z_n x_{n,k} \geq \lambda_o x_{n,o}$

[2b] $\sum_{n=1}^{N} z_n x_{n,k} = \lambda_o x_{n,o}$

[3] $\sum_{m=1}^{M} z_m y_{m,k} \leq y_{m.o}$

[4a] $z_k \geq 0$

[4b] $\sum_{k=1}^{K} z_k = 1,\ z_k \geq 0$

Using the objective function [1], restrictions [2a], [3] and [4a] will measure technical efficiency imposing constant returns to scale and strong disposability of inputs [$TE(S, CRS)$], or long-run technical efficiency. By replacing restriction [4a] by [4b] the model will measure technical efficiency imposing variable returns to scale and strong disposability of inputs [$TE(S,VRS)$]. Finally, by replacing restriction

[6] There are a number of ways to assess congestion, and there has been a recent debate concerning the differences between the different approaches. In general, all the approaches have advantages and disadvantages, and the choice of approach for measuring congestion depends on the question put forward. See e.g. Haghighi et al. (2014) or Khodabakhshi et al. (2014) for reviews of the different approaches.

[2a] with [2b] we get the corresponding results under the assumption of weak disposability, $TE(W,CRS)$ and $TE(W,VRS)$. Given these models, the long-run technical efficiency can be decomposed into three components: pure technical efficiency, scale efficiency and congestion efficiency:

$$TE(S,CRS) = \underbrace{TE(W,VRS)}_{\text{pure technical efficiency}} \cdot \underbrace{\frac{TE(W,CRS)}{TE(W,VRS)}}_{\text{scale efficiency}} \cdot \underbrace{\frac{TE(S,CRS)}{TE(W,CRS)}}_{\text{congestion}} \qquad [5]$$

5. Results

Table 3 presents the results of the analysis. The first row indicates the year for the analysis. In column 2 the level of long run technical inefficiency is presented. Technical inefficiency is computed as one minus the efficiency score. For example; if the computed efficiency score equals 0.8, this means that the hospital could produce the same amount of output using 80% of the observed input. This equals a potential reduction of inputs of 20%, i.e. 1-0.8. In the following columns we present computations of how much of the observed inefficiency is attributed to each of pure technical efficiency, scale efficiency and congestion. These are expressed as percentage points of the long run inefficiency. For example, in 2014 Mbarara had a long run inefficiency of 23 per cent. This means that Mbarara in 2013/14 could have reduced its use of inputs by 23% if it had mimicked the operation of one of the efficient hospitals. To illustrate what this means, note that Mbarara had a total cost of approximately UGX 4,528 million. A reduction of 23 per cent means a saving equal to approximately UGX 1,041 million. Further, 20.7 percentage points of the long run inefficiency related to pure technical efficiency, 1.1 percentage points to not producing on an optimal scale and 1.1 percentage points to congestion.

Table 3. Long run technical inefficiency (per cent) and the share of the observed inefficiency attributed to each of pure technical inefficiency, scale inefficiency and congestion for Ugandan referral hospitals in 2012, 2013 and 2014

	2012				2013				2014			
	Long run Technical In-efficiency (Per cent)	Pure Technical In-efficiency (Percentage points)	Scale In-efficiency (Percentage points)	Congestion (Percentage points)	Long run Technical In-efficiency (Per cent)	Pure Technical In-efficiency (Percentage points)	Scale In-efficiency (Percentage points)	Congestion (Percentage points)	Long run Technical Inefficiency (Per cent)	Pure Technical In-efficiency (Percentage points)	Scale In-efficiency (Percentage points)	Congestion (Percentage points)
Arua	16.0	0.0	1.1	14.9	35.0	22.3	7.17	5.53	29.0	0.0	4.6	24.4
Fort Portal	8.0	0.0	1.0	7.0	24.0	13.2	9.79	1.02	11.0	8.9	1.1	1.0
Gulu	4.0	0.0	1.0	3.0	34.0	0.0	3.64	30.36	23.0	20.7	0.0	2.3
Hoima	0.0	0.0	0.0	0.0	7.0	0.0	7.00	0.00	1.0	0.0	1.0	0.0
Jinja	5.0	0.0	1.0	4.0	35.0	25.6	4.85	4.58	25.0	0.0	8.8	16.2
Kabale	40.0	5.7	22.5	11.8	26.0	0.0	10.94	15.06	10.0	0.0	1.0	9.0
Lira	11.0	0.0	1.1	9.9	27.0	0.0	12.04	14.96	8.0	0.0	1.0	7.0
Masaka	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.00	1.0	0.0	1.0	0.0
Mbale	14.0	0.0	14.0	0.0	1.0	0.0	1.00	0.00	0.0	0.0	0.0	0.0
Mbarara	0.0	0.0	0.0	0.0	20.0	0.0	3.30	16.70	23.0	20.7	1.1	1.1
Moroto	16.0	0.0	16.0	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0
Mubende	0.0	0.0	0.0	0.0	13.0	0.0	13.00	0.00	0.0	0.0	0.0	0.0
Soroti	0.0	0.0	0.0	0.0	22.0	0.0	7.61	14.39	2.0	0.0	1.0	1.0
Average	**8.8**	**0.4**	**4.4**	**3.9**	**18.77**	**4.70**	**6.18**	**7.89**	**10.2**	**3.9**	**1.6**	**4.8**

Source: Authors' own elaboration

Table 3 reveals an average yearly long run inefficiency of between 9 and 19 per cent, with 2012/13 being the year with the highest amount of inefficiency. These results are in line with, or below, other studies of hospital efficiency in African countries. In columns three to five the sources of the observed inefficiency are expressed as percentage points of long run inefficiency. Pure technical inefficiency refers to the excess use of inputs. For the years 2013/14, an average 3.9 percentage points of the 10.2 per cent long run inefficiency relates to the excess use of inputs, 1.6 percentage points are related to not producing at an optimal scale, and, finally, 4.8 percentage points can be referred to as congestion. Looking at the individual hospitals, Gulu, Mbarara and Jinja show the highest amount of long run inefficiency, but the sources of inefficiency differ considerably. While the majority of the long run technical inefficiency in Gulu and Mbarara relates to input use (pure technical inefficiency), the situation in Jinja is different. In fact, none of the observed long run technical inefficiency is related to input use in Jinja. Instead, 8.8 percentage points relate to operating outside the optimal scale, and as much as 16.2 percentage points relate to congestion. In Kabale and Lira the major part of the observed long run technical inefficiency also relates to congestion rather than the scale of input use.

6. Conclusion and concluding remarks

The aim of this study is to investigate efficiency in Ugandan referral hospitals by decomposing long run technical efficiency into three components: Pure technical efficiency, scale efficiency and congestion. The long run results showed a potential for improving efficiency in the RRHs by saving on the inputs currently used to produce the outputs. The inefficiency ranges from 0% to 40%, with an average inefficiency score of 12.6% across the three years. Another finding is that the saving potential of each RRH may not be uniform across the hospitals. This implies that the policy to make referral hospitals more efficient should target those hospitals that have the potential to save costs. Cutting resources from hospitals that are already efficient might, in fact, create a situation where inefficiency is induced because of an inappropriate efficiency improvement policy. The policy recommendation is that committees should be instituted in the inefficient RRHs to re-examine their operational procedures with a view to identifying inefficiencies in their utilisation of resources. This could be done by encouraging inefficient hospitals to interact with efficient RRHs, especially the consistently efficient RRHs, to compare their usage of inputs and organisation. A third finding is that inefficiency for some hospitals can be related to existence of congestion. This is not surprising since the Office of the Audit General (2015) indicate existence of congestion. For example, the study reports bed occupancy rates exceeding 100 per cent. It is beyond the scope of this study to further investigate the causes to the observed inefficiency relating to congestion. However, based on our results we feel confident to recommend that resources are spent to further investigate what in the production organisation that might be the cause for the identified congestion.

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Appendix A

Table A1. Summary of previous research in Africa with respect to number of hospitals, inputs and outputs and scale assumptions

Author	Number of hospitals	Inputs and outputs	Returns to scale
Akazili et al. (2008)[a]	89	*Inputs*: numbers of clinical staff and non-clinical staff, expenditure on drugs and other consumables and numbers of beds and cots. *Outputs*: outpatient visits, and numbers of antenatal care visits, deliveries, children immunised, and family planning visits.	CRS VRS
Akazili et al. (2008b)	113	*Inputs*: numbers of staff and beds/cots, costs of supplies and recurrent expenditure. *Outputs:* number of outpatients, antenatal care, deliveries, children immunised, and family planning updates.	CRS
Djema & Djerdjouri (2012)	174	*Inputs*: numbers of paramedical, medical and administrative staff, and number of beds. *Outputs*: number of admissions, days of hospitalisation, average duration of the stay rate of rotation and hospital mortality.	VRS
Ichoku et al. (2011)	200	*Inputs*: numbers of beds in the facility, patients, pharmacists employed by the facility, registered and auxiliary nurses employed, and other paramedical staff employed; and annual expenditure on drugs, power including running of generators, and equipment including maintenance. Dummy variables: urban or rural location, facility is in Enugu or Anambra state, government or private *Outputs*: numbers of outpatients treated in facility in the last year, inpatient admissions, laboratory tests conducted and X-rays attended	CRS VRS
Kibambe & Koch (2007)	14	*Inputs:* numbers of physicians (doctors and specialists), nurses, and active beds. *Outputs*: total admissions, inpatient visits, outpatient days and total surgeries.	CRS VRS
Kirigia et al. (2001)	115	*Inputs:* numbers of nurses and of general staff (administrative and subordinate staff). *Outputs*: numbers of antenatal care visits, deliveries/births, child health care visits, dental care visits, family planning visits, psychiatric visits, sexually transmitted disease related care visits, and tuberculosis related care visits.	CRS VRS

Table A1. Continuation

Author	Number of hospitals	Inputs and outputs	Returns to scale
Kirigia et al. (2002)	54	*Inputs*: Medical officers/pharmacists/dentists, clinic officers, nurses (including enrolled, registered, and community nurses), administrative staff, technicians/technologists, other staff, subordinate staff, pharmaceuticals, non-pharmaceutical supplies, maintenance of equipment, vehicles, and buildings, and food and rations *Outputs*: Outpatient Department casualty visits, special clinic visits, MCH/FP visits, dental care visits, general medical admissions, paediatric admissions, maternity admissions, and amenity ward admissions	CRS, VRS
Kirigia et al. (2007)	17 primary health care	*Inputs*: total number of doctor hours and total number of nurse hours. *Outputs*: numbers of patients dressed, domiciliary cases treated, school health sessions, maternal and child health (MCH) visits, antenatal visits, postnatal visits, immunisations, pap smear visits, family planning clinic visits.	CRS VRS
Kirigia et al. (2008)	28 public municipal hospitals	*Inputs*: Sum of doctors and nurses, the amounts spent on drugs and maintenance, and the number of beds *Outputs*: Numbers of outpatients visits and number of inpatient admissions	CRS, VRS
Linden (2013)	138	*Inputs*: numbers of FTE RN, medical doctors, specialists, active beds, staffed beds, and non-nursing medical and dental staff, costs of drugs, capital charge. *Outputs*: numbers of OPD attendances, births, surgeries, emergency room visits, admissions, and acute discharges	CRS, VRS
Masiye (2007)	32	*Inputs*: non-labour expenditure, medical doctors, sum of nurses cost, laboratory technicians, radiographers and pharmacists, administrative and other staff *Outputs*: number of ambulatory care visits, inpatient days, MCH, sum of number of lab tests, X-rays and theatre operations	CRS VRS
Masiye et al. (2006)	40 health centres	*Inputs*: clinical officers, number of nurses, other staff, *Outputs*: outreach services, number of visits, immunisations	CRS, VRS

Table A1. Continuation

Author	Number of hospitals	Inputs and outputs	Returns to scale
Marschall & Flessa (2009)	20, Health centres	*Inputs*: Personnel costs in 2005 [US$], CSPS building area [$m^2$], depreciation of CSPS equipment in 2005 [US$], and vaccination costs in 2005 [US$]. *Outputs*: General consultation and nursing care, deliveries, immunisations, special services e.g. family planning, and prenatal and postnatal consultations.	CRS
Marschall & Flessa (2011)	25, Primary care	*Inputs*: Personnel costs in 2005 [US$], CSPS building area [$m^2$], depreciation of CSPS equipment in 2005 [US$] and vaccination costs in 2005 [US$]. *Outputs*: General consultation and nursing care, deliveries, immunisations, special services, e.g. family planning, and prenatal and postnatal consultations.	CRS VRS
Mujasi et al. (2016)	14 referral hospitals	*Inputs*: Beds and medical staff *Outputs*: Outpatient visits and inpatient admissions.	CRS VRS
Osei et al. (2005)	17 hospitals and 17 health centres	*Inputs*: number of medical officers, number of technical officers (including medical assistants, nurses and paramedical staff), number of support or subordinate staff (including orderlies, ward assistants, cleaners, drivers, gardeners, watchmen, etc.), and number of hospital beds. *Outputs*: number of maternal and child care (i.e. antenatal care, postnatal care, family planning, tetanus toxoid, child immunisation and growth monitoring), number of babies delivered, and number of patients discharged (not including deaths)	CRS VRS
Ramanathan et al. (2003)	13	*Inputs*: numbers of health posts, beds, doctors, nurses and health staff. *Outputs*: numbers of outpatients from eleven different ailment groups, all outpatients, inpatients discharged alive, new births discharged alive and patient days.	CRS

Table A1. Continuation

Author	Number of hospitals	Inputs and outputs	Returns to scale
Renner et al. (2005)	37 health units	*Inputs*: numbers of technical staff (vaccinators, community health nurses, emergency and humanitarian officers, maternal and child health aides) and subordinate staff (traditional birth attendant, porter, watchman), costs of materials and supplies, capital inputs *Outputs*: numbers of antenatal and postnatal care visits, babies delivered, nutrition/growth monitoring visits, family planning visits, under 5's and pregnant women immunised, health education sessions	CRS VRS
San Sebastian & Lemma (2010)	60	*Inputs*: number of health extension workers and number of voluntary health workers (traditional birth attendants and community health workers). *Outputs*: number of health education sessions given by HEWs; number of completed (three) antenatal care visits; number of babies delivered; number of people repeatedly visiting the family planning service; number of cases of diarrhoea treated in children under five; number of visits carried out by community health workers; number of totally new patients attending hospital; number of malaria cases treated.	CRS VRS
Tlotlego et al. (2010)	21 (3 year)	*Inputs*: numbers of clinical staff (physicians, nursing and midwifery personnel, dentistry personnel, and other technical health service providers) and hospital beds. *Outputs*: numbers of outpatient department visits and inpatient days.	CRS VRS
Zere et al. (2001)		*Inputs*: recurrent expenditure, beds *Outputs*: outpatient visits, inpatient days	CRS VRS
Zere et al. (2006)	30	*Inputs*: recurrent expenditure, numbers of beds and nursing staff *Outputs*: numbers of outpatient visits and inpatient days	CRS
Yawe (2010)	25	*Inputs*: numbers of doctors, nurses, other staff, and beds *Outputs*: numbers of total annual admissions, annual outpatient department attendances, surgical operations, deliveries in the hospital	Super efficiency model

Appendix B: Results of Sensitivity Analysis

Sensitivity analysis was carried out using four models. The input and output variables of each model are:

Table B1. Different models in the sensitivity analysis

Model	Inputs	Outputs
Preferred Model	Beds Health Workers Drugs	Standard Unit of Output Mortality
Model 1	Beds Health Workers Drugs	Adjusted Standard Unit of Output*
Model 2	Beds Health Workers Drugs	Standard Unit of Output Average Length of Stay
Model 3	Beds Health Workers Drugs	Standard Unit of Output
Model 4	Beds All Staff Drugs	Standard Unit of Output Mortality

a) Model 1

This model uses the same variables as the preferred model but applies floor admissions as a quality measure rather than mortality. This is because the Hospital Directors considered floor admissions to be an indicator of the quality of health care. The average efficiency scores change slightly from the preferred model because most of the hospitals report few or no floor admissions. Of interest are Masaka and Mbale RRHs, which report the highest number of floor admissions in 2011/12 (Masaka) and in 2012/13 (Mbale), resulting in a drop in their average efficiency scores from 100% to 91% and 96% respectively.

b) Model 2

This model uses the same variables as the preferred model but applies average length of stay as a quality measure rather than mortality. The average scores generally remain the same for all the RRHs, with only marginal changes from the preferred model results of 1%-3% for three RRHs. This model does not, therefore, offer unique information.

c) Model 3
This model uses the same variables as the preferred model but excludes mortality, therefore leaving quality measures out of the model. There are slight changes in the average efficiency scores of four RRHs, but a considerable change for Soroti RRH which goes from 95% to 100% efficiency. However, this model has not been chosen because Carey and Burgess (1999) and Ferrier and Trivitt (2013) argue that disregarding quality results in omitted variable bias.

d) Model 4
This model uses the same variables as the preferred model but replaces health workers with total number of staff, therefore incorporating administrative and support staff in the model. This changes the average efficiency score of five RRHs. However, this model has not been chosen because the administrative and support staff are not directly involved in delivering the health service to patients.

The sensitivity analysis conducted to ascertain the reaction of the model to changes in the mix of inputs and outputs did not show much change in the score and rankings of the RRHs. This further emphasises the comprehensiveness of the input and output variables used and the credibility of the preferred model.

Analiza (rozkład) wydajności technicznej – przykład ugandyjskich szpitali

Streszczenie

Cel: W audytoryjnym raporcie przekazanym do Parlamentu Ugandyjskiego przez Główne Biuro Audytu (ang.: *Office of the Audit General*) w Ugandzie zawarto wyniki pomiaru i analizy wydajności technicznej w ugandyjskich szpitalach, w których pacjenci są przyjmowani ze skierowaniem. Raport audytoryjny wskazał na względnie niski poziom niewydajności technicznej, przynajmniej w porównaniu do innych krajów afrykańskich. Celem niniejszego artykułu jest głębsze zbadanie kwestii dotyczących przyczyn występowania niewydajności.

Metodyka badań: Autorzy wykorzystali analizę obwiedni danych (ang.: Data Envelopment Analysis) i dokonali rozkładu długoterminowej wydajności technicznej w krótkoterminową wydajność techniczną, wydajność skalową i kongestię.

Wnioski: Wyniki badań wykazały, że źródła długoterminowej niewydajności różnią się na przestrzeni lat. W 2012 roku ponad 50% obserwowanej niewydajności odnosi się do czynników skalowych. Jednak w 2013 i 2014 roku głównym powodem długoterminowej niewydajności była kongestia na wejściu.

Wartość artykułu: Mimo że problemowi wydajności w afrykańskich szpitalach poświęcono znaczącą liczbę badań, żadne z nich nie koncentrowało się na występowaniu kongestii. Z tego względu niniejsze badanie przyczynia się do poszerzenia wiedzy wynikającej z dotychczasowych badań.

Implikacje: Zgodnie z rekomendacjami autorów, niewydajne szpitale powinny wykorzystywać wydajne szpitale jako wzorce i punkty odniesienia dla poprawy własnej wydajności. Co więcej, ponieważ spora część niewydajności technicznej odnosi się do kongestii, należy nadal prowadzić badania w celu identyfikacji czynników dotyczących produkcji lub organizacji, które mogą być związane z kongestią.

Słowa kluczowe: wydajność techniczna, wydajność skalowa, kongestia, Uganda, szpitali

JEL: D2, H4, I2

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Efficiency analysis of public health spending in Brazilian capitals using network Data Envelopment Analysis

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Abstract:

Aim: In 1988, Brazil implemented profound changes in the organization and financing of its public health system, with the creation of the Unified Health System (Sistema Unico de Saúde – SUS), establishing universal health coverage. The gradual expansion of the health system and entitlements to services has been accompanied by the debate about the appropriate level of government spending and health system efficiency.

Design / Research methods: The study uses Variable Returns to Scale output-oriented, Dynamic Network Slacks-Based-Measure Data Envelopment Analysis (DEA) model, period 2008-2013, to depict the relationships that take place between diverse levels of care (primary health care/PHC and secondary-tertiary health care/STC). Decision Making Units are Brazilian state capitals, which implement key health policies and assist patients from smaller surrounding municipalities, especially for STC. Inputs are PHC and STC budgets; outputs are their respective services provided and avoidable deaths. The link variable is PHC medical consultation, entrance door to the system and gatekeeper for more complex levels of care. Dynamic model evaluates efficiency across time.

Conclusions / findings: Overall performance was 0.86; for PHC, 0.90; for STC, 0.85 (SD=0.15). 8 out of 27 capitals were fully efficient. Capitals increased average scores in both levels of care, but only STC had a positive technological change (frontier shift >1). Link variable behavior denotes a bottleneck between levels of care. Projections onto the frontier enable establish own management diagnosis and goals for financing and development.

Originality / value of the article: Network models mimic hierarchically organized health systems. The appliance of results aids health policy.

Keywords: network DEA, efficiency measurement, health and economic development, public health
JEL: H21, H51, O10, O54

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1. Introduction

Brazil covers 8.5 million km², or 47% of South America, with an estimated population of 204,482,509 in 2015. As a federative republic, its political organizational system has three levels of autonomous government—federal government, 26 states and a federal district (federal capital), and 5,570 municipalities. The country is divided into five geographical regions (north, northeast, center-west, southeast, and south) with differing demographic, economic, social, cultural, and health conditions, and widespread internal inequalities. The north region, which contains most of the Amazon rainforest, has the country's lowest population density (3.9 people per km^2) and is the second poorest region, after the northeast region.

Since 1970, Brazil underwent a demographic transition: urban population increased (from 55.9% to 84.0%); fertility rate and infant mortality rate decreased (respectively, from 5.8 to 1.8 and from 114.0 per 1,000 livebirths to 15.3 per 1,000 livebirths). The population older than 60 years doubled (11.0% in 2012) and life expectancy at birth increased to 74.8 years, resulting in epidemiological transition. Nowadays, diseases of the circulatory system are the leading cause of death, followed by cancer and external causes (mainly traffic accidents and homicides). Chronic diseases are the biggest contributor to the burden of disease (24.3% of adult population have hypertensive disorders; 11.7% are diabetic), although communicable diseases still affect a substantial proportion of the population, especially in the poorest areas in the country (Ministry of Health: DATASUS 2017).

Over the last decades, Brazil implemented profound changes in the organization and financing of its public health system. The creation of the Unified Health System (*Sistema Unico de Saúde* – SUS) in 1988 Constitution, establishing universal health coverage, has been associated with the expansion of the health service delivery system with remarkable improvements in access, financial protection and health outcomes (Gragnolati et al. 2013: 16).

The SUS main principles are universal coverage and equity of care; its main guidelines are decentralization, community participation and comprehensive care, which means continuous provision of health services at all levels of complexity (from preventive actions to curative high technology procedures) (Paim et al. 2011: 1787).

Primary health care (PHC) is the main entrance door to the system. PHC aims to provide universal access and comprehensive health care, coordinate and expand coverage to more complex levels of care (specialist care and hospital care, that is, STC or secondary – tertiary levels of care), and implement intersectorial actions for health promotion and disease prevention.

Since its creation, the SUS network expanded considerably, particularly outpatient services driven by the expansion of the family health strategy (*FHS*), to guarantee comprehensive primary care. Between 1998 and 2015, FHS teams increased from 4,000 to over 50,000, covering 56.2% of the population (Malta et al. 2016: 328). From 2008 to 2015, the percentage of STC admissions due to conditions sensible to primary care fell from 35.8 % to 30.6%.

By decentralization, municipalities took on a leading role in the delivery of health services, while states and federal government maintained responsibility for some referral services. Tripartite councils – municipal, state and federal – sign commitments to health goals and guarantee shared financing responsibility, but municipalities still define priorities, set goals with local health services and allocate the final budget according to management contracts.

Budget transfer to municipalities considers six financing blocks or sub-functions: 1) Primary Care (PHC); 2**)** Medium/ High Complexity Outpatient Hospital Care (Secondary – Tertiary Care – STC); 3) Health Surveillance, 4) Pharmaceutical Care, 5) SUS Management, 6) Investments on Healthcare Services Network. By 2010, primary care and outpatient /hospital care consumed 14.3% and 52.0%, respectively, from total federal public health spending. (Paim et al. 2011: 1782).

The gradual expansion of the health system and entitlements to services has been accompanied by the debate about the appropriate level of government spending and health system efficiency. Total health expenditures in Brazil is comparable to the average of the Organization for Economic Cooperation and Development (OECD) countries; Brazil spends 8.3 % (2015) of its gross domestic product (GDP) on health while the average for OECD countries is 9.0 % (2015). However, health spending in Brazil is dominated by private insurance, which accounts for more than half of the health expenditure, and covers approximately a quarter of the population who pays for it. This results in large inequalities in the per capita spending between private and public sector (USD 2,678 at PPP versus USD 1,028 at PPP). Additionally, health indicators in Brazil are still below the average among OECD countries and, in many cases, worse than its regional and economic peers. In terms of health services delivery indicators, such as consultations per physician or bed occupancy rates, Brazil lags behind comparable countries (OECD and regional and structural peers) (OECD 2015: 14). Despite its considerable achievements, the SUS still faces vital challenges across all levels of care. There remain significant coverage gaps in PHC, barriers to access specialist and high-complexity care (STC), weak quality and coordination of care, and weaknesses in the referral and counter-referral systems (Gragnolati et al. 2013: 66).

Altogether, despite the efforts to establish a public universal health system, Brazil struggles to achieve a good balance between an appropriate level of (public) spending and to obtain better value for the resources invested in its health system. The objective of this study is to measure efficiency in public health spending in a model that considers efficiency´s operational (delivery of health services) and quality (health indicators) dimensions, and the interconnectedness between levels of care, which systemically influence the final results.

2. Methods: conceptual framework for current analysis

Health care systems (HCS) have great impact on society, demand complex decision making and operational research (OR) can provide useful tools to help managers (Alexander 2008: 97). HCS structure is multidimensional, hierarchically organized, demands communication skills to understand it in depth and presents gaps of data, sometimes being difficult to formulate and define boundaries to model. In operational terms, to analyze the health system as a whole, it is important to consider not only the interconnectivity between components of the system (levels of care), but also the diverse perspectives of stakeholders (quantitative – volume of health services delivery; qualitative – health indicators) and the influence of environment (socioeconomic influences) (Emrouznejad, de Witte 2010: 1574-1575).

Moreover, with always expanding incorporation of new technologies and divergent market interests guiding regulation, healthcare services consume increasing proportions of GDP, not necessarily associated with quality of care. For these reasons, OR efficiency and performance studies have been frequently chosen to handle the problem and monitor public expending (Lobo, Lins 2010: 380).

Data Envelopment Analysis (DEA) is a non-parametric technique which allows to construct a data driven production frontier. The estimated best practice efficiency frontier represents the maximum level of outputs given the inputs and the technology available. By comparing similar decision making units (DMU), the technique identifies the DMUs with higher level of production for fixed amounts of inputs (output-oriented model) and/or the ones that use fewer resources to generate a fixed amount of products (input-oriented model). Generally, DEA production frontiers can be either constant returns scale (CRS) or variable returns to scale (VRS). To be fully efficient, a DMU should be located in Pareto-efficient portions of the frontier, that is, a place where it is not possible to reduce any input, or increase any output, without having to also increase another input or reduce another output, simultaneously (Cooper et al. 2007: 1-39, 45-46).

The traditional DEA model is often considered a black-box model, as it specifies what enters and gets out of the transformation process (exogenous inputs and outputs) without explicitly modelling what happens inside it. To overcome these challenges, an extension of the DEA black box model is the network DEA model (Färe, Grosskopf 2000: 35).

The network model attempts to analyze inside of a production process and to explicitly model the relationships among variables that take place inside the DMU. For example, when dealing with more than one dimension, division or sub-process inside the black box, there are connections among them and there may exist link variables present in more than one dimension, which function as inputs for one dimension and as outputs for another. Network model allows to calculate the total efficiency score and specific efficiency scores, to define benchmarks for each sub-process, and recommend for each variable to project onto the best practice frontier (Tone, Tsutsui 2009: 244-246).

Selecting different inputs and outputs in DEA models can heavily influence the results; the same happens when arranging variables and relationships inside the black box. In other words, the architecture of the relationships inside the black box influence the efficiency scores and possibilities for projections onto the best practice frontier. This calls for the importance of the managerial analysis and close interaction with stakeholders when designing accurate models (Emrouznejad, de Witte 2010: 1579).

A DEA dynamic network model allows to incorporate changes in the efficiency score across years, by incorporating the existence of time intermediate carry-overs that connect two consecutive terms. Longitudinal analysis uses a modified Malmquist Index, that evaluates individual DMU score changes across time (catch-up component) and the technological or frontier dislocation of all units on the analyzed period (frontier shift component). Finally, to cope only with Pareto-efficient projections, a network slacks-based measure (NSBM) approach is proposed. Slack-based measure is a non-radial method and is suitable for measuring efficiencies when inputs and outputs may change non-proportionally, turning recommendations more reliable (Tone 2001).

2.1 Dynamic Network SBM DEA Model: mathematical modeling

This paper utilizes network SBM (non-radial) DEA model, as proposed by Tone and Tsutsui (2009), in which the definition of efficiency scores of each observed DMU depends on the selected orientation, input, output or non-oriented. Thus, we work with output-oriented SBM network model under the assumption of VRS and free link case. It considers a system of two sub-processes or divisions, linked by one intermediate product from process one to process two.

To formalize, we deal with n DMUs (j=1, …, n) consisting of K divisions (k=1, …, K). Let m_k and r_k be the numbers of inputs and outputs to Division k, respectively. We denote the link leading from Division k to Division h by (k,h). ρ^*_o denotes the overall efficiency of DMU_o ; s_r^{k-} and s_r^{k+} are input and output slacks of process K.

The production possibility set $\{(x^{K}, y^{k}, z^{(k,h)})\}$ is defined by:

$$x^k \geq \sum_{j-1}^{n} x_j^k \lambda_j^k \ (k = 1, \dots, K$$
$$y^k \leq \sum_{j-1}^{n} y_j^k \lambda_j^k \ (k = 1, \dots, K) \qquad (1)$$
$$z^{(k,h)} = \sum_{j-1}^{n} z_j^{(k,h)} \lambda_j^k \ (\forall (k,h)) \qquad \text{(as outputs from } k\text{)}$$
$$z^{(k,h)} = \sum_{j-1}^{n} z_j^{(k,h)} \lambda_j^h \ (\forall (k,h)) \qquad \text{(as inputs to } h\text{)}$$
$$\sum_{j-1}^{n} \lambda_j^k = 1 \ (\forall k), \quad \lambda_j^k \geq 0 \ (\forall j,k)$$

where λ_j^k is the intensity vector corresponding to Division k (k=1, …, K).

DMU*o* (*o*= 1, …, n) can be represented by:

$$\begin{aligned} x_o^k &= X^k \lambda^k + s^{k-} \ (k = 1, \dots, K), \\ y_o^k &= Y^k \lambda^k + s^{k+} \ (k = 1, \dots, K), \\ e\lambda^k &= 1 \ (k - 1, \dots, K), \\ \lambda^k &\geq 0, s^{k-} \geq 0, s^{k+} \geq 0, \qquad (\forall k), \end{aligned} \qquad (2)$$

And

$$\begin{aligned} X^k &= \left(x_1^k, \dots, x_n^k\right) \in \mathbb{R}^{m_k \times n} \\ Y^k &= \left(y_1^k, \dots, y_n^k\right) \in \mathbb{R}^{r_k \times n} \end{aligned} \qquad (3)$$

As regard to the linking constraints, considering the ‘‘free” link value case, linking activities are discretionary and link flow may increase or decrease in the optimal solution:

$$Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k \ \left(\forall k(k,h)\right), \qquad (4)$$

$$Z^{(k,h)} = \left(z_1^{(k,h)}, \dots, z_n^{(k,h)}\right) \in \mathbb{R}^{t_{(k,h)} \times n} \qquad (5)$$

We evaluate the output-oriented overall efficiency of DMU*o* (τ_o^*) by solving the following linear program:

$$\frac{1}{\tau_o^*} = \max_{\lambda^k s^{k+}} \quad \sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_r^{k+}}{y_{ro}^{k+}}\right)\right] \qquad (6)$$

Where $\sum_{k=1}^{K} w^k = 1; w^k \geq 0 \quad (\forall K)$ and w^k is the relative weight of Division k which is determined corresponding to its importance (in this paper, $w_1 = w_2 = 0.5$).

In order to confine the score into the range [0, 1], we define the output-oriented divisional efficiency score by:

$$\tau_k = \frac{1}{1+\frac{1}{r_k}\left(\sum_{r-1}^{r_k}\frac{s_r^{k=1}}{y_{r_o}^k}\right)} \quad (k = 1, \dots, K), \tag{7}$$

Where s^{k+} is the optimal output-slacks for (6). The output-oriented overall efficiency score is the weighted harmonic mean of the divisional scores:

$$\frac{1}{\tau_o^*} = \sum_{k-1}^{K}\frac{W_k}{\tau_k}. \tag{8}$$

In Dynamic slacks-based DEA model, intertemporal efficiency change considers carry-over activities (in this study, treated as fixed, non-discretionary variables). The objective function for output-oriented dynamic model is an extension of the output-oriented SBM network model and deals with shortfalls in output products and desirable (good) links because both have similar features, i.e. larger amount is favorable. As it produces a modified Malmquist Productivity Index (MPI), we bring the equation from the later, where *y* represents the output vector that can be produced using the input vector *x*. Two of the four distance functions, $D_t(x_t, y_t)$ and $D_{t+1}(x_{t+1}, y_{t+1})$, are technical efficiency measures in times t and t+1, respectively, and the remaining functions, $D_t(x_{t+1}, y_{t+1})$ and $D_{t+1}(x_t, y_t)$, indicate cross-period distance functions. $D_t(x_{t+1}, y_{t+1})$ shows the efficiency measure using the observation in time t+1 relative to the frontier technology in time t. $D_{t+1}(x_t, y_t)$ shows the efficiency measure using observation in t relative to the frontier technology in time t+1 (Färe at al. 1992, 1994).

$$\text{MPI}=\left[\frac{D_t(x_{t+1},y_{t+1})}{D_t(x_t,y_t)} \times \frac{D_{t+1}(x_{t+1},y_{t+1})}{D_{t+1}(x_t,y_t)}\right]^{1/2} \tag{9}$$

An important feature of the DEA based Malmquist index is that it can decompose the overall productivity measure into two mutually exclusive components (10), one measuring change in technical efficiency (catching-up effect, outside the brackets) and the other measuring change in technology (frontier shift or innovation, inside), with a cut-off point set at the unit for progression or regression across time.

$$\text{MPI}=\frac{D_{t+1}(x_{t+1},y_{t+1})}{D_t(x_t,y_t)}\left[\frac{D_t(x_{t+1},y_{t+1})}{D_{t+1}(x_{t+1},y_{t+1})}\times\frac{D_t(x_t,y_t)}{D_{t+1}(x_t,y_t)}\right]^{1/2} \qquad (10)$$

2.2 Empirical model for Brazilian public health spending analysis: DMUs, variables and data sources

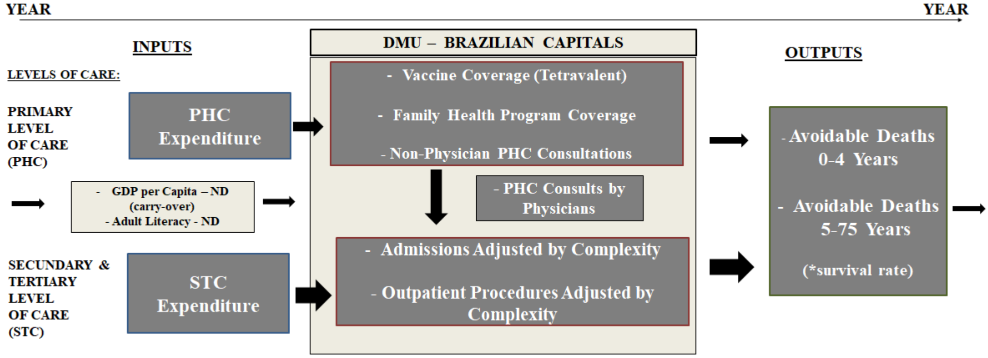
For public health spending analysis, DMUs are the Brazilian state capitals, the core and main municipalities of each state. They implement key health policies, operate service delivery and have high socio-political influence over surrounding municipalities of the same state, frequently receiving patients from the latter, especially for secondary-tertiary (STC) care.

As already mentioned, the analysis applies a VRS output-oriented, Dynamic Network SBM DEA (DNSBM) model, and considers period 2008-2013. The output-oriented model is chosen given the ultimate objective is to maximize outputs, that is, increase operational productivity and ameliorate health indicators, given the resources provided. The VRS model is justified since state capitals are different in scale. The two sub-processes or divisions are the PHC and STC levels of care, which are linked by one free intermediate link: PHC medical consults (output for PHC and input for STC).

In order to understand the architecture of the model, Figure 1 presents DNSBM model with two independent exogenous inputs: (i) total health expenditure on PHC; and (ii) total health expenditures on STC; the width of the latter arrow depicts larger quantity of money in Brazilian local currency (BRL). The model uses two health indicators as final exogenous outputs: (i) the number of avoidable deaths in the population of 0-4 years-old; and (ii) the number of avoidable deaths in the population aged between 5-74 years-old (again, the difference in width of the arrow shows different volume of deaths, higher for adults and occurring inside hospitals). The avoidable or reducible causes of death are defined as those totally or partially preventable by health service effective actions, accessible in a determined place and time. The list is periodically revised worldwide by local committees of experts according to the International Code of Diseases (ICD). In Brazil, these causes were reviewed considering the available knowledge and technology for the practice of health care by a working-group organized by the Brazilian Ministry of Health, 2008. They are mostly associated with vaccination programs; prenatal, delivery, neonatal care; opportune diagnosis and treatment; health promotion and prevention for chronic diseases (Malta et al. 2010).

Considering that avoidable causes of death are undesirable final outputs, survival rates (complement of mortality) were used to maintain output-oriented maximizing model, as proposed by Afonso and Aubyn (2005: 238). Since mortality is the usual epidemiologic indicator, the data is reversed again and presented as mortality in results section in order to be consistent with the public health audience. That is why the output projection for mortality related outputs appears negative.

Figure 1. DEA SBM Dynamic Network Model for public health spending analysis



Source: Authors' own study

To understand how the public health care funds are allocated to purchase health services at different levels of care, it is necessary to explore the health care production process within each DMU. The production process within each DMU has two sub-processes or divisions: primary care (PHC) and secondary-tertiary services

(STC). PHC usually comprises appointments with physicians; primary dental care; primary procedures with other types of professionals, with medium or high degrees of skill; ambulatory and home assistance of FHP; vaccination; educational activities to community groups; pre-natal assistance; family planning activities; minor surgeries; activities of community workers; emergency help in basic unit of health. For STC, either medium or high complexity, there are outpatient and inpatient procedures (Varela et al. 2009: 115). Outpatient procedures comprise diagnostic and therapeutic activities, clinical or surgical, performed in ambulatory settings (in Brazilian time series, 15% of them consist of specialized consults). When admissions are necessary, inpatient hospital procedures occur at hospital level.

Inside the model, each dimension has its specific set of outputs. For PHC, they are: number of doses of tetra vaccine, number of persons registered in Family Health Program (FHP), number of non-medical primary care consultations. For STC, they are: number of admissions adjusted by complexity; number of outpatient procedures adjusted by complexity. Finally, the variable 'number of medical PHC consultations' links these two sub-processes, since PHC physicians play a role of gatekeepers, referring patients to STC level as needed. At STC level, the main point of contact is the specialized consult, unless an urgent admission is necessary. Inside the model, PHC consultations are outputs of PHC and inputs for secondary-tertiary care. Note the arrow-out means output, and arrow-in means input for a given level or sub-process.

The dynamic component to compare the frontier shift and observe the influence of specific policies on the DMUs performance across the years uses two fixed non-discretionary carry-over variables, namely: number of literate people over 15 years-old and GDP per capita. By definition, carry-over variables in dynamic network DEA are outputs in a given year and inputs for subsequent year. The sociodemographic variables control for socio-demographic diversities. They are both influenced by health status and health practices (output of the previous year), and also influence health status and health practices in the near future (input for the next year), with impact on performance scores.

Table 1. Variables and sources according to levels of care and behavior inside the model

Level		Variables – Characteristics (exogenous, inside DMU, carry-over)	Sources***
PHC	Inputs	Total public spending on PHC – EXOGENOUS	SIOPS
	Outputs	Avoidable causes of death mortality, 0-4 years-old * (outside hospital) – EXOGENOUS	SIM
		Avoidable causes of death mortality, 5-75 years-old *(outside hospital) – EXOGENOUS	SIM
		Number of administered doses of tetra or pentavalent vaccine – INSIDE DMU	SI- PNI
		FHP Coverage (number of persons) – INSIDE DMU	SIAB
		Number of primary care consultations (except physicians) – INSIDE DMU	SIA/SUS
		Number of primary care consultations (by physicians) – INSIDE DMU – LINK to STC	SIA/SUS
	Non-discretionary	GDP per capita – CARRY – OVER	IBGE
		Adult Literacy - CARRY – OVER	IBGE
STC	Inputs	Total public spending on STC - EXOGENOUS	SIOPS
		Number of primary care consultations (by physicians) – INSIDE DMU - LINK to STC	SIA/SUS
	Outputs	Number of Admissions Adjusted by Complexity ** – INSIDE DMU	SIH/SUS
		Number of Outpatient Procedures Adjusted by Complexity ** – INSIDE DMU	SIA/SUS
		Avoidable causes of death mortality, 0-4 years-old * (inside hospital) – EXOGENOUS	SIM
		Avoidable causes of death mortality, 5-75 years-old *(inside hospital) – EXOGENOUS	SIM
	Non-discretionary	GDP per capita – CARRY – OVER	IBGE
		Adult Literacy – CARRY – OVER	IBGE

Source: Authors' own study
* Undesirable final outputs treated as the complement (survival rates, as in Afonso, Aubyn 2005: 238). In Brazil, almost 85% of registered deaths occur inside hospitals.
**For hospital care, the adjustment factor was 6.0 for high complexity procedures (medium complexity admissions are 13.8 times more frequent while the system spends only 2.3 more compared to high complexity). For outpatient care, the adjustment factor was 1.1.
***Sources: SIOPS – Information System for Public Budgets for Health (Ministry of Health – MoH), SIAB – Information System for Primary Care – MoH, SI- PNI – Information System for the National Immunization Program – MoH, SIA/SUS and SIH/SUS, respectively, Information System for Ambulatory Care and Information System for Hospital Care – MoH, SIM – Information System for Mortality – MoH, IBGE – Geography and Statistics Brazilian Institute – Census Data.

Table 1 presents the list of variables and sources included in the model. Most sources or databases are administered by the Ministry of Health. As for Brazilian capitals, with robust administrative structure, data quality has not been a concern (that would be different if DMUs were the smaller or less equipped municipalities). Given accurate data, there was no need to create confidence intervals.

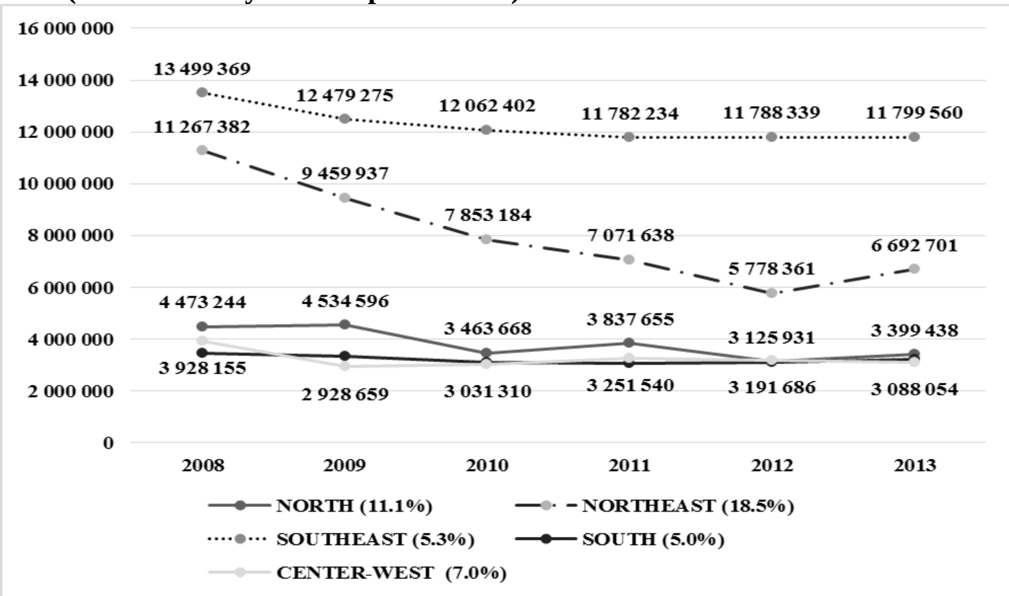
The variables were preferably treated as absolute numbers for two reasons (except for non-discretionary GDP per capita): first, the DEA literature argue that the use of ratios may damage the linear properties of the frontier, especially the convexity assumption (Emrouznejad, Amin 2009: 486). Second, in order to give recommendations based on projections onto the best practice frontier, absolute numbers seem more appropriate.

3. Results

From 2008 to 2013, there was an increase in both levels of expenditure, PHC spending increased by 66.2% and STC increased by 51.6%. At PHC level, FHP coverage, vaccination and non-medical consultations increased by 8.4%, 4.0% and 5.0%, respectively. Nevertheless, PHC medical consultations decreased by 23.0% in the period. At STC level, there was 32.1% and 12.9% increase of outpatient procedures and hospital admissions, respectively. Finally, there was a decrease in avoidable deaths for children below 5 years old (by 8.7%). For people 5-74 years-old, avoidable deaths increased by 4.4%. (Table 2)

Note that decreasing proportions of PHC medical consults were diverse among regions, which may reflect the difficulties in attracting physicians to work at this level. Figure 2 shows the differences in the number of PHC medical consultations across regions; the decline being sharper in the Northeast region, which complies a more challenging sociodemographic scenario, with the worse adult illiteracy rates (18.5% versus Brazilian average 9.4%).

Figure 2. Brazilian capitals´ average PHC medical consults by regions: 2008-2013 (adult illiteracy rates in parenthesis)



Source: Authors' own study

Table 2. Descriptive statistics of data, 2008-2013

	PRIMARY CARE						LINK	SECONDARY-TERTIARY				
YEAR	PHC Expenditure (R$ mi)	Avoidable Deaths 0-4 yo	Avoidable Deaths 5-74 yo	FHP (1,000)	Tetravalent Vaccine	Nonmedical Consults	Medical Consults	STC Expenditure (R$ mi)	Avoidable Deaths 0-4 yo	Avoidable Deaths 5-74 yo	Outpatient adjusted (1,000)	Admissions adjusted
2008												
Average	46.81	76	1,993	855	72,610	575,065	1,356,317	512.35	687	5,979	24,505	114,564
Max	281.32	300	10,798	5,789	473,723	3,243,461	8,324,869	3,179.42	2,699	32,393	174,742	564,640
Min	10.90	14	190	134	11,505	38,432	97,796	40.18	127	569	2,165	12,982
St Dev	54.22	61	2,425	1,070	93,051	646,580	1,575,830	635.11	545	7,275	32,891	111,278
2013												
Average	77.78	70	2,081	926	75,527	603,719	1,043,997	776.90	627	6,243	32,375	129,361
Max	491.38	274	11,441	6,126	520,912	3,158,932	6,403,400	4,680.08	2,470	34,322	231,198	666,210
Min	11.62	13	253	99	13,639	46,544	168,311	72.28	115	758	2,343	26,427
St Dev	99.93	56	2,473	1,202	102,984	732,955	1,249,480	920.98	504	7,420	44,230	129,924
Change (2013/2008)	66.2%	-8.7%	4.4%	8.4%	4.0%	5.0%	-23.0%	51.6%	-8.7%	4.4%	32.1%	12.9%

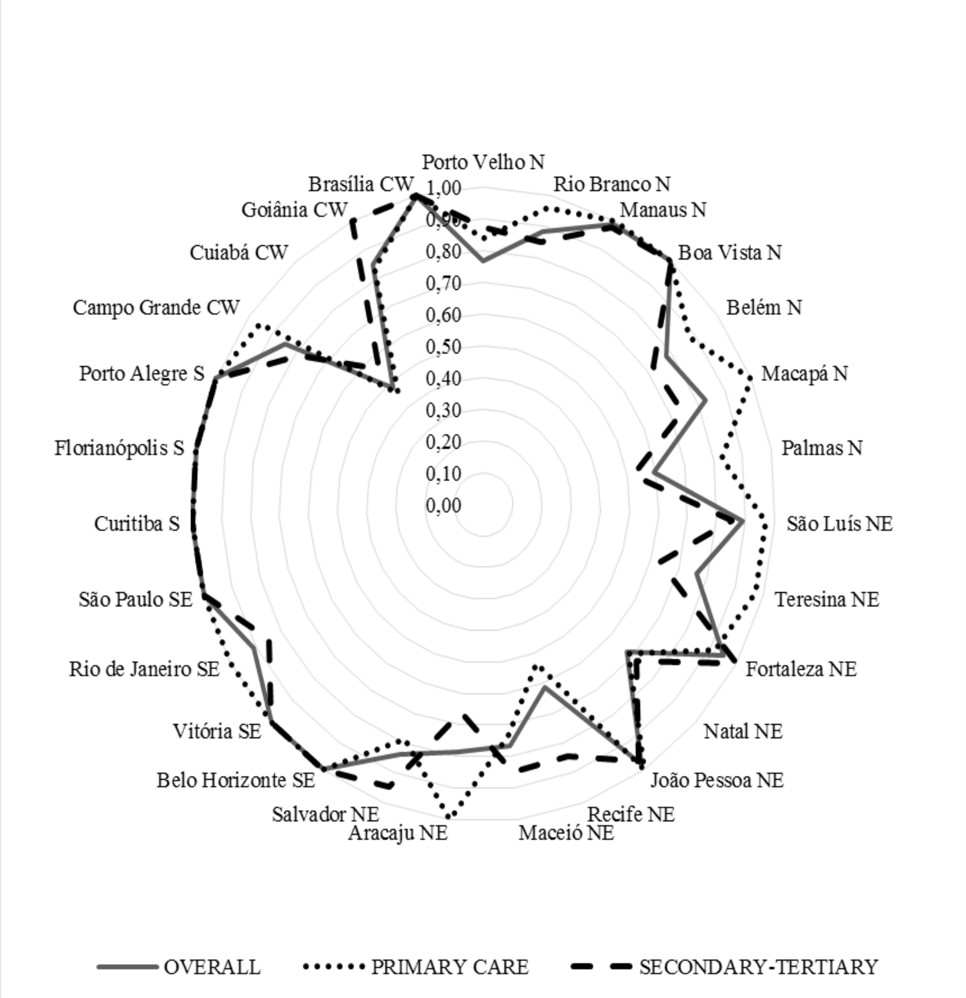
Source: Authors' own study

The average overall efficiency score for all Brazilian capitals was 0.86 (SD= 0.15). Figure 3 presents the overall, PHC and STC efficiency scores for each capital in the analyzed period. The continuous grey line represents the overall score and eight efficient capitals are fully efficient at both, PHC and STC levels of analysis. All capitals from the South – S region, three out of four capitals in Southeast region – SE, one out of five in North region - N and the capital of Brazil (federal district), in Center-West - CW, were efficient. None in the Northeast – NE was fully efficient.

For the remaining inefficient capitals, 11 had superior performance on PHC activities (mainly from N and NE); 8, on STC activities. In the case of Rio de Janeiro – SE, for instance, the capital was a hundred percent efficient at PHC level, but was inefficient at STC level (STC score equals 0.85). The opposite happened to Fortaleza – NE, 100% efficient at STC level, but inefficient at PHC (PHC score equals of 0.91). Twelve capitals were inefficient at both levels. The minimum observed efficiency score was 0.48 (Cuiabá – CW; 0.46 in PHC and 0.56 in STC).

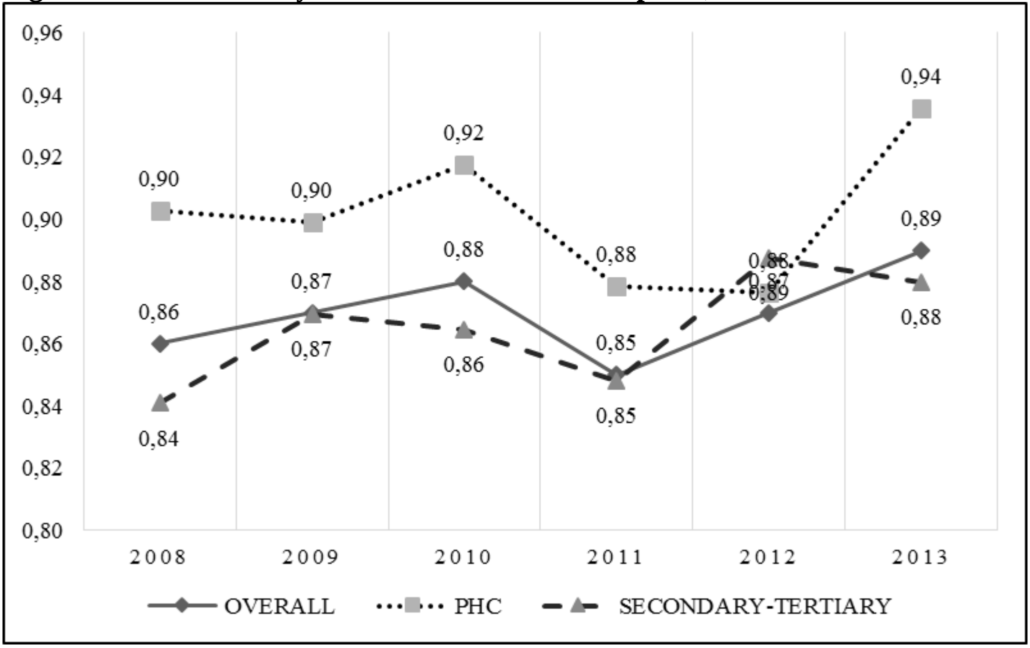
Given the model is dynamic, there were variations across the years (Figure 4). In short, the panel nature of the data allowed the computation of productivity growth for all capitals over the period of 2008-2013. Overall performance increased from 0.86 (SD=0.16) to 0.89 (SD=0.15); PHC, from 0.90 (SD=0.17) to 0.94 (SD=0.14); STC level, from 0.84 (SD=0.18) to 0.88 (SD=0.19). Although there was approximation to the frontier, with ascending scores and catch-up average values above the unit, a positive rate for frontier shift or technological change occurred only for STC, by 3.0%. The STC technological change presented difference among regions according to sociodemographic gradient: South had the best performance (positive rate 6.1%), followed by Southeast (2.8%), North (2.2%). Northeast and Center-West had negative rates (-0.8% and -3.8%, respectively). Overall Malmquist stayed nearly unchanged in the period (=1.008). (Figure 5)

Figure 3. Efficiency scores - Brazilian state capitals, 2008-2013



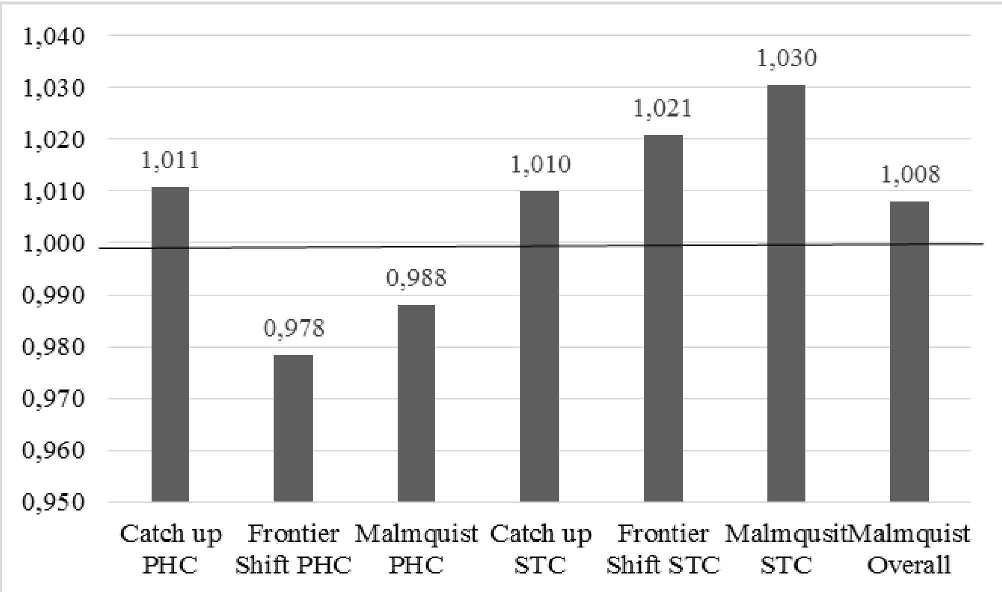
Source: Authors' own study

Figure 4. DEA efficiency scores - Brazilian state capitals, 2008-2013.



Source: Authors' own study

Figure 5. Malmquist Index, and its components, Brazilian capitals- 2008 to 2013: Overall, PHC and STC.



Source: Authors' own study

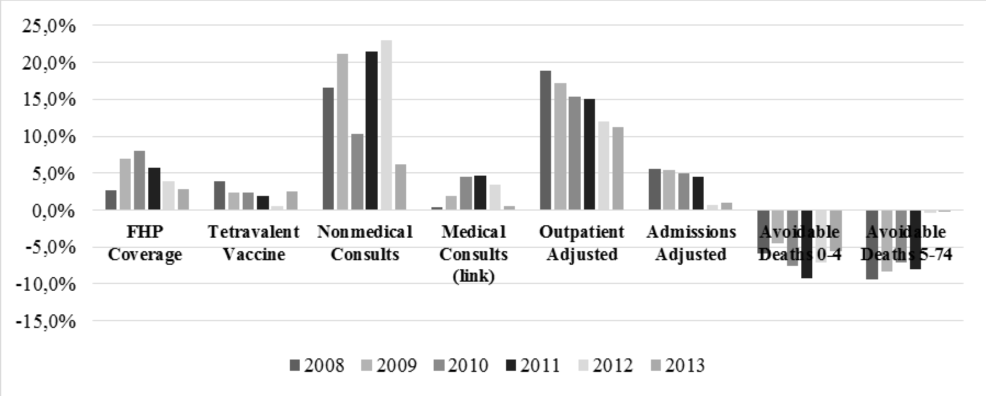
Figure 6 presents average projections to achieve the best production frontier across the years. For service delivery outputs, there is scope to a considerable large expansion in the number of nonmedical consultations (by 16.4%) and outpatients adjusted procedures (by 14.9%), which are PHC and STC outputs, respectively. The need to increase adjusted outpatient care is especially important because it is the main way of entrance into the STC level of care, by means of specialized consults and exams, suggesting there is a bottleneck at this point of the health network.

Note that medical consults, which have reduced their absolute numbers from 2008 to 2013 (Table 2) had to increase their production by only 2.5%, in average. As a link variable between PHC and STC, the projected values can be positive or negative. In order to achieve better efficiency scores, some capitals "asked" for reduction of the medical consults when there was overload of that variable to STC care, compatible with the hypothesis of a possible bottleneck in the interface between levels. Across the analyzed years, 7% to 22% of the capitals had negative projections, with magnitudes varying from to -3.3% to -65.5% of the actual values. The same capitals with negative projections had highest needs to increase the adjusted outpatient procedures (which are referenced from PHC physicians), corroborating the bottleneck effect hypothesis.

For both STC service delivery variables, there is a clear gradient towards decaying the projection needs in the analyzed period, compatible with the positive STC frontier shift shown above. For outcome quality health indicators, avoidable deaths still have to decrease by 5.9% and 9.4% for 0-4 years-old and 4-74 years-old, respectively, in 2013 projections.

Finally, in terms of expenditures (input slacks), there is scope to reduce PHC expenditures and STC expenditures by approximately 1.2 and 1.5 %, respectively, to produce the same level of outputs. These negative values for PHC and STC expenditures (input variables) consist of projections onto Pareto-inefficient portions of the frontier, which means that the same efficient scores would be found if the expenditures were reduced by the outlined percentage.

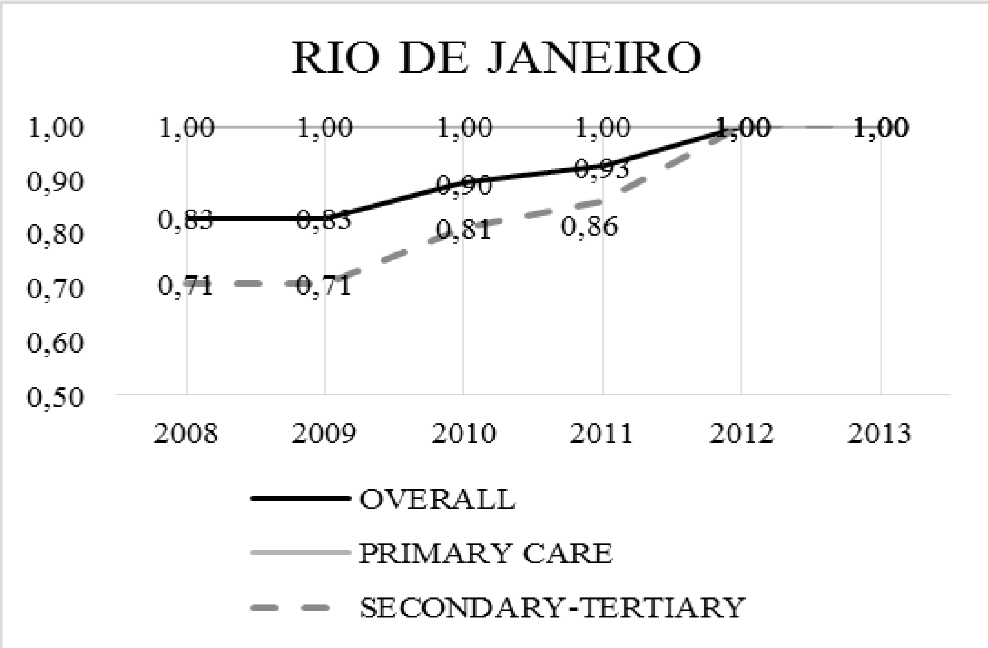
Figure 6: Output projections to reach the best practice frontier

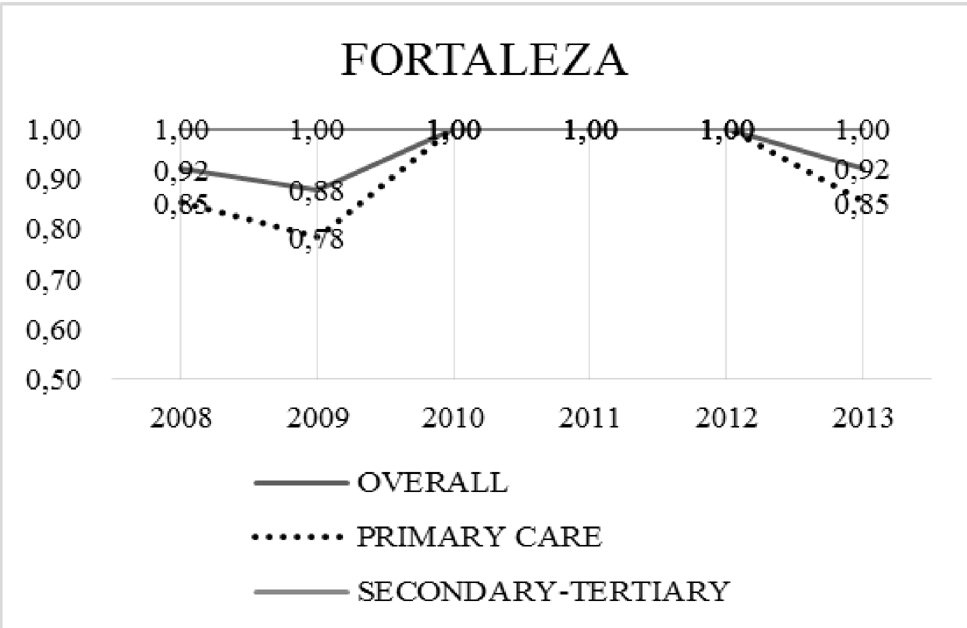


Source: Authors' own study

Instead of average projections, individual DMU analysis can help to understand its behavior. When analyzing each capital in separate, the focus on projections will depend on the efficiency level and the pattern of inefficiency (either PHC or STC), facilitating establishment of goals to improve efficiency (Figure 7). For example, Rio de Janeiro, efficient in PHC, needed to increase outpatient procedures by 50% and adjusted admissions by 20% and reduce hospital avoidable deaths by 30%, in 2008. The gradual adjustment of these figures guaranteed STC efficiency in 2012 (Rio de Janeiro´s STC catch-up equals 1,071). On the other side, Fortaleza needed to increase PHC outputs, especially from 2008 to 2010 (HFP coverage by 30% and tetravalent vaccination, by 10%). Once accomplished the projected goal, Fortaleza appeared PHC efficient from 2010 until 2012, but did not maintain PHC efficiency in 2013 (the capital did not keep pace with the FHP coverage; so, Fortaleza´s PHC catch-up remained stationary = 1,001).

Figure 7. Overall, PHC and STC efficiency in Rio de Janeiro-SE and Fortaleza-NE, 2008-2013.





Source: Authors' own study

4. Discussion and final remarks

Health Care Systems can be thought as complex adaptative systems which do have many interacting agents and components in a changing environment (Peters 2014: 2). Resources (money, qualified personnel, facilities), biomedical knowledge (epidemiology, evidence-based medical practice) and population (health and sick) are inputs for the system; their interconnection determines capacity do learn an adapt to a sociocultural environment; and the latter exerts a powerful feedback effect on its inputs, dynamics and outputs (Costa 2012: 31). In this context, Data Envelopment Analysis is shown as a decision science method that carries few required model parameter choices while providing and effective means to analyze otherwise hard to model decision problems: it suits problems with a large number of input and output variables, heterogeneous data types within the model and differing scales while at the same time not being sensitive to distribution, autocorrelation and collinearity, issues found in parametric models (Alexander 2008: 109). While deepening interconnectivity approach, it is not surprising that a survey of the first forty years of scholarly literature has pointed out the use of network models as one of the main fields of current studies and future trends in DEA (Emrouznejad, Yang 2018: 4).

Most frequently, DEA health applications research published deal with cross-geographic (countries, states, municipalities), cross-facility (hospitals, primary care centers, nursing care, and so on) or health human resources (general practitioners, surgeons, specialists) comparisons, and use intermediate outputs (services delivered instead of health improvement), with little thoughts to model specifications (Hollingsworth 2008: 1108-1111). In Brazil, for public spending assessment, there are published DEA models to examine primary care efficiency (Varela et al. 2009) or outpatient productivity, either primary outpatient care or medium/high complexity (Ferreira, Pitta 2008). For secondary-tertiary performance analysis, hospitals are the most frequently used DMUs (Gonçalves et al. 2007; Cesconetto et al. 2008; Guerra et al. 2012; Souza et al. 2013; de Souza et al. 2016), although there are initiatives for specific high complexity procedures, as transplants (Costa et al., 2014). Network DEA model was used by Lobo et al. (2010, 2016) with university hospitals aiming to integrate teaching and health care dimensions and to aid financing decisions. As each level or procedure was analyzed separately in each study, there would be limitations to infer the Brazilian health system as a whole from the sum of partial results of its components: primary care, outpatient, hospital, transplants, university hospitals.

In this study, DNSBM DEA model intended to represent Brazilian health care architecture in order to bring insights on how to monitor health systems achievements by linking PHC and STC levels of care through the SUS production function. The basic assumption was that the health system has its own components organized at a hierarchical structure, all interconnected and influenced by the others. The network model was a way to depict the relationships between levels of care, by opening the black box, instead of analyzing each level separately, which could compromise the interpretation of results. Additionally, the network DEA model allowed to consider, for different levels of care, intermediary or operational outputs (intermediary outputs or service delivery indicators) and quality outcomes (avoidable deaths).

During the analyzed period, there was huge investment on PHC and STC expending (above fifty percent increase), and the simultaneous evaluation of various outputs was necessary to conclude for or against efficiency in the use of resources. Once there are more resources, operational outputs changes can be observed in a short timeframe, but health indicators usually take more time – sometimes years or decades – to show steady variation clearly attributable to health policies undertaken.

Concerning operational outputs, at PHC level, there was a clear priority for FHP coverage in the analyzed period. It was noteworthy the decrease in PHC medical consults, problem that might be even bigger in poorer and smaller municipalities away from metropolitan areas. At STC level, both outputs – outpatients and admissions – increased substantially, and the need to augment decayed across time.

Concerning final outputs, avoidable deaths amelioration was evident for children under 5 years old. This result is attributed worldwide to high immunization coverage of the National Immunization Program, following the forth Millennium Development Goal (MDG) (Castro Lobo et al., 2014: 55), but there was projection to further decrease in 2013 (5.9%).

Given the 0.86 average score, there is still a great room to enhance efficiency. Individual analysis shows there was substantial differences among capitals, possibly correlated with socioeconomic disparities, given that inefficiency, especially for STC, prevails in poorer Northeast and North regions. Variations in time showed trends towards catching-up with the frontier at both, PHC and STC levels, but the technological change or positive frontier shift was only observed for STC level (which consumes about 90% of the budget) and at the richest regions. This may have resulted from the fact that managers invested in high complexity facilities inside capitals, which are STC reference for surrounding smaller municipalities and, not rarely, for all state municipalities.

The bottleneck effect seems to be an important challenge to overcome in Brazilian health system. When the entrance door to STC is blocked, individuals will enter the system directly from the emergency rooms, instead of being transferred from PHC level of care, distorting the system´s architecture as a whole. The reasons range from incapacity of PHC services to manage and coordinate patient care and tendency to focus on high-cost procedures (Paim et al. 2011: 1791).

The bottleneck hypothesis can be evaluated against other data. The Brazilian average number of physicians per 1,000 population equals 1.83. The same capitals that “asked” to reduce the number of PHC medical consults and to increase the outpatient procedures belong to states that have the lowest ratio of physicians per 1,000 population, varying from 0.58 (São Luis – NE) to 1.54 (Campo Grande – CW). In short, there is shortage of PHC physicians in these capitals and, simultaneously, overload of patients to access STC level of care; a scenario perfectly compatible with a bottleneck.

The observed input slacks (1.2% for PHC and 1.5% for STC) represent possible waste that could somewhat be invested in other healthcare activities.

For policy purposes, DNSBM DEA model can be used as an efficiency-based strategic tool for diagnosis and planning, to set and evaluate the accomplishment of service delivery goals, by comparing parameters of production among peers, vis-à-vis financing in one side (inputs for the production function), and health indicators on the other side (ultimate desired outputs). Assuming that each municipality sign annual management contracts with the public health manager, establishing budget and quantitative volumes for service delivery, the study of projections for the goals under commitment is useful to understand and negotiate possibilities and benchmarks. The examples of Rio de Janeiro and Fortaleza showed how to monitor accomplishment of goals across time. Besides, policies to stimulate PHC medical consults in remote areas and intensify access and coordination between levels of care are important pathways to enhance efficiency.

For future research, new models can be designed according to diverse health systems architectures; diverse variables may be inserted according to policy priorities and management arrangements inside the system; and new boundaries must be defined (state, regions, microregions) to be compared. The important lesson that must always be kept in mind is that, no matter how much complex and uncertain the real world is, researchers need to understand it in depth and try to mimic subsets of it in order to have answers acceptable to managers and stakeholders (to guarantee face validity) instead of bringing the problem to academic silos and becoming distant from those who apply the solutions.

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Analiza efektywności wydatków na służbę zdrowia w brazylijskich stolicach stanowych w oparciu o metodę Network Data Envelopment Analysis

Streszczenie

Cel: W 1988 roku Brazylia wdrożyła dogłębne zmiany w organizacji oraz finansowaniu systemu służby zdrowia, powołując do życia Zunifikowany System Opieki Zdrowotnej („Sistema Unico de Saúde" – SUS), zakładający powszechny dostęp do służby zdrowia. Stopniowemu rozszerzaniu systemu opieki zdrowotnej oraz uprawnień do usług medycznych towarzyszyła debata dotycząca odpowiedniego poziomu wydatków rządowych i wydajności systemu.

Metodyka badań: W badaniu wykorzystano zmienne efekty skali zorientowane na wyniki, model Slacks-Based-Measure oparty na dynamicznej sieciowej metodzie obwiedni danych (ang.: Data Envelopment Analysis (DEA)) dla danych z lat 2008-2013, aby zobrazować zależność, jaka zachodzi pomiędzy różnymi poziomami opieki (podstawowa opieka zdrowotna (ang. primary health care (PHC)) oraz opieka zdrowotna drugiego i trzeciego stopnia (ang. secondary-tertiary health care (STC)). Jednostkami podejmującymi decyzje są brazylijskie stolice stanowe, które wdrażają kluczowe założenia polityki zdrowotnej oraz wspierają pacjentów z okolicznych, mniejszych jednostek administracyjnych, szczególnie w zakresie STC. Nakłady stanowią budżety PHC i STC, natomiast wynikami są wynikające z nich usługi oraz przypadki zagrożenia życia, w których udało się uratować pacjentów. Powiązana zmienna to konsultacje medyczne w ramach PHC, drzwi wejściowe do systemu oraz strażnik bramy do bardziej kompleksowych poziomów opieki. Dynamiczny model pozwala oceniać wydajność w czasie.

Wnioski: Ogólny stan wyniósł 0,86, przy czym dla PHC kształtował się na poziomie 0,90, a dla STC 0,85 (SD=0,15). 8 z 27 stolic okazało się w pełni wydajnych. Stolice zdołały zwiększyć wyniki w obu poziomach opieki zdrowotnej, ale tylko STC doświadczyło pozytywnej zmiany technologicznej (frontier shift > 1). Zmienna powiązana wykazała wąskie gardło pomiędzy poziomami opieki. Projekcje dotyczące granic (frontier shift) pozwoliły ustalić własną diagnozę dotyczącą zarządzania oraz cele związane z finansowaniem i rozwojem.

Wartość artykułu: Modele sieciowe naśladują hierarchicznie zorganizowane systemy opieki zdrowotnej. Wykorzystanie wyników wspiera politykę służby zdrowia.

Słowa kluczowe: Network DEA, pomiar wydajności, rozwój zdrowotny i gospodarczy, służba zdrowia
JEL: H21, H51, O10, O54

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An evaluation of the determinants of total factor productivity growth in Indian information technology industry: an application of DEA-based Malmquist Index

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Abstract:

Aim: This study aims at assessing the Total Factor Productivity Growth (TFPG) and its determinants in the Indian Information Technology (IT) industry.

Design / Research methods: To realize the objectives of the study, firm level data has been collected from the Centre for Monitoring Indian Economy (CMIE) PROWESS database. For empirical analysis, we have applied a two-stage method. In the first-stage, we have used Data Envelopment Analysis (DEA) based Malmquist Productivity Index (MPI) to evaluate the TFPG in the Indian IT industry during the period from 2004-05 to 2014-15. For this purpose, a balanced panel dataset consisting 70 IT firms has been considered. Further, the TFPG has been decomposed into three components, viz. catch-up, frontier-shift, and scale efficiency change (SEC). Consequently, in the second-stage, three random-effects panel regression models are considered to investigate the determinants of TFPG, catch-up, and frontier-shift separately.

Conclusions / findings: During the study period, on an average, the TFPG and frontier-shift has been improved. On the other hand, catch up effect is found to have declined. The variables, such as export intensity, salaries and wages intensity have positive and statistically significant impact on the catch-up and frontier-shift. Export intensity and Salaries and wages have positive impact on TFPG. Age of the firms has positive impact on catch-up and TFPG. On an average, the firms which spent on research and Development (R&D) have experienced improvement in TFPG and frontier-shift. The public limited firms performed better than their private counterparts in terms of catch-up, frontier-shift, and TFPG. The non-group firms have performed better than the group firms in case of catch-up. On the other hand, on an average, the firms exhibiting decreasing Returns to Scale (DRS) are found to have registered deterioration in catch-up and TFPG with respect to the benchmark Constant Returns to Scale (CRS) firms. The firms exhibiting Increasing Returns to Scale (IRS) have shown improvement in catch-up and TFPG over the benchmark CRS firms. The impact of the US subprime crisis has been negative on

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catch-up, frontier-shift, and TFPG. The firms, which have spent on royalty, have experienced improvement in catch-up and TFPG.

Originality / value of the article: So far in our knowledge, we have not found so many empirical studies of this kind pertaining to the IT industry, especially in a developing country like India. Moreover, we have not found any study that covers the span of the dataset considered in this study. In addition to this, the present study has employed a random-effects model to accommodate a number of time-invariant dummy variables which would not be possible in case of a fixed-effects model incorporated by some previous studies of this genre.

Implications of the research (if applicable): The identification of the determinants of TFPG and its components would help the stakeholders and policy makers to formulate appropriate policies which could mitigate the risks faced by the Indian IT industry on one hand, and stimulate the forces that would enhance the growth of this industry on the other. For instance, to mitigate future risks, Indian IT industry should reduce its dependence on the US and UK markets. In other words, it should explore new markets in domestic as well as foreign economies such as the EU, Australia and the emerging economies where the IT markets are seem to be promising. To maintain India’s robust global position in the long run, Government of India should play a key role in providing world class infrastructure and telecommunication facilities to its IT industry. In addition to this, Indian Government needs to rationalise and simplify the existing Indian labour law to facilitate the business of IT industry. Various stakeholders along with the Government should put necessary efforts to develop the domestic IT market where ample opportunities are present.

Keywords: Information Technology industry, data envelopment analysis, Malmquist productivity index, random-effects model, total factor productivity, catch-up, frontier-shift, India.

JEL: C23, C61, L86, O47

1. Introduction

The Indian Information Technology and Information Technology-enabled Services (IT-ITeS) industry has been playing an instrumental role in software development globally and providing various IT-enabled back office services since the beginning of the 21st century. As of now, India holds a prestigious position in the world as an off-shoring destination nation. On the other hand, the Indian IT-ITeS sector has occupied a distinguished position in the international market of software and different IT-enabled services. Indian IT companies have been enjoying remarkable position internationally in providing a variety of on-shore as well as off-shore services to their foreign clients. During the last decade, this sector has grown almost six times in terms of its revenue. In the financial year 2016-17, the relative contribution of this sector to India’s GDP is estimated to be more than 9.3 percent

(NASSCOM[1] 2017). India's competitive advantage in IT-ITeS industry mainly comes from the abundance of cheap, technically skilled, and English-language proficient workforce. Furthermore, over time, Indian IT sector has become capable of delivering high end quality services in the global sourcing market with supreme reliability and cost-effective manner. During 2016-17, India is able to retain her leading position in IT-ITeS sourcing business globally with a robust share of 55% (NASSCOM 2017).

However, some recent global incidents such as slowdown in the world economic activity followed by U.S. subprime crisis, Britain's exit from the European Union (EU) in 2016, new U.S. administration's policy towards H-1B visa programme in 2017, etc. are likely to have unfavourable impact on the performance of the Indian IT-ITeS sector. In addition to this, the emergence of capital deepening technology (or automation) in IT-ITeS industry may further worsen the situation. There is a perception that increasing automation could diminish job availability in this industry. On the other hand, some internal factors like dearth of quality manpower, inability of the industry to move up the value-chain, underdeveloped domestic market and unpreparedness of the industry for disruptive technologies pose challenges to the growth of this industry in the future (Sharma 2014).

Against this background, maintenance of a steady performance is critical to the sustainability of the Indian IT industry in the future. Therefore, it is pertinent to assess the performance of the Indian IT industry. In this paper, an attempt has been made to measure performance of this industry in terms of total factor productivity change over time. In this context, very few empirical studies are found that investigated the productivity change in Indian IT industry. Moreover, in our knowledge, no study has been conducted so far wherein the productivity change in Indian IT industry is evaluated during 2004-05 to 2014-15. To fill this research gap, this paper aims at exploring the following objectives:

- The trends in total factor productivity growth (TFPG) in the industry over the study period

[1] NASSCOM refers to the National association of Software and Services Companies, which is a premier trade body and the chamber of commerce of the IT-ITeS industry in India.

- The trends in various constituent components of TFPG, viz. catch-up, frontier-shift over the study period
- Decomposition of catch-up effect into pure technical efficiency change (PTEC) and scale efficiency change (SEC)
- To indentify the influence of various environmental variables on TFPG, catch-up, and frontier-shift.

To evaluate the TFPG over time, this study employs Malmquist Productivity Index (MPI) which is based on DEA technique. The TFPG is further decomposed into three components, namely, technical change (innovation), technical efficiency change (catch-up), and scale efficiency change. The TFPG is evaluated on the basis of base period as well as adjacent period. Subsequently, random-effect panel model is used to find out the determinants of TFPG, technical change, and technical efficiency change.

The paper is divided into five sections. Section-1 presents introduction and objectives of the study. Section-2 contains review of literature. Section-3 describes the methodology. Section-4 discusses the data. Section-5 consists of the results and discussion. Finally, Section-6 provides the summary and concluding remarks.

2. Review of Literature

This section summarizes the studies pertaining to the performance analysis in the IT industry. Shao and Shu (2004) evaluate the TFPG in the IT industry across 14 OECD countries during 1978-1990. They employ DEA-based MPI method to estimate TFPG. For this purpose, they collect data from two databases, viz. OECD Stan Database and OECD International Sectoral database. The TFPG is further decomposed into two components, namely, technological change and technical efficiency change. The results of this study reveal that 10 countries experienced TFP growth among the 14 countries during the study period. The technological change is found to be the prime contributor to the TFP growth relative to the technical efficiency change. Furthermore, change in scale efficiency is observed to be played a dampening role in TFP growth.

Shu and Lee (2003) examine productivity and productive efficiency of IT industries of 14 OECD countries during 1998 using stochastic frontier analysis. This study evaluates three types of inefficiency: technical, allocative, and scale. The results reveal that both the technical and scale efficiencies are low among the study countries. The study suggests that a country with low technical efficiency should either provide more high tech job trainings or balance the employment growth in high tech and other industries in order to achieve higher technical efficiency. Furthermore, mergers have been recommended to improve scale efficiency.

Chen and Ali (2004) extend the DEA-based Malmquist index approach by further interpreting its two components viz. technical efficiency change and frontier shift, with managerial implication of each component. In addition to this, they try to identify the strategy shifts of individual DMUs during a particular time period with respect to changes in isoquant. Finally, this new approach is empirically applied to a set of Fortune Global 500 Computer and office Equipment companies.

Mathur (2007a) estimates the technical efficiency of Indian software industry by during 2005-06. Data for 92 software companies is collected from CMIE PROWESS database. An input-oriented DEA model is applied to calculate technical efficiency. Further, the paper investigates the impact ofvarious determinants on technical efficiency of these companies by using Tobit regression model. The average technical efficiency of 92 software companies is found to be 0.69. The regression results show that net export and company size have positive and statistically significant impact on the technical efficiency. On the other hand, total cost has negative and statistically significant impact on the technical efficiency. This study also evaluates the TFPG of Indian software companies during 1996-2006. The TFP and its decomposition results depict that TFP growth mainly occurred due improvement in technological change rather than change in technical efficiencyin the study period.

Mathur (2007b) examines the technical efficiency of the Information and Communication Technology (ICT) sector for selected 12 countries including India by applying DEA. The study found that Taiwan was the most efficient country while India was the least efficient country with technical efficiency scores 1 and 0.72, respectively. This study suggests that India should use its ICT environment and ICT readiness judiciously for higher ICT usage in order to catch up with the efficient countries such as Taiwan, Japan and South Korea.

Chen et al. (2011) estimate overall, managerial, and scale efficiencies in 73 Chinese IT companies during 2005-2007 using DEA technique. This paper also calculates the TFP growth applying Malmquist productivity index. The efficiency results reveal that on an average, the Chinese IT industry was technically and managerially inefficient by 6.8 percent and 5.1 percent, respectively, during the study period. The study does not find any significant progress in productivity during the reference period. The efficiency convergence analysis points out the occurrence of substantial technical diffusion along with a decline in the technical convergence during the study period. The study suggests that the IT-companies may invest in R&D activities and develop intellectual capital to attain competitive advantages and enhancement in performance.

Bhattacharjee (2012) examines the technical efficiency of Kolkata's Software Technology Park (STP)'s IT-ITeS firms using output-oriented DEA model under VRS assumption. For this purpose, data is collected from the STP, Kolkata for the period of 15 years (from 1993-94 to 2007-08). The results illustrate that on an average, the technical efficiency of IT-ITeS firms declines over the study period. The determinants of technical efficiency are assessed by using an OLS regression model. In regression analysis, net foreign exchange earnings and the international orientation (the ratio of foreign exchange outflow to the total cost) are considered as independent variables and the technical efficiency scores as dependent variable. Both the coefficients of the independent variables are observed to be positive and statistically significant. The paper suggests that with rising foreign exchange earnings and the higher the global orientation, the performance of the IT-ITeS industry also improves during the reference period of the study.

Sahoo (2013) evaluates TFP growth in Indian software industry during 1998-2008 using Malmquist productivity index. The study also investigates the determinants of TFP growth applying fixed-effects panel regression model. The results depict that on an average, Indian software industry experiences TFP growth by 0.4 percent during the study period. The older companies are found to be registered higher productivity growth as compared to their newer counterparts. The

Indian-owned companies are observed to be more productive than the group-owned companies. The regression analysis shows that the initial overall technical efficiency has negatively impacted the TFP growth. Finally, the R&D has no statistically significant impact on TFP growth of software industry during the study period.

Sahoo and Nauriyal (2014) analyze the trends in technical efficiency of Indian software companies during 1999-2008. They apply an input-oriented DEA model under VRS assumption to evaluate the technical efficiency. For this purpose, input and output data for a sample of 72 software firms is taken from CMIE PROWESS database. The overall technical efficiency (OTE) is further decomposed in to pure (or managerial) efficiency (PTE) and scale efficiency (SE). The study also investigates the determinants of OTE, PTE and SE of Indian software companies during the study period by using Tobit regression model. The results reveal that the mean OTE is 0.477 during 1999-2008, suggesting thereby on an average, the software industry wastes 52.3% of inputs. Pure technical inefficiency is found to be the main source of overall technical inefficiency. Further, it is found that the number of companies operating on most productive scale size has declined during the study period. The Tobit regression results show that the Indian-owned companies are more efficient that their foreign and group-owned counterparts. The firm size is found to have positive impact on technical efficiency. On the other hand, wages and salaries intensity negatively impacted overall technical efficiency, pure technical efficiency and scale efficiency. Finally, the older companies are found to be more efficient that their younger counterparts.

Chou and Shao (2014) study the TFP growth of IT services industries in 25 OECD countries during 1995-2007 using DEA-based Malmquist productivity index (MPI). MPI is further decomposed into three components, namely, technical change, efficiency change, and scale change. The findings show that technological progress is the major driver of the TFP growth. Efficiency change and scale change have negative effect on TFP growth. On an average, these IT services industries have experienced 1.9% annual TFP growth during the study period.

Das (2017) and Das and Datta (2017) apply a two-stage DEA method to study the trends in and determinants of technical efficiency in Indian IT and ITeS industry, respectively, during 2000-2014. Both the papers estimate the Pareto-Koopmans efficiency along with CCR and BCC[2] efficiency scores to take care of the presence of input and output slacks. These two studies also estimate the input and output specific technical efficiencies.

3. Methodology

3.1. Notion of total factor productivity

According to OECD (2001), productivity can be defined as a ratio of a volume measure of output to a volume measure of inputs. In simple word, productivity implies how efficiently output is produced from a given input combination (Syverson 2011). Moreover, productivity growth can be considered as a major indicator of innovation associated with creation of new production process and product, organizational structure etc. (Jorgenson 2009). The growth of output is often higher than the growth of inputs as a result of innovation. There are two ways to measure productivity: (a) for a single factor of production, and (b) for multi factor of production. Productivity of a single factor of production is also known as partial productivity. The latter is known as total or multi-factor productivity. In our study, we focus on the total factor productivity.

The Total Factor Productivity (TFP) is basically refer to the growth of output which is not explained by the growth in regular factors of production such as labour, capital, raw materials etc. (Comin 2008). Basically, TFP shows how productively the inputs are employed in a production process. Furthermore, differences in TFP show shifts in isoproduct curve which captures variation in output produced from a given input combination (Syverson 2011). There are various methods to measure the TFP. One of the most common techniques is the growth accounting approach introduced by Solow (1957). This approach calculates the TFP by as a residual (popularly known as Solow residual). Since the estimation of productivity growth reflects the changes in output which has not been explained by the changes in the individual inputs, it can be regarded as a residual measure. On the other hand, TFP is

2 CCR and BCC DEA models are developed by Charnes et al. (1978) and Banker et al. (1984), respectively.

also known as a measurement of ignorance as its outcome is unknown to us (Abramovitz 1956). Although this approach allows separating out the effect of technical change on TFP, it does not permit to separate out the changes in technical efficiency from TFP. There are two popular alternative empirical techniques to measures TFP, namely, parametric and non-parametric. Whereas the parametric approach requires an explicit consideration of the production function, the non-parametric approach does not need any prior specification of the production function.

The most popular parametric and non-parametric approaches to measure the TFP are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), respectively. The SFA is based on regression method. In contrast, the DEA[3] is based on mathematical programming method. There are two other popular index-based approaches to measure TFP such as Fisher and Tornqvist productivity indexes. Whereas the construction of these two indexes requires a priori price information, DEA[4] does not require any price information of input/ output for estimating TFP index. On the other hand, both Tornqvist and Fisher indexes are descriptive in nature while Malmquist index is a normative one (Ray 2004).

3.2. The Malmquist Productivity Index

This study employs DEA-based Malmquist Productivity Index (MPI) to evaluate the Total Factor Productivity Growth (TFPG) of 70 Indian software firms during 2004-05 to 2014-15. Caves et al. (1982) first introduced the MPI on the basis of Malmquist (1953). The index is further decomposed into two components, namely, technical change (frontier shift) and technical efficiency change (catch up). There are two ways to measure the TFPG on the basis of MPI. One is based on a fixed base period and the other is between two adjacent periods. In the present study, both measures are used to measure TFPG. Following Färe et al. (1994a) and Coelli et al. (1998), we calculate the MPI on the basis of an output-oriented DEA model. The output-oriented MPI is based on four output (Shepherd) distance functions. The

[3] See Cook and Seiford (2009) for a comprehensive review of studies pertain to methodological development in DEA.

[4] See Emrouznejad and Yang (2017), Emrouznejad et al. (2008) for a comprehensive survey and bibliography of studies based on DEA.

output distance function is equivalent to the Farrell measure of technical efficiency[5] and associated with the maximum expansion of the output vector given the input vector. The MPI can be decomposed in the following manner:
Malmquist Index (MI) = Technical Change (TC) x Technical Efficiency Change (TEC)

Technical change is associated with the shift of the production frontier, whereas the technical efficiency change is associated with the movement towards the frontier. The terms 'technical change' and 'technical efficiency change' are also known as frontier-shift and catch-up, respectively. Now, we assume there are 'N' numbers DMUs or firms. Each firm is producing 'm' outputs from 'n' inputs. The production possibility set (S) under CRS can be defined as follows:

$$S = \{(x, y): x \geq \lambda_j x^j,\ y \leq \lambda_j y^j;\ \lambda_j \geq 0,\ (j = 1, 2\ldots, N)\} \qquad (1)$$

Where, (x^j, y^j) is the observed input and output bundle of DMU 'j'. To compute the MPI, we need to evaluate four output-oriented distance functions under CRS by solving four linear programming problems (LPP). Among four LPPs, two are for the same period and remaining two are for cross periods.
The four output distance functions are given as:

$$Dot\ (xt, yt) = \min\{\theta : xt, yt / \theta \in St\}. \qquad (2)$$
$$Dot+1\ (xt+1, yt+1) = \min\{\theta : xt+1, yt+1 / \theta \in St+1\} \qquad (3)$$
$$Dot\ (xt+1, yt+1) = \min\{\theta : xt+1, yt+1 / \theta \in St\} \qquad (4)$$
$$Dot+1\ (xt, yt) = \min\{\theta : xt, yt / \theta \in St+1\} \qquad (5)$$

Equations 2 and 3 represent the same period distance functions for the periods t and t+1, respectively. Equations 4 and 5 represent the cross period distance functions.

5 See Farrell (1957) for more details.

The same period output-oriented distance function for firm 'h' under CRS can be derived by solving the following LPP:

$$\varphi_h^* = \text{Max } \varphi_h$$
$$\text{Subject to}$$
$$\sum_{j=1}^{N} \lambda_j y_j^t \geq \varphi y_h^t \;;$$
$$\sum_{j=1}^{N} \lambda_j x_j^t \leq x_h^t \;; \qquad (6)$$
$$\lambda_j \geq 0 \; (j = 1, 2, \ldots, N)$$

The optimal value of the distance function $D_o^t(x^t, y^t)$ can be obtained as:

$$D_o^t(x^t, y^t) = \theta_h^* = \frac{1}{\varphi_h^*}$$

The optimal value of the distance function $D_o^{t+1}(x^{t+1}, y^{t+1})$ can also be obtain in similar manner by solving the LPP for period t+1.

Now, the cross period distance function (CRS) $D_o^t(x^{t+1}, y^{t+1})$ for firm 'h' for period t+1 with respect to the t-period's technology can be derived by solving the following LPP:

$$\varphi_h^* = \text{Max } \varphi_h$$
$$\text{Subject to,}$$
$$\sum_{j=1}^{N} \lambda_j y_j^t \geq \varphi y_h^{t+1} \;;$$
$$\sum_{j=1}^{N} \lambda_j x_j^t \leq x_h^{t+1} \;; \qquad (7)$$
$$\lambda_j \geq 0, \; (j = 1, 2, \ldots, N)$$

The optimal value of the distance function $D_o^t(x^{t+1}, y^{t+1})$ can be obtained as:

$$D_o^t(x^{t+1}, y^{t+1}) = \theta_h^* = \frac{1}{\varphi_h^*}$$

Similarly, the cross period distance function $D_o^{t+1}(x^t, y^t)$ can be estimated by using the LPP stated above after interchanging the superscripts t and t+1.

Here, it may be noted that the value of the distance function and output-oriented technical efficiency are the same.

The MPI for period t can be given as:

$$M_o^t = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \qquad (8)$$

The MPI for period t+1 can be given as:

$$M_o^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \qquad (9)$$

Now, following Färe et al. (1994a), the output-oriented MPI for period t+1 with respect to period t can be represented as the geometric mean of the two indices:

$$\text{MPI} = M_o^t\,(x^t, y^t, x^{t+1}, y^{t+1}) = (M_o^t * M_o^{t+1})^{\frac{1}{2}}$$

$$= \left\{\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right) * \left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right)\right\}^{\frac{1}{2}} \tag{10}$$

After some algebraic modification, the MPI can be represented as:

$$\text{MPI} = \underbrace{\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right)}_{\text{Catch-up (C)}} * \underbrace{\left\{\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right) * \left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right\}^{\frac{1}{2}}}_{\text{Frontier-shift (F)}} \tag{11}$$

Therefore, MPI = catch-up (C) * Frontier-shift (F) (12)

When MPI>1, it implies TFP growth or improvement in productivity from period t to t+1. A unitary value of MPI (i.e., MPI =1) indicates no change in TFP from period t to t+1. If the value of MPI<1, it indicates deterioration in TFP from period t to t+1. The catch-up (or technical efficiency change) component of MPI indicates change in overall technical efficiency under CRS technology between periods t and t+1. When C>1, it implies that the firm has been able to transform its inputs to output more efficiently in period t+1 as compared to period t. A unitary value (C=1) of C implies no change in technical efficiency between periods t and t+1. Further, if C<1, it means the firm becomes technically less efficient in period t+1 in comparison to period t. The second component of MPI, i.e., frontier-shift (or technical change) measures change in technology between two time periods t and t+1. If the value of F is greater than one (F>1), it shows technological improvement or innovation from period t to t+1. When F=1, it indicates status quo or no change in technology. Finally, F<1 implies regress in technology from period t to t+1.

To assess the impact of scale size change on TFP, the catch-up effect can further be decomposed into two components, viz. pure technical efficiency change (PTEC) and scale efficiency change (SEC). The decomposition of catch-up (or overall technical efficiency change) can be represented in the following way as proposed by Färe et al. (1994b):

$$\text{Catch-up (C)} = \underbrace{\frac{D_{ov}^{t}(x^{t+1},y^{t+1})}{D_{ov}^{t}(x^{t},y^{t})}}_{\text{PTEC}} * \underbrace{\frac{(D_{oc}^{t+1}(x^{t+1},y^{t+1})/D_{oc}^{t}(x^{t},y^{t}))}{(D_{ov}^{t+1}(x^{t+1},y^{t+1})/D_{ov}^{t}(x^{t},y^{t}))}}_{\text{SEC}} \qquad (13)$$

It is to be mentioned that while distance functions under catch-up are evaluated under CRS technology, the PTEC is estimated under VRS technology. In the real world, a technology exhibiting CRS seldom exists. Further, globally CRS is a restrictive assumption about the underlying technology (Ray 2004). In other words, a technology exhibiting VRS seems to be more realistic. Therefore, in this paper, we have considered the MPI under the VRS framework. The subscripts ‘c’ and ‘v’ in distance functions in equation (13) indicate the technical efficiency under CRS and VRS technologies, respectively. If the value of PTEC is found to be greater than unity (PTEC>1), it means the firm reaches nearer to the efficient frontier in period t+1 compared to period t. A unitary value of PTEC (PTEC=1) shows no change in pure (or managerial) technical efficiency between period t and t+1. If PTEC<1, it implies the firm under question further away from the efficient frontier from period t to t+1. Moreover, it can be said that the management of the firm has become less efficient in transforming inputs in output during period t+1 relative to period t.

The SEC captures the impact of change in scale of production on TFP. If the value of SEC is greater than one (SEC>1), it reflects improvement in scale efficiency during period t+1 compared to period t. if SEC=1, it indicates status quo in scale efficiency between periods t and t+1. Finally, SEC<1 implies decline in scale efficiency in period t+1 than period t.

Finally, the MPI can be represented as:

$$\text{MPI} = = \frac{D_{ov}^{t+1}(x^{t+1},y^{t+1})}{D_{ov}^{t}(x^{t},y^{t})} * \frac{(D_{oc}^{t+1}(x^{t+1},y^{t+1})/D_{oc}^{t}(x^{t},y^{t}))}{(D_{ov}^{t+1}(x^{t+1},y^{t+1})/D_{ov}^{t}(x^{t},y^{t}))} *$$

$$\left\{\left(\frac{D_{oc}^{t}(x^{t+1},y^{t+1})}{D_{oc}^{t+1}(x^{t+1},y^{t+1})}\right) * \left(\frac{D_{oc}^{t}(x^{t},y^{t})}{D_{oc}^{t+1}(x^{t},y^{t})}\right)\right\}^{\frac{1}{2}} \qquad (14)$$

Where, $D_{ov}^{t+1}(x^{t+1},y^{t+1})$ and $D_{ov}^{t}(x^{t},y^{t})$ denote the same period distance functions under VRS technology.

Therefore, MPI = PTEC * SEC * TC (15)

3.3. Econometric Methodology

Now, we discuss the econometric method employed to investigate the determinants of catch-up and frontier-shift, TFPG. In this regard, we use panel data regression to explore the environmental factors that influence the productivity change of Indian IT industry over the study period. Catch-up, frontier shift and Malmquist index are considered as dependent variables. Therefore, we have to estimate three regression equations as follows:

I. Catch $up_{it} = \alpha + \beta$ (explanatory variable) + u_{it}
II. Frontier $shift_{it} = \gamma + \delta$ (explanatory variable) + v_{it}
III. $MPI_{it} = \varepsilon + \eta$ (explanatory variable) + w_{it}

Where the subscripts 'i' and 't' denote the cross-sectional and time series dimensions, respectively, such that i = 1, 2, ….,70 and t = 1, 2, ….,10.

Now, we are going to conduct some relevant model selection tests to determine the most appropriate model for our regression analysis. The details of these tests are described below.

3.3.1. Poolability Test

This test indicates whether the pooled OLS model or fixed-effects panel model provides more reliable estimates of the parameters of the regression model. We assume the OLS and fixed-effects panel models as follows:

OLS model: $y_{it} = a + bX_{it} + u_{it}$ (a)
Fixed-effects model: $y_{it} = a + bX_{it} + \mu_i + u_{it}$ (b)

Where μ_i captures the firm-specific effects and u_{it} denotes the idiosyncratic error.
The corresponding null and alternative hypotheses are given by

H_0: pooled OLS model is appropriate
H_1: fixed-effects panel model is appropriate

Basically, under the null hypothesis (H_0), the firm-specific individual effects are assumed to be zero. The F statistic of poolability test can be constructed as

$$F = \frac{(RSS_R - RSS_U)/(N-1)}{RSS_U/[(T-1)N-K]}$$

Where RSS refers to the residual sum of squares, the subscripts 'R' and 'U' denote restricted and unrestricted models, respectively. N, K and T stand for number of firms, number of regressors and total time period (year), respectively. The aforementioned test statistic follows F distribution with [(N-1), {(T-1)N-K}] degrees of freedom.

3.3.2. Breusch and Pagan LM Test

Breusch and Pagan (1980) developed a Lagrange Multiplier (LM) test to find out the most suitable model between pooled OLS model and random effect panel model. The null and alternative hypotheses are as follows:

H_0: pooled OLS model is appropriate
H_1: random-effects model is appropriate

The corresponding test statistic is:

$$LM = \frac{NT}{2(T-1)}\left\{1 - \frac{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\tilde{u}_{it}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{u}_{it}^2}\right\}^2$$

Where, ũ refers to the residuals from pooled OLS model. The test statistic follows χ^2 distribution with one degree of freedom.

3.3.3. Housman Test

Housman test, developed by Hausman (1978), is another crucial model selection test that indicates whether the random-effects panel model or the fixed-effects panel model is suitable for analyzing the dataset. Generally, the Housman test can be performed to those hypotheses testing problems where two estimators from different regression models are available (Greene 2008). To explain this test under present scenario, we assume $\hat{b}$ and $\tilde{b}$ are the vectors of estimated slope parameters obtained from the fixed-effects and random-effects panel models, respectively. In this context, the null and alternative hypotheses can be given as:

H_0: random-effects model is appropriate
H_1: fixed-effects model is appropriate

Under the null hypothesis, $\hat{b}$ is considered to be efficient, while inconsistent under alternative hypothesis. On the other hand, the other estimator $\tilde{b}$ is inefficient under both hypotheses whereas consistent under both hypotheses. The corresponding test statistic is:

$$M = q'(\text{var}q)^{-1} q,$$

where $q = (\hat{b} - \tilde{b})$ and $\text{var}q = (\text{var}\hat{b} - \text{var}\tilde{b})$. The test statistic 'M' follows χ^2 distribution.

3.3.4. Unit root Test

To examine the presence of unit root in regression variables, we incorporate Fisher-type unit root test applicable for panel dataset. This unit root test was first proposed by R. A. Fisher and latter further discussed and developed by Choi (2001). This test consists of the following steps:

A. Initially, this test performs either Augmented Dickey-Fuller (ADF) test or Phillips-Perron (PP) test (depending on the researcher's choice) on each panel's series separately.

B. Thereafter, it combines the P-values obtained from each panel-specific unit root test to construct an overall test statistic for the entire panel series to check whether variable under consideration is stationary or not.

There are four alternative methods to transform the individual P-values into the overall test statistic as proposed by Choi (2001). These methods are: inverse χ^2

method, inverse normal method, inverse logit method, and modified inverse χ^2 method. The corresponding null and alternative hypotheses are as follows:

H_0: all panels are having a unit root
H_1: at least one panel is stationary

Now, we briefly discuss the four alternative test statistics in Fisher-type test given by Choi (2001) below:
The inverse chi-squared test statistic (P) can be given as

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

Where, p_i denotes the p-value of the unit root test on the i^{th} panel. N denotes the number of firms. The test statistic P follows the chi-square distribution with 2N degrees of freedom.

The test statistic (Z) of inverse normal distribution is given as:

$$Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \phi^{-1}(p_i)$$

Where, ϕ^{-1} refers to the inverse of the standard normal cumulative distribution function.
The corresponding test statistic of inverse logit t can be presented as

$$L^* = \sqrt{k}L$$

Where, $L = \sum_{i=1}^{N} \ln\left(\frac{p_i}{1-p_i}\right)$ and $k = \frac{3(5N+4)}{\Pi^2 N(5N+2)}$. L^* consists of (5N + 4) degrees of freedom.
Finally, the modified inverse chi-squared test statistic is given as

$$P_m = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\{\ln(p_i) + 1\}$$

Where, P_m follows standard normal distribution.

3.3.5. Fixed-effects vs. Random-effects Panel Models

There are various linear models available for panel data analysis. Among these models, the primary difference occurs between random-effects and fixed-effects models. In regression model presented in equation (b), the component μ_i captures the firm-specific heterogeneity. Now, in fixed effects model, μ_i is assumed to be correlated with the explanatory variables. On the other hand, μ_i is assumed to be purely random and uncorrelated with the regressors in random effects model. The error component u_i is assumed to be uncorrelated with regressors in both the models. Apart from the Housman test, the choice between random effect and fixed effect models depends on the relative size difference between time (T) and individual (N) dimensions. For instance, if the individual (here, firm) dimension is relatively larger than that of time (i.e., N>T), one would choose random effect model. On the other hand, fixed effect model would be more attractive if the time dimension is relatively higher than the number of firms (i.e., T>N). Moreover, a fixed effects model cannot estimate the effect of any time-invariant variables (such as time invariant dummies), unlike a random effects model (Baltagi 2001).

4. Data

4.1. Variables for First stage TFPG (MI) estimation

For the measurement of total factor productivity growth based on Malmquist Productivity Index, we have considered three input variables, viz. salaries and wages, net fixed assets and operating expenses and one output variable, viz. sales. The inputs and output data is collected from the Centre for Monitoring Indian Economy (CMIE) PROWESS online database for the financial year[6] 2004 to 2014. All the inputs and output data collected from the CMIE PROWESS database are reported in rupees millions. The selection of the salaries and wages as one of the input variables is based on some previous studies (Das 2017; Das et al. 2017;

[6] In this paper, the dataset is collected for each financial year. For instance, any data for the financial year (FY) 2004 implies the data belongs to the period during April 2004 to March 2005. For notational simplicity, we have used 2004 instead of 2004-05 to denote the FY. The same explanation is applicable for the other FYs.

Mahajan et al. 2014). Since the firm-level data on number of employees is not frequently reported in the CMIE PROWESS database, salaries and wages data is considered as a measure of labour input of the firm. Salaries and wages refer to the total annual expenses incurred by an IT firm on its all employees. A significant number of previous studies have used either net fixed assets or gross fixed assets as one of the input variables in performance evaluation by applying DEA in different industries (Ahuja, Majumdar 1995; Subramanyam, Reddy 2008; Mogha et al. 2012; Zhang et al. 2012). In our study, we have considered the net fixed assets as input variable instead of the gross fixed assets to take care of the depreciation of fixed assets. Net fixed assets of an IT firm comprise of buildings, computer equipment, software, furniture, land, machinery etc. less the accumulated depreciation. We have considered operating expenses as another input variable as a measure of capital input of the firm in line with the existing studies of this genre (Cinca et al. 2005; Chen et al. 2011). Operating expenses of an IT firm generally consist of salaries and wages, rent, official supplies, utilities, marketing, taxes, insurance, R&D expenses, inventory cost etc. Since we have considered salaries and wages as an input variable, we have excluded the salaries and wages during the calculation of operating expenses. Sales revenue is considered as the output variable on the basis of the previous studies (Sahoo 2011; Sahoo, Nauriyal 2014; Bhattachrjee 2012; Mathur 2007a). The output and input variables are deflated by GDP deflator to mitigate the impact of price change.

The year-wise summary statistics of input and output variables are reported in the following Table 1.

Table 1. Year-wise summary statistics of output and input variables. (at constant prices, 2004 = 100)

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Sales revenue											
Mean	5373	7130.1	9271.7	10901.5	12212.0	11520.5	12447.9	14178.1	15068.6	17672.6	18998.6
Median	1076	1393.0	1589.7	2175.6	2730.1	2339.8	1656.9	1880.5	1650.9	1809.8	1739.3
Std. Dev.	15370	20419	26219.2	30616.0	34712.5	33801.4	37493.3	43302.0	47682.4	57450.2	61843.6
Skewness	4.1	4.1	4.0	4.0	4.1	4.3	4.3	4.4	4.5	4.5	4.7
Kurtosis	16.5	16.4	15.9	15.7	16.5	17.6	18.0	18.7	20.3	21.5	23.1
Minimum	129.9	134.1	116.7	74.1	40.8	22.1	11.5	5.3	4.8	4.5	4.3
Maximum	80545	107862	134757	155558	175748	170342	198892	239209	281897	354609	393082
Count	70	70	70	70	70	70	70	70	70	70	70
Salaries and wages											
Mean	2239	2973.9	3864.7	4673.5	5262.1	4852.1	5368.0	6213.5	6832.4	7849.5	8307.3
Median	309.7	359.1	462.8	486.5	589.7	555.2	616.6	717.7	636.8	595.8	606.0
Std. Dev.	6798	8870.0	11525.3	13935.1	15924.5	14822.7	16645.9	19346.2	22639.1	26533.4	28429.6
Skewness	4.0	4.0	4.0	4.0	4.1	4.3	4.3	4.4	4.5	4.5	4.7
Kurtosis	15.8	15.2	15.7	15.6	16.3	17.8	18.5	19.2	20.1	20.9	23.0
Minimum	9.6	16.1	7.6	8.6	6.4	3.5	3.3	5.1	2.6	2.9	2.8
Maximum	35619	45011	60202.9	73538.9	84113.8	79477.2	91150.5	108345	127386	155364	176214
Count	70	70	70	70	70	70	70	70	70	70	70

Table 1. Continuation

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Operating expenses											
Mean	1657	2012.9	2593.3	3087.4	3433.7	3204.0	3642.1	3970.2	4270.5	4835.0	5548.4
Median	452.9	492.7	546.8	655.1	715.2	648.4	834.0	551.4	616.8	587.8	576.1
Std. Dev.	4177	5434.9	6838.8	8337.3	8932.4	9056.9	9902.0	11657.5	12406.1	14211.1	17006.0
Skewness	4.3	4.6	4.4	4.7	4.6	5.0	4.7	4.8	4.4	4.2	4.4
Kurtosis	18.6	21.9	21.2	24.7	23.8	28.8	24.5	24.7	20.2	18.0	20.4
Minimum	57.8	33.0	51.1	24.1	22.5	10.0	83.6	4.0	6.2	5.6	5.3
Maximum	23964	33512	43003.6	55142.9	58674.5	62530.7	65103.3	75958.6	70844.5	81688.0	104801
Count	70	70	70	70	70	70	70	70	70	70	70
Net fixed assets											
Mean	922.5	1121.0	1372.0	1653.6	2097.3	2028.4	2083.7	2344.7	2452.1	2539.6	2833.7
Median	237.0	278.8	370.9	534.7	607.5	521.9	462.0	514.6	452.5	414.4	360.8
Std. Dev.	2072	2581.3	3283.3	4020.3	5237.5	5272.1	5606.3	5840.2	6168.8	6462.1	7920.3
Skewness	4.0	4.0	4.2	4.2	4.2	4.1	3.9	3.7	3.5	3.6	3.9
Kurtosis	16.4	16.9	18.4	17.8	17.7	16.6	15.3	12.8	11.4	12.7	15.7
Minimum	8.7	14.0	11.6	11.6	9.6	10.3	4.1	3.8	2.9	2.6	2.3
Maximum	11770	14990	19386.8	22712.6	29796.1	27930.5	28784.0	29189.0	29710.6	32506.5	42715.2
Count	70	70	70	70	70	70	70	70	70	70	70

Source: Author's calculations based on CMIE PROWESS database.
Note: All the variables are reported in rupees millions.

4.2. Variables for second stage Regression analysis

In our study, we would like to investigate the determinants of technical change (frontier shift), technical efficiency change (catch up) and total factor productivity growth (MI). According to Caves (1992), the determinants of industrial efficiency and productivity can be classified into five categories, viz. 1) organizational features, 2) structural heterogeneity, 3) competitive conditions, 4) dynamic disturbances, and finally 5) regulation.

Organizational features of an industry consist of firm's age, location of the firm, size of firm, organization type, extent of foreign investment, multi-plant operation, diversification, structure of labour force such as use of part-time workers and degree of unionization. *Structural heterogeneity* includes capital vintage, intensity of capital, diversity of product, regional dispersion, fuel intensity, diversity of plant scale etc. *Competitive conditions* consist of those factors related to export intensity, import competition and market structure such as concentration. The factors pertain to the competitive conditions are generally external to the firm. Dynamic disturbances are primarily responsible for deviations from the long run equilibrium condition. Factors such as rate of productivity growth, rate of output growth, variability of output growth, expenditures pertaining to research and development (R & D), imported technology and receipt for exported technology are considered as *dynamic disturbances*. The occurrence of dynamic disturbances is mainly due to either change in demand pattern for the product or the extent of technical innovation in the long term. Finally, the *regulatory environment* of the State reflected in tariff protection policy, entry regulation etc. also have significant influence on industrial efficiency. Since stringent governmental intervention may discourage competition, entry of new firms and desire to innovate; the regulatory environment should be considered as one of the important determinants of efficiency. Ownership of the firm does also matter for efficiency. For instance, public and private limited firms may have different efficiency levels.

It should be noted that all the determinants of efficiency and productivity discussed above may not be pertinent to the IT industry as this industry is relatively more human capital (or skill) intensive unlike the manufacturing industry which is either relatively physical capital intensive or labour intensive. On the basis of the above discussion, the following explanatory variables are considered to explain TFPG (or MPI), technical efficiency change (or catch up) and technical change (or frontier shift) in Indian IT industry. In IT industry, the market is mostly dominated by the export-oriented firms. Hence, to assess the impact of the extent of openness or external competition on productivity change, we have considered *export intensity* as one of the independent variables. It is measured as the ratio of total export to sales. On the other hand, we consider *market concentration*, which captures the extent of internal competition in the software industry, as another independent variable. Market concentration is measured by Hirschman-Herfindahl index.

To analyze the influence of various organizational factors on efficiency and productivity, we have considered firm's age, size, wages and salaries intensity, and plant size as independent variables. Age of firms is measured as the natural logarithm of years in business. Firm size is assessed in terms of the natural logarithm of real sales. The wages and salaries intensity is measured as the ratio of wages and salaries to operating expenses. Plant size is considered as the indicator of structural heterogeneity. Plant size is incorporated as dummy variable. On the basis of returns to scale, plant size is measured in terms of increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS). Dynamic disturbances are incorporated by considering two factors, viz. R&D expenditure and royalty payments. R&D expenditure is considered as proxy for innovation. The R&D and non R&D software firms have been segregated by using dummy variable. On the other hand, Royalty payment consists of expenditure towards imported technologies, viz. drawings, blueprints, designs of software products. In regression analysis, the royalty paying and non paying firms are distinguished by incorporating dummy variable approach. Lastly, the ownership dummies have been introduced to investigate the differences in efficiency and productivity between: (1) public limited and private limited firms and (2) Group and non-group firms. Since the variables, namely, export intensity, wages and salaries intensity, plant scale, R&D expenditure and royalty payments are less likely to influence catch-up, frontier-shift and TFP instantaneously; these five variables are considered with one-year lag for regression analysis. Table 2 summarizes the variables discussed above for regression analysis.

Now, we have three regression models corresponding to three dependent variables, viz. catch up, frontier shift and Malmquist Productivity Index (MPI). The functional relationship of these variables can be represented in the following way:

Catch up = f (export intensity, market concentration, age, size, salaries and wages intensity, plant scale dummy, R&D dummy, royalty dummy, ownership dummy, group dummy, US subprime crisis dummy)

Frontier shift = g (export intensity, market concentration, age, size, salaries and wages intensity, plant scale dummy, R&D dummy, royalty dummy, ownership dummy, group dummy, US subprime crisis dummy)

MI = h (export intensity, market concentration, age, size, salaries and wages intensity, plant scale dummy, R&D dummy, royalty dummy, ownership dummy, group dummy, US subprime crisis dummy)

Table 2. Variable measurement for regression analysis

Variable	**Construction**
Dependent variables: Catch up, frontier shift and Malmquist index (MI)	
Independent variables	
1. Export intensity	Total exports/sales
2. Market concentration	Hirshman-Herfindahl index
3. Age	Natural log of years in business
4. Size	Natural log of real sales
5. Wages and salaries intensity	Ratio of wages and salaries to operating expenses
6. Plant scale dummy	Returns to scale (RTS) dummies. a) CRS dummy =1, if the firm exhibits CRS =0, otherwise b) DRS dummy =1, if the firm exhibits IRS =0, otherwise
7. Research and Development (R&D) dummy	R&D dummy =1, if the firm spends on R&D =0, if the firm does not spend on R&D
8. Royalty dummy	Royalty dummy =1, if the firm pays for royalty =0, if the firm does not pay for royalty
9. Ownership dummy	=1, for public limited company =0, for private limited company
10. Group dummy	=1, if the firm belongs to a group of companies =0, otherwise
11. US subprime crisis dummy	=1, for the years 2008 to 2014 =0, otherwise

Source: Author’s own elaboration.

5. Results and Discussion

5.1. Results Pertaining to the Productivity Analysis

In this section, we intend to analyze the trend in Malmquist productivity index for 70 Indian IT firms during 2004-05 to 2014-15. The TFPG is calculated on the basis of two methods. One is based on the base period and another is based on adjacent period. In base period method, the year 2004 is considered as the benchmark. The MPI and its three components on the basis of the base period frontier are represented in Table 3 below.

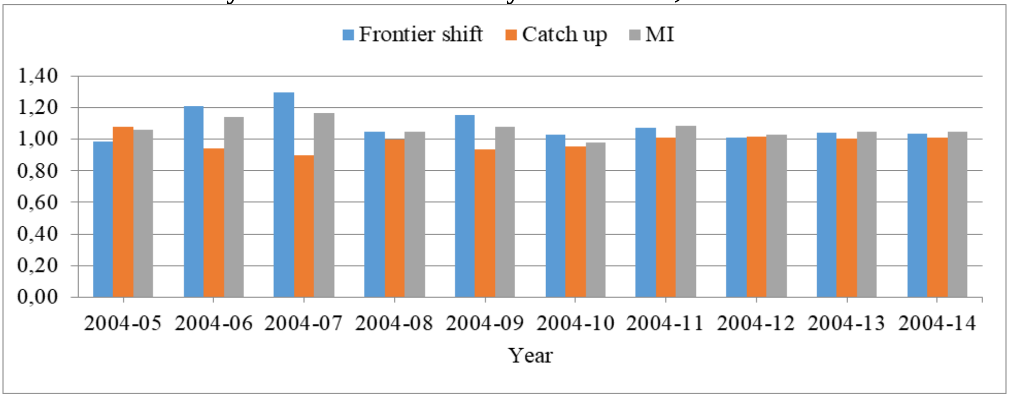
Table 3. Year-wise average Frontier shift, Catch up, Pure Technical Efficiency Change (PTEC), Scale Efficiency Change (SEC) and Malmquist Index (MI) in Indian IT industry on the basis of base-year frontier, 2004

Year	Frontier shift	Catch up	PTEC	SEC	MI
2004-05	0.984	1.079	1.062	1.016	1.062
2004-06	1.211	0.941	0.991	0.949	1.139
2004-07	1.294	0.901	0.988	0.911	1.166
2004-08	1.050	0.999	1.013	0.985	1.048
2004-09	1.155	0.933	0.986	0.946	1.077
2004-10	1.026	0.952	0.988	0.964	0.977
2004-11	1.075	1.009	1.002	1.007	1.085
2004-12	1.011	1.015	1.002	1.013	1.026
2004-13	1.043	1.003	0.990	1.014	1.047
2004-14	1.035	1.011	0.980	1.031	1.046
Average	**1.085**	**0.983**	**1.000**	**0.983**	**1.066**

Source: Author’s calculations based on CMIE PROWESS database.

It is revealed from Table 3 that the MPI is greater than one for most of the study periods except the year 2010. The average MI is found to be 1.066 for the entire study period. It implies that on an average, the total factor productivity of Indian IT industry has improved during the study period. The technical change (TC) or frontier shift component of MPI is found to be greater than one for most of the study years except 2005. The average TC for the overall study period is found to be 1.085, which implies improvement in TC during the study period. The change in technical efficiency component (or catch up) of MPI is found to be greater than one for the years 2006, 2007, 2008, 2009 and 2010, implying improvement of TEC. For the years 2007, 2010, 2012 and 2014; it is found to be less than one, indicating deterioration of TEC. The TEC for the entire study period is found to be less than one (0.983) which indicates a decline in average TEC over the study period. The PTEC is observed to be regressing during 2006, 2007, 2009, 2010, 2013 and 2014. On the other hand, PTEC is found to be improved during 2005, 2008, 2011 and 2012. PTEC is 1.00 during the entire study period, suggesting thereby on an average, neither regress nor progress in managerial efficiency. Finally, scale efficiency deteriorated during the years 2006, 2007, 2008, 2009 and 2010. On the other hand, it improved during the years 2005, 2011, 2012, 2013 and 2014. Overall, SEC is found to be less than one (0.983) during the study period implying deterioration of scale efficiency during the entire study period.

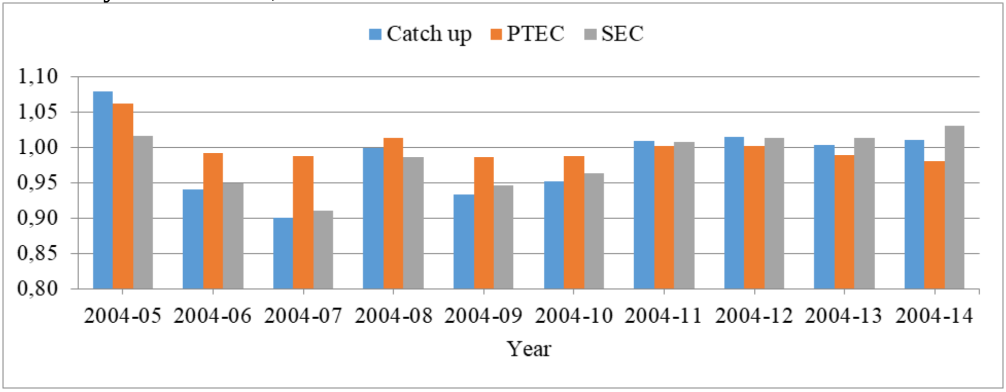
Figure 1. Year-wise average Frontier shift, Catch up and Malmquist Index in Indian IT Industry on the Basis of Base-year Frontier, 2004



Source: Author's own elaboration.

Figure 1 depicts the year-wise average MI and its components (frontier shift and catch up) as illustrated in Table 3. It can be seen that the frontier shift (TC) is highest during 2007 (1.294), with a growth rate of 29.4 percent. On the other hand, TC is lowest during 2005 (0.984) with a negative growth rate of -1.6 percent. The catch up (or TEC) is found to be highest during 2005 (1.079) with a growth rate of 7.9 percent. The catch up effect is lowest (0.901) during 2007 with a negative growth rate of -9.9 percent.

Figure 2. Year-wise average Catch up, Pure Technical Efficiency Change (PTEC) and Scale Efficiency Change (SEC) in Indian IT Industry on the Basis of Base-year Frontier, 2004



Source: Author's own elaboration.

Figure 2 shows the year-wise average catch up and its two components (PTEC and SEC) as presented in Table 3.The PTEC is found to be highest (1.062) and lowest (0.980) with growth rate of 6.2 percent and -2.0 percent during 2005 and 2014, respectively. The SEC is highest during 2014 (1.031) with a growth rate of 3.1 percent. The SEC is lowest during 2007 (0.911) with a negative growth rate of -8.9 percent. The TFPG (or MI) is highest during 2007 (1.166) with a growth rate of 16.6 percent and lowest (0.977) during 2010 with a growth rate of -2.3 percent. For the entire study period, the growth rate of frontier shift, catch up, SEC and MI is found to be 8.5 percent, -1.7 percent, -1.7 percent and 6.6 percent, respectively. PTEC has shown no change during the overall study period. From this discussion, it can be inferred that on an average, the TFPG of Indian software industry has improved. However, the decomposition analysis of MI shows deterioration in scale efficiency. On the other hand, the frontier shift effect (or technical change) has improved during the overall study period.

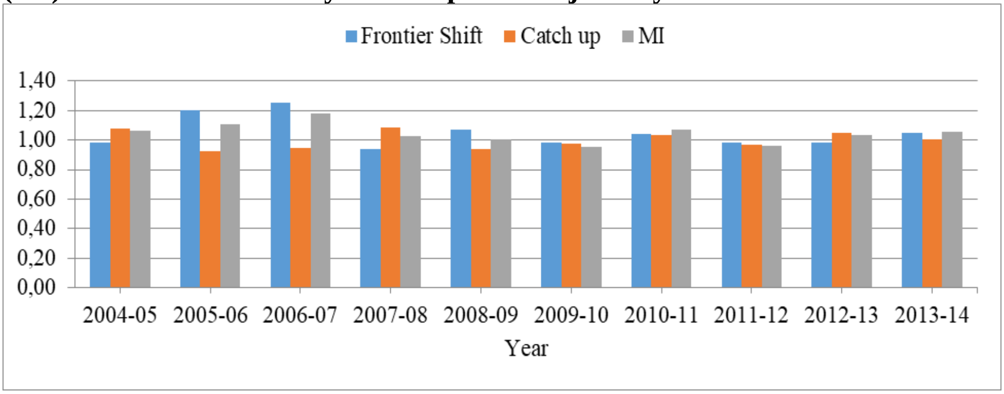
Table 4 illustrates the MI and its components on the basis of adjacent year frontier. It is revealed from Table 4 that TFPG (MI) is greater than one (or shown improvement) during most of the study periods except for the years 2010 and 2012. The frontier shift (TC) effect is greater than one for the years 2006, 2007, 2009, 2011 and 2014. It is less than one for the remaining years. The catch up is greater than one for the years 2005, 2008, 2011, 2013 and 2014. For the remaining years, it is less than one. PTEC is found to be improving during 2005, 2011 and 2013 and deteriorating for the remaining years. The SEC is greater than one for the years 2005, 2008, 2010, 2011 and 2014. It is less than one for the remaining study periods.

Table 4: Year-wise average Frontier shift, Catch up, Pure Technical Efficiency Change (TEC), Scale Efficiency Change (SEC) and Malmquist Index (MI) in Indian IT Industry on the basis of adjacent year frontier

Year	Frontier Shift	Catch up	PTEC	SEC	MI
2004-05	0.984	1.079	1.062	1.016	1.062
2005-06	1.199	0.925	0.972	0.952	1.109
2006-07	1.251	0.944	0.989	0.954	1.180
2007-08	0.943	1.087	0.989	1.099	1.025
2008-09	1.069	0.943	0.973	0.969	1.008
2009-10	0.981	0.975	0.958	1.018	0.957
2010-11	1.042	1.031	1.008	1.023	1.074
2011-12	0.986	0.972	0.975	0.997	0.958
2012-13	0.982	1.050	1.074	0.978	1.032
2013-14	1.049	1.004	0.985	1.019	1.053
Average	**1.045**	**0.999**	**0.998**	**1.002**	**1.044**

Source: Author's calculations based on CMIE PROWESS database.

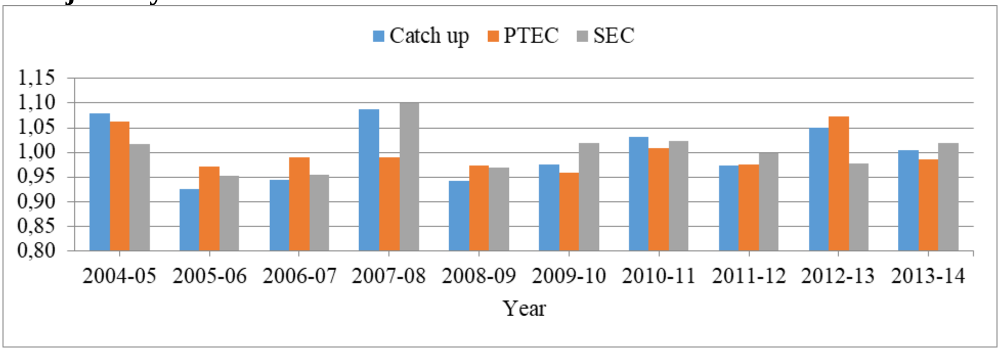
Figure 3. Year-wise average Frontier shift, Catch up and Malmquist Index (MI) in Indian IT Industry with respect to adjacent year frontier



Source: Author's own elaboration.

Figure 3 shows the year-wise average frontier shift, catch up and MI with respect to adjacent year frontier. The MI attained maximum (1.180) with a growth rate of 18 percent during the year 2007 and minimum (0.957) with a negative growth rate of -4.3 percent during the year 2010. The frontier shift (TC) is highest (1.251) with a growth rate of 25.1 percent during 2007 and lowest (0.943) with a negative growth rate of -5.7 percent during 2008. The catch up effect is highest (1.087) with a growth rate of 8.7 percent during 2008 and lowest (0.925) with a negative growth rate of -7.5 percent during 2006.

Figure 4. Year-wise average Catch up, Pure Technical Efficiency Change (PTEC) and Scale Efficiency Change (SEC) in Indian IT Industry on the basis of adjacent year frontier



Source: Author's own elaboration.

Figure 4 presents the year-wise average catch up and its components (PTEC and SEC) on the basis of adjacent year frontier. PTEC is found to be highest (1.074) with a growth rate of 7.4 percent during 2013 and lowest (0.958) with a growth rate of 4.2 percent during 2010. The SEC is maximum (1.099) during 2008 with a growth rate of 9.9 percent and minimum (0.952) during 2006 with a negative growth rate of -4.8 percent. The average MI, frontier shift, catch up, PTEC and SEC for the entire study period are worked out to be 1.044, 1.045, 0.999, 0.998, 1.002 respectively. The corresponding growth rates are 4.4 percent, 4.5 percent, -0.1 percent, -0.2 percent and 0.2 percent, respectively.

It is evident from the above discussion that, on an average, technical change has experienced improvement during the entire study period. On the other hand, catch up has experienced deterioration over the study period. The average PTEC shows negative growth (i.e., regress) during the overall study period. The average scale efficiency has been found to be improving during the study period. It can be inferred from this analysis that on an average, MI and frontier shift have improved in Indian IT industry on the basis of base year (2004) as well as adjacent year frontiers during the study period. In case of average overall technical efficiency (or catch up), it shows regress with respect to base year (2004) as well as adjacent year frontiers during the study period. While PTEC shows deterioration under base year (2004) frontier, it shows improvement under adjacent year frontier analysis. Finally, the average scale efficiency has improved with respect to base year (2004) frontier but deteriorated under adjacent year frontier.

Table 5. Company-wise annual average Frontier shift, Catch up, Scale Efficiency Change (SEC) and Malmquist Index (MI) with respect to base year (2004) frontier

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
1	3D P L M Software Solutions Ltd.	1.092	0.919	0.946	0.971	1.004
2	3I Infotech Ltd.	1.155	0.903	0.965	0.937	1.044
3	Accel Transmatic Ltd.	1.036	0.918	0.945	0.972	0.951
4	Accelya Kale Solutions Ltd.	0.961	1.131	1.139	0.994	1.087
5	Aftek Ltd.	1.008	0.919	0.962	0.955	0.926
6	Agnite Education Ltd.	0.990	0.938	0.967	0.970	0.928
7	Birlasoft (India) Ltd.	1.014	1.163	1.226	0.949	1.179
8	Blue Star Infotech Ltd.	1.012	0.929	0.961	0.967	0.940
9	Bristlecone India Ltd.	0.957	1.274	1.307	0.975	1.220
10	California Software Co. Ltd.	1.113	0.958	0.975	0.982	1.066
11	Compucom Software Ltd.	0.944	1.125	1.215	0.925	1.062
12	Cranes Software Intl. Ltd.	1.238	0.922	0.944	0.977	1.141
13	Datamatics Global Services Ltd.	1.121	0.921	0.942	0.978	1.033
14	F C S Software Solutions Ltd.	1.023	0.917	0.937	0.979	0.938
15	Four Soft Ltd.	1.009	0.926	0.921	1.006	0.935
16	Genesys International Corpn. Ltd.	1.018	1.440	1.349	1.067	1.466
17	Geodesic Ltd.	1.060	1.000	1.000	1.000	1.060

Table 5. Continuation

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
18	Geometric Ltd.	1.056	0.993	1.017	0.977	1.049
19	Glodyne Technoserve Ltd.	0.985	0.951	0.965	0.985	0.937
20	Goldstone Technologies Ltd.	1.046	0.928	0.956	0.970	0.970
21	Green Fire Agri Commodities Ltd.	1.091	0.918	0.954	0.962	1.002
22	H C L Technologies Ltd.	1.065	1.064	0.978	1.087	1.132
23	Hexaware Technologies Ltd.	1.063	1.013	1.080	0.939	1.077
24	I C S A (India) Ltd.	0.933	1.377	0.932	1.478	1.285
25	I T C Infotech India Ltd.	0.979	1.295	1.323	0.979	1.268
26	Infosys Ltd.	1.114	0.916	1.000	0.917	1.021
27	Infotech Enterprises Ltd.	1.002	0.928	0.970	0.957	0.930
28	K P I T Technologies Ltd.	1.034	1.088	1.161	0.937	1.125
29	Larsen & Toubro Infotech Ltd.	1.045	1.096	1.171	0.936	1.146
30	Mascon Global Ltd.	1.049	1.330	0.989	1.345	1.395
31	Mastek Ltd.	1.023	0.922	0.926	0.995	0.942
32	Megasoft Ltd.	1.134	0.940	1.000	0.940	1.066
33	Mphasis Ltd.	0.943	1.102	0.948	1.162	1.039
34	N I I T Gis Ltd.	0.983	0.958	0.984	0.974	0.942
35	N I I T Ltd.	1.087	0.917	0.914	1.004	0.997
36	N I I T Technologies Ltd.	1.098	0.991	1.006	0.985	1.088
37	Nucleus Software Exports Ltd.	1.104	0.968	1.001	0.967	1.068
38	Ontrack Systems Ltd.	0.925	1.109	1.067	1.040	1.027
39	Onward Technologies Ltd.	0.992	1.113	1.164	0.956	1.104
40	Oracle Financial Services Software Ltd.	1.095	1.020	1.044	0.976	1.117
41	Patni Computer Systems Ltd.	1.067	0.928	0.972	0.955	0.991
42	Pentamedia Graphics Ltd.	1.030	0.924	1.001	0.923	0.951
43	Persistent Systems Ltd.	1.070	0.978	1.028	0.951	1.046
44	Polaris Financial Technology Ltd.	1.015	1.122	0.996	1.127	1.138
45	Quintegra Solutions Ltd.	1.023	0.917	0.947	0.969	0.938
46	R S Software (India) Ltd.	1.085	0.973	1.017	0.956	1.056
47	R Systems International Ltd.	1.032	1.158	1.207	0.960	1.195

Table 5. Continuation

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
48	Rolta India Ltd.	1.014	1.005	1.024	0.981	1.019
49	S Q L Star International Ltd.	1.050	0.933	0.997	0.936	0.980
50	Sankhya Infotech Ltd.	1.029	1.021	0.921	1.108	1.050
51	Sasken Communication Technologies Ltd.	1.059	1.088	1.114	0.977	1.152
52	Satyam Computer Services Ltd.	1.022	0.921	0.974	0.945	0.941
53	Software Technology Group International Ltd.	1.053	0.925	0.954	0.970	0.974
54	Sonata Software Ltd.	1.058	1.116	1.163	0.959	1.181
55	Steria (India) Ltd.	1.060	1.049	1.018	1.030	1.111
56	Subex Ltd.	1.012	1.204	1.201	1.002	1.218
57	Syntel Ltd.	1.078	0.944	0.979	0.964	1.017
58	Take Solutions Ltd.	1.029	0.987	0.932	1.059	1.016
59	Tata Consultancy Services Ltd.	1.121	0.936	1.000	0.936	1.048
60	Tata Elxsi Ltd.	1.027	0.923	0.940	0.982	0.948
61	Tata Industries Ltd.	1.113	0.916	0.942	0.972	1.019
62	Tata Technologies Ltd.	1.058	1.104	1.150	0.959	1.168
63	Tech Mahindra Ltd.	1.088	1.015	1.046	0.971	1.105
64	Tera Software Ltd.	0.998	1.109	0.948	1.169	1.106
65	V J I L Consulting Ltd.	1.080	0.911	0.972	0.937	0.984
66	Vakrangee Ltd.	0.935	1.475	1.465	1.007	1.379
67	Wipro Ltd.	1.043	1.003	0.988	1.015	1.046
68	Xchanging Solutions Ltd.	0.995	1.105	0.947	1.166	1.100
69	Zensar Technologies Ltd.	1.036	1.162	1.168	0.995	1.204
70	Zylog Systems Ltd.	1.012	0.967	0.992	0.975	0.979
	Mean	**1.040**	**1.022**	**1.026**	**0.996**	**1.062**
	Median	**1.036**	**0.982**	**0.990**	**0.974**	**1.049**
	Std. Dev.	**0.056**	**0.133**	**0.117**	**0.091**	**0.115**

Source: Author's calculations based on CMIE PROWESS database.

Table 5 reveals that among 70 software companies, on an average 56 companies experienced improvement in technology (i.e., TC>1) and the remaining 14 companies exhibited technological regress (i.e., TC<1) over the study period. On the other hand, on an average, 32 companies were found to have experienced improvement in technical efficiency and the remaining 38 firms were exhibiting deterioration in technical efficiency during the study period. It has also been observed from Table 4 that on an average, 32 firms have recorded growth in managerial efficiency (or PTEC) and the remaining 38 firms experienced regress in PTEC. 17 firms registered enhancement in scale efficiency, one firm (Geodesic Ltd.) experienced status quo in scale efficiency and the remaining 52 firms experienced deterioration in scale efficiency over the study period. Lastly, it is observed that on an average, 49 companies registered improvement in TFPG, whereas 21 companies experienced decline in TFPG during the study period.

From Table 5, it can be seen that on an average, 56 firms registered improvement in technology (or innovation) during the study period. Among these 56 firms, 38 firms were found to have experienced improvement in total factor productivity (measured by MI). It indicates that the remaining 18 firms were exhibiting deterioration in TFP despite the growth in technology (or frontier shift). This phenomenon clearly depicts that for the 18 firms, on an average, the magnitude of the fall in TEC or SEC or both was much severe than that of the increase in TC, as a result, the MI showed decline in TFPG during the study period. Moreover, out of these 56 companies, on an average, only 21 companies were found to have registered rise in overall technical efficiency (catch up), 25 companies have exhibited improvement in PTEC and 12 companies have recorded improvement in scale efficiency during the study period.

Table 4 also reveals that among 70 companies, on an average, 32 companies experienced improvement in overall technical efficiency (or catch up) over the study period. Out of these 32 companies, TFP of all those 32 companies was found to be improving. On the other hand, out of these 32 companies, on an average, TC of 21 companies was found to be improving and SEC of 15 companies was found to be improving during the study period. Hence, it can be inferred that on an average, both the frontier shift (TC) and catch up had been moving towards the same direction (i.e., improved) for 21 companies that attributed to improvement in TFP despite regress in SEC for 12 companies among those 21 companies. Finally, it can be said that improvement in frontier shift (or TC) is the primary contributor to the TFPG followed by catch up effect (or TEC) and SEC. During the overall study period, the average TFPG, frontier shift, catch up, PTEC and SEC are found o be 1.062, 1.040, 1.022, 1.026, and 0.996 with growth rates of 6.2 percent, 4 percent, 2.2 percent and 0.4 percent, respectively.

Table 6. Company-wise annual average Frontier shift, Catch up, Pure Technical Efficiency Change (PTEC) Scale Efficiency Change (SEC) and Malmquist Index (MI) in Indian IT Industry with Respect to adjacent year frontier

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
1	3D P L M Software Solutions Ltd.	1.023	1.015	1.015	1.000	1.038
2	3I Infotech Ltd.	1.056	0.987	0.966	1.023	1.043
3	Accel Transmatic Ltd.	1.088	0.923	0.978	0.943	1.004
4	Accelya Kale Solutions Ltd.	1.066	1.128	1.074	1.051	1.202
5	Aftek Ltd.	1.070	1.012	1.000	1.012	1.083
6	Agnite Education Ltd.	0.999	0.947	0.959	0.988	0.946
7	Birlasoft (India) Ltd.	1.045	1.084	1.047	1.036	1.133
8	Blue Star Infotech Ltd.	1.054	0.983	0.963	1.021	1.036
9	Bristlecone India Ltd.	1.011	1.035	1.037	0.999	1.046
10	California Software Co. Ltd.	1.062	0.950	0.931	1.021	1.009
11	Compucom Software Ltd.	1.078	1.045	1.025	1.019	1.126
12	Cranes Software Intl. Ltd.	1.075	0.883	0.889	0.993	0.949
13	Datamatics Global Services Ltd.	1.065	1.030	1.001	1.029	1.097
14	F C S Software Solutions Ltd.	0.973	0.996	0.999	0.997	0.969
15	Four Soft Ltd.	1.049	0.950	0.918	1.034	0.996
16	Genesys International Corpn. Ltd.	1.028	1.023	1.007	1.016	1.051
17	Geodesic Ltd.	0.993	1.000	1.000	1.000	0.993
18	Geometric Ltd.	1.072	1.026	0.974	1.053	1.100
19	Glodyne Technoserve Ltd.	0.977	0.944	0.954	0.989	0.922
20	Goldstone Technologies Ltd.	1.045	0.933	0.924	1.010	0.976
21	Green Fire Agri Commodities Ltd.	1.067	1.007	1.000	1.007	1.075
22	H C L Technologies Ltd.	1.044	1.065	1.010	1.055	1.112
23	Hexaware Technologies Ltd.	1.048	0.975	1.017	0.959	1.022
24	I C S A (India) Ltd.	0.990	0.966	0.931	1.038	0.957

Table 6. Continuation

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
25	I T C Infotech India Ltd.	1.024	1.027	1.031	0.997	1.052
26	Infosys Ltd.	1.045	0.999	1.000	0.999	1.044
27	Infotech Enterprises Ltd.	1.067	1.056	0.997	1.058	1.126
28	K P I T Technologies Ltd.	1.044	1.047	1.043	1.003	1.093
29	Larsen & Toubro Infotech Ltd.	1.023	0.993	0.999	0.994	1.016
30	Mascon Global Ltd.	1.034	1.031	1.000	1.031	1.066
31	Mastek Ltd.	1.033	1.004	0.980	1.024	1.037
32	Megasoft Ltd.	1.087	0.999	0.966	1.034	1.086
33	Mphasis Ltd.	1.038	1.037	0.992	1.046	1.076
34	N I I T Gis Ltd.	0.993	0.977	0.981	0.996	0.970
35	N I I T Ltd.	1.042	0.997	0.969	1.028	1.039
36	N I I T Technologies Ltd.	1.021	0.958	0.991	0.967	0.978
37	Nucleus Software Exports Ltd.	1.062	0.960	0.993	0.967	1.019
38	Ontrack Systems Ltd.	1.025	1.053	1.031	1.021	1.080
39	Onward Technologies Ltd.	1.084	1.043	1.069	0.976	1.130
40	Oracle Financial Services Software Ltd.	1.022	1.012	1.005	1.007	1.033
41	Patni Computer Systems Ltd.	1.069	1.056	1.052	1.004	1.129
42	Pentamedia Graphics Ltd.	1.046	1.010	1.010	1.000	1.057
43	Persistent Systems Ltd.	1.037	1.004	0.959	1.048	1.041
44	Polaris Financial Technology Ltd.	0.994	1.039	1.001	1.038	1.033
45	Quintegra Solutions Ltd.	1.079	1.058	1.153	0.917	1.141
46	R S Software (India) Ltd.	1.045	1.013	1.001	1.013	1.059
47	R Systems International Ltd.	1.011	0.981	0.993	0.988	0.992
48	Rolta India Ltd.	1.078	0.984	1.000	0.984	1.061
49	S Q L Star International Ltd.	1.033	0.924	1.021	0.905	0.955
50	Sankhya Infotech Ltd.	1.042	1.093	1.036	1.056	1.139
51	Sasken Communication Technologies Ltd.	1.081	0.973	1.001	0.972	1.052
52	Satyam Computer Services Ltd.	1.073	1.032	1.039	0.993	1.107
53	Software Technology Group International Ltd.	1.070	0.914	0.996	0.917	0.978
54	Sonata Software Ltd.	1.057	1.010	1.039	0.971	1.067

Table 6. Continuation

Sl. No.	Company Name	Frontier shift	Catch up	PTEC	SEC	MI
55	Steria (India) Ltd.	1.054	1.007	1.005	1.002	1.061
56	Subex Ltd.	1.033	1.023	0.997	1.026	1.057
57	Syntel Ltd.	1.088	1.058	1.030	1.026	1.151
58	Take Solutions Ltd.	1.025	1.063	1.038	1.024	1.090
59	Tata Consultancy Services Ltd.	1.019	1.042	1.000	1.042	1.061
60	Tata Elxsi Ltd.	1.126	0.993	1.000	0.993	1.118
61	Tata Industries Ltd.	1.047	0.941	0.939	1.002	0.986
62	Tata Technologies Ltd.	1.115	1.085	1.047	1.037	1.210
63	Tech Mahindra Ltd.	1.025	0.983	1.016	0.967	1.008
64	Tera Software Ltd.	1.027	1.051	1.024	1.026	1.079
65	V J I L Consulting Ltd.	1.072	0.906	0.935	0.969	0.971
66	Vakrangee Ltd.	1.042	1.069	1.066	1.003	1.114
67	Wipro Ltd.	1.089	0.988	1.000	0.988	1.076
68	Xchanging Solutions Ltd.	1.069	0.957	0.939	1.019	1.023
69	Zensar Technologies Ltd.	1.048	0.974	1.013	0.962	1.021
70	Zylog Systems Ltd.	1.031	0.929	0.926	1.002	0.958
	Mean	**1.046**	**1.003**	**0.998**	**1.004**	**1.049**
	Median	**1.045**	**1.005**	**1.000**	**1.004**	**1.052**
	Std. Dev.	**0.031**	**0.049**	**0.042**	**0.033**	**0.062**

Source: Author's calculations based on CMIE PROWESS database.

A perusal of Table 6 shows that on an average, 63 software firms have experienced technical progress (or innovation), implying that these firms experienced an upward shift in the production frontier, and remaining 7 firms have experienced technical regress, suggesting that these firms experienced a downward shift in the production frontier. Out of these 63 firms, on an average, 36 firms are found to have exhibited improvement in overall technical efficiency (catch up), 38 firms are found to be experiencing progress in scale efficiency, and 53 firms are found to have attained growth in TFP during the overall study period.

As far as the relative significance of the three components of MI in TFPG is concerned, it has been found from Tables that frontier-shift effect has the highest contribution to the MI (TFPG) followed by scale efficiency change and catch-up in the Indian IT companies during the overall study period. From this discussion, it can be inferred that innovation played a pivotal role in improving total factor productivity of IT companies during the study period. One of the prime reasons behind this robust frontier shift effect in the Indian IT-companies could be the necessity to maintain their position in volatile and competitive global environment.

5.2 Analysis of Regression Results

To investigate the determinants of TFPG, catch-up and frontier shift, we have employed panel data regression technique. Before going to discuss the regression results, we would like to introduce the results of pre-regression diagnostic tests, which have been theoretically discussed earlier in this paper.

5.2.1. Results of Pre-regression Diagnosis Tests

At first, we apply poolability test on our data. This test helps the researchers to choose between OLS and Fixed-Effect (FE) models. The corresponding values of F-test statistic for three regression models have been reported in the following Table 7. It is found that the F-statistics for all the three regression models are statistically significant at 1% level. This implies that there exists firm-specific heterogeneity across all these models and simple pooled OLS model would produce misleading conclusions. Therefore, according to poolability test, the FE panel regression method would be suitable for estimating these three models.

Table 7. Summary results of poolability test pertaining to the regression models

Regression Equation no.	Dependent Variable	Value of F-test statistic	P-value
1.	Catch-up	35.55***	0.0001
2.	Frontier-shift	29.84***	0.0010
3.	Malmquist Index	31.16***	0.0004

Source: Author's Calculations based on CMIE PROWESS database.
*** => Significant at 1%level.

Now, we apply the Breusch and Pagan LM test to examine whether pooled OLS model or Random Effect (RE) model is appropriate for our empirical analysis. The chi-square test statistic pertaining to the LM test is found to be statistically significant at 1% level for all three models as depicted in Table 8. This result clearly indicates rejection of null hypothesis, which considers that the pooled OLS model is suitable. On the other hand, it is established from this test that the RE panel model is suitable for all the regression models we intend to estimate.

Table 8. Summary results of LM test pertaining to the regression models

Regression Equation no.	Dependent Variable	Value of χ^2-test statistic	P-value
1.	Catch-up	124.47***	0.0001
2.	Frontier-shift	102.63***	0.0001
3.	Malmquist Index	93.05***	0.0003

Source: Author's Calculations based on CMIE PROWESS database.
*** => Significant at 1%level

To examine whether FE or RE model is suitable for our study, we apply Housman test. Table 9 summarizes the results of this test for three regression models. It can be seen that the value of the test statistic is statistically insignificant across all these models. This implies that the RE panel regression model would be appropriate to analyze our dataset.

Table 9. Summary results of Housman test pertaining to three regression models

Regression Equation no.	Dependent Variable	Value of χ^2-test statistic	P-value
1.	Catch-up	18.66	0.8561
2.	Frontier-shift	16.54	0.2291
3.	Malmquist Index	17.69	0.4637

Source: Author's Calculations based on CMIE PROWESS database.

Now, we apply the Fisher-type unit root test on four independent variables, viz. export intensity, age, size, and salaries and wages intensity separately to test whether these variables are stationary or not. Here, the Fisher-type test is based on the ADF test. The test results are summarized in the following Table 10.

All the four tests reported in Table 10 are based on ADF unit root test. It is observed that all the test statistics are significant at 1% level, indicating thereby rejection of the null hypothesis and acceptance of the alternative hypothesis. Alternatively, it can be said that there exists at least one panel series in every variable without having any unit root. Moreover, on the basis of the Fisher-type tests, it can be inferred that all the four variables are stationary at the level. Hence, these variables can be used as independent variable in the RE-panel regression model at their level without any transformation. Finally, we have examined the partial correlation coefficients between various independent variables by constructing a correlation matrix to check the presence of multicollinearity problem. However, the correlation matrix does not show any presence of severe correlation between the independent variables, suggesting thereby the absence of multicollinearity among independent variables.

Table 10. Summary results of Fisher-type unit root tests

	Export intensity		**Age**		**Size**		**Salaries and wages intensity**	
Method	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Inverse Chi-squared (P)	426.43***	0.000	265.31***	0.000	218.58***	0.000	194.61***	0.000
Inverse normal (Z)	-13.80***	0.000	-10.21***	0.000	-9.14***	0.002	-9.05***	0.000
Inverse logit t (L^*)	-14.69***	0.000	-11.02***	0.003	-9.76***	0.007	-9.62***	0.000
Modified inv. Chi-squared (P_m)	31.17***	0.000	23.87***	0.000	12.05***	0.000	10.18***	0.000

Source: Author's Calculations based on CMIE PROWESS database.
*** => Significant at 1% level.

On the basis of the results of the diagnostic tests discussed above, it is quite clear that random-effects panel regression model would be the most suitable for our present study. It is to mention that all the data analysis pertains to various diagnostic tests and RE-panel regression are carried out in the statistical software package *Stata*. All these regression results are obtained under the clustered robust specification in *Stata*. The summary results of regression analysis are reported in Table 11.

Table 11. Summary results of three random-effects Generalized Least Square (GLS) regression models

Indepen-dent variables	Regression 1 (R1) Dependent variable: Catch-up		Regression 2 (R2) Dependent variable: Frontier-shift		Regression 3 (R3) Dependent variable: Malmquist Index	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Export intensity	0.614**	0.042	0.849*	0.072	0.701***	0.002
Market concentration	0.053***	0.001	0.036	0.267	0.064**	0.033
Age	0.018**	0.012	0.004	0.106	0.009*	0.069
Size	0.007**	0.048	0.004	0.283	0.002	0.109
Salaries and wages intensity	0.795***	0.000	0.443**	0.046	0.656**	0.018
IRS dummy	0.011**	0.030	0.005	0.198	0.012*	0.058
DRS dummy	-0.007*	0.084	0.004	0.526	-0.005*	0.067
R&D dummy	0.001	0.127	0.009**	0.028	0.004*	0.085
royalty dummy	0.012**	0.028	0.002	0.194	0.008**	0.029
Ownership dummy	0.004***	0.000	0.008*	0.059	0.010*	0.061
Group dummy	-0.005**	0.066	0.005	0.331	0.015	0.482
US subprime crisis dummy	-0.091*	0.091	-0.061**	0.020	-0.059**	0.043
Constant	1.415***	0.000	0.826***	0.000	1.583***	0.000
Wald χ^2-statistic	387.21***	0.000	331.24***	0.000	459.85***	0.000
R Squared	Within=0.201 Between=0.566 Overall=0.171		Within=0.244 Between=0.622 Overall=0.216		Within=0.398 Between=0.70 Overall=0.282	
Number of observations	700		700		700	
sigma_u sigma_e rho	0.3691 0.2201 0.7376		0.4710 0.3315 0.6687		0.2778 0.1484 0.7779	

Source: Author’s calculations based on CMIE PROWESS database.
*, **, *** =>Significant at 10%, 5%, and 1% level, respectively.

It can be seen that the value of Wald chi-square statistic is statistically significant at 1% level in three regression models, implying that all the models are overall significant. Table 11 also reports the values of rho (ρ). Mathematically, the rho can be given as follows:

$$\rho = \frac{\sigma_u^2}{(\sigma_u^2 + \sigma_e^2)}$$

Where, σ_u^2 and σ_e^2 denote the variance of the error components u and e, respectively. In Table 11, sigma_u and sigma_e refer to the standard deviations of u and e, respectively. It is found the value of rho is not equal to zero across all models. On the other hand, it indicates that the variance of the panel-level error component is not zero, which is also evident from Table 11. Therefore, it is established that the panel estimator is different from the pooled estimator. Furthermore, it can also be said that there exists firm specific heterogeneity in our dataset. This also supports the selection of RE-panel regression model for our study.

Now, we are going to discuss the coefficients of the regression models as reported in Table 11. The coefficient of export intensity is observed to be positive and statistically significant in all the three models. The coefficients of export intensity are found to be 0.614, 0.849, and 0.701 in R1, R2, and R3, respectively. We can say that on an average, technical efficiency (or catch-up), technology (or frontier-shift), and TFP of IT firms would improve by 61.4%, 84.9%, and 70.1%, respectively, due to 100% increase in export intensity during the study period. The coefficients of market concentration (MC) and age are positive across three models but statistically significant in R1 and R3. In R1, the coefficient (0.053) of MC implies that on an average, a 100% rise in MC would result 5.3% increase in technical efficiency during the study period. Similarly, in R3, the coefficient (0.064) of MC indicates that on an average, there would be 6.4% improvement in TFP due to 100% increase in MC during the study period. The coefficients of age in R1 and R3 are found to be 0.018 and 0.009, respectively.

The coefficient of size is positive in all the models but statistically significant in R1 only. The coefficient of size is 0.007 in R1, implying that on an average, there would be 0.7% progress in catch-up for 100% increase in size of the industry during the study period. The positive and statistically significant coefficient of salaries and wages intensity (SWI) across three models indicates that SWI plays a key role in promoting technical efficiency, technology, and TFP growth during the study period. In particular, the coefficients of SWI are observed to be 0.795, 0.443, and 0.656 in R1, R2, and R3, respectively. This implies that on an average, there would be 79.5% improvement in technical efficiency, 44.3% progress in technology, and 65.6% enhancement in TFP due to 100% increase in SWI during the study period.

Both IRS and DRS dummies are found to be statistically significant in R1 and R3. The sign of the coefficient of the IRS dummy is found to be positive, whereas that of the DRS dummy is found to be negative in R1 and R3. This indicates that on an average, the firms exhibiting IRS technology experienced better improvement in technical efficiency and TFP compared to the benchmark CRS firms. On the other hand, the DRS firms are found to have registered lesser progress in technical efficiency and TFP than the firms exhibiting benchmark CRS technology during the study period. R&D dummy is positive across all models but found significant only in R2 and R3. The coefficients of R&D dummy in R2 and R3 indicate that on an average, the IT firms which spent on R&D have experienced higher growth in technology (or frontier-shift) and TFP than those which did not spend on R&D (i.e., the reference firms) during the study period. On the other hand, the relation between change in technical efficiency and expenditure on R&D has not been established as we have not found any statistically significant relation between R&D dummy and catch-up during the study period.

Now, the coefficients of royalty dummy are positive in all models but statistically significant at 5 % level in only R1 and R3. It can be inferred that on an average, the IT firms, which paid royalty for importing blueprints, designs of software from abroad, were shown relatively higher improvement in catch-up and TFP than those IT firms which did not incur any expenditure on royalty during the study period. The coefficients of ownership dummy are positive and statistically significant across all three models. It means that on an average, the public limited IT firms were experienced comparatively better improvement in technical efficiency, technology, and TFP than the benchmark private limited IT firms during the study period.

The coefficient of group dummy is negative and statistically significant in R1, implying that on an average, the non-group IT companies (i.e., the reference companies) had experienced more improvement in technical efficiency than the group owned IT companies during the study period. On the other hand, the coefficients of group dummy are found to be positive but statistically insignificant in R2 and R3. Hence, it can be said that there is no significant difference between group and non-group IT firms as far as improvement in technology and TFP are concerned during the study period. Finally, the last but not the least, the coefficient of crisis dummy is observed to be negative and statistically significant in all three models. This indicates that on an average, the technical efficiency, technology, and TFP of Indian IT industry had been deteriorated during the post subprime crisis period (2008 onwards) as compared to the pre-crisis period.

6. Summary and Concluding Remarks

This paper attempted to evaluate the total factor productivity of Indian Information technology industry during the period from FY 2004-05 to FY 2014-15. For this purpose, a DEA-based Malmquist Productivity Index is applied to calculate TFPG over the study period. The TFPG is decomposed into three components, viz. technical efficiency change (or catch-up), technological change (or frontier-shift), and scale efficiency change. The Malmquist index is evaluated on the basis of output-oriented DEA approach, where the goal is to examine whether the firm under consideration is able to produce maximum output with given input combinations. The Malmquist productivity index is evaluated on the basis of the base period frontier as well as adjacent period frontier. Furthermore, to investigate the determinants of catch-up, frontier-shift, and TFP growth; three separate regression models are estimated by applying random-effects panel regression method. For the regression analysis, we have used a balanced panel dataset consists of 70 Indian IT firms for the period from FY 2005 to FY 2014.

The productivity analysis suggests that the technological progress is the major source of productivity growth in Indian IT industry during the study period. On the other hand, catch up has played a dampening role in productivity growth during the study period. On an average, the TFP shows improvement during the study period, thereby implying that the positive impact of innovation has compensated the adverse impact of catch up effect during the reference period. Moreover, it can be inferred that although Indian IT industry performs well in innovation front, the technical efficiency needs to be improved in the future. On the other hand, the inefficient IT companies should improve their managerial efficiency to catch up with the efficient IT companies over time.

The regression results reveal that export intensity and salaries and wages intensity have positive impact on catch up, frontier shift, and TFPG. This suggests that on an average, the companies with higher export-orientation and salaries and wages intensity have experienced improvement in productivity. The result suggests a positive relationship between market concentration and TFPG. R&D is found have positive impact on innovation and productivity in IT industry. Therefore, policy should be formulated to encourage more investment in R&D in IT industry in the future. Royalty payment is observed to have positive impact on catch up and TFPG. Hence, royalty expenditure towards importing designs, blueprints of proprietary software technologies etc. should be encouraged for achieving higher productivity.

The impact of the US subprime crisis is found to be negative on frontier shift and TFPG. This result indicates that during the years after the US subprime crisis, the productivity of Indian IT industry has deteriorated as compared to the pre crisis years. Since a significant portion of revenue comes from export, income of the Indian IT firms is highly susceptible to various global adversities. In view of this, the Indian IT industry should explore new business in domestic as well as foreign markets such as the European Union, Australia and the emerging economies such as Africa and Latin America where the IT markets are in nascent stage and opportunities are plenty. Further, various stakeholders of this industry require to develop relevant strategies towards innovation, infrastructure and diversification to keep pace with the evolving technological and business environment in the future. In addition to this, the Government of India should play a pivotal role in simplifying the existing Indian labour law and providing world class infrastructure and telecommunication to facilitate the IT industry in the long run.

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Ocena determinant wzrostu całkowitej produktywności czynników produkcji w indyjskim przemyśle technologii informacyjnych: zastosowanie indeksu Malmquista opartego na metodzie DEA

Streszczenie

Cel: Niniejsze badanie ma na celu ocenę wzrostu całkowitej produktywności czynników produkcji (ang. Total Factor Productivity Growth (TFPG)) i jego determinant w indyjskim przemysle technologii informacyjnych (ang. Information Technology (IT)).

Metodyka badań: Aby zrealizować cel badań, zgromadzono dane na poziomie firm z bazy danych PROWESS z Centrum Monitoringu Indyjskiej Gospodarki (ang. Centre for Monitoring Indian Economy (CMIE)). W analizie empirycznej wykorzystano metodę dwuetapową. W pierwszym etapie zastosowano Indeks Produktywności Malmquista (ang. Malmquist Productivity Index (MPI)) oparty na Metodzie Obwiedni Danych (ang.: Data Envelopment Analysis (DEA)), aby ocenić TFPG w indyjskim przemyśle IT w okresie od 2004-05 do 2014-15. W tym celu uwzględniono zrównoważony panel 70 firm z branży IT. Następnie dokonano rozkładu TFPG na trzy komponenty, mianowicie catch-up , frontier-shift oraz zmiana efektywności skali (ang. scale efficiency change (SEC)). W drugim etapie rozważono trzy modele regresji dotyczące efektów losowych paneli, aby zbadać oddzielnie determinanty TFPG, catch-up i frontier-shift.

Wnioski: W okresie badawczym, poprawił się średnio TFPG i frontier-shift. Z drugiej strony zmalał efekt catch-up. Zmienne, takie jak intensywność eksportu czy intensywność wynagrodzeń miały pozytywny i statystycznie znaczący wpływ na catch-up i frontier-shift. Intensywność eksportu oraz wynagrodzenia pozytywnie oddziaływały na TFPG. Wiek przedsiębiorstw pozytywnie wpływał na catch-up i TFPG. Średnio, firmy, które dokonały wydatków na badania i rozwój (ang. Research and Development (R&D)), doświadczyły poprawy TFPG i frontier-shift. Publiczne przedsiębiorstwa z ograniczoną odpowiedzialnością radziły sobie lepiej niż ich prywatni odpowiednicy pod względem catch-up, frontier-shift i TFPG. Niezgrupowane firmy miały lepsze osiągnięcia z punktu widzenia catch-up aniżeli firmy zgrupowane. Z drugiej strony, przeciętnie, firmy osiągające malejące efekty skali (ang. decreasing Returns to Scale (DRS)) odnotowały pogorszenie w catch-up i TFPG w porównaniu do wyznacznika, jakim są firmy o stałych efektach skali (ang. Constant Returns to Scale (CRS)). Przedsiębiorstwa osiągające rosnące efekty skali (ang.: Increasing Returns to Scale (IRS)) uzyskały poprawę w zakresie catch-up i TFPG w większym stopniu niż będące wyznacznikiem firmy CRS. Kryzys na amerykańskim rynku kredytów hipotecznych negatywnie odbił się na catch-up, frontier-shift i TFPG. Przedsiębiorstwa, które poniosły wydatki na należności, doświadczyły poprawy catch-up i TFPG.

Wartość artykułu: Autorzy dotychczas nie spotkali tak licznych badań empirycznych tego typu odnoszących się do przemysłu IT, zwłaszcza w krajach rozwijających się, jak Indie. Co więcej, autorzy nie doszukali się żadnych badań obejmujących tak dużą rozpiętość danych, jaką uwzględniono w niniejszym artykule. W dodatku w niniejszym badaniu zastosowano model efektów losowych, aby dostosować pewne niezmienne w czasie zmienne, co nie byłoby możliwe w przypadku modelu stałych efektów, który wykorzystywano w niektórych wcześniejszych badaniach tego rodzaju.

Implikacje: Identyfikacja determinant TFPG i jego komponentów mogłaby pomóc interesariuszom i decydentom w sformułowaniu odpowiedniej polityki, co pozwoliłoby z jednej strony zmniejszyć ryzyko, którego doświadcza indyjski przemysł IT, a z drugiej pobudzić siły, które mogłyby przyczynić się do rozwoju tego przemysłu. Na przykład, aby ograniczyć przyszłe ryzyko, indyjski przemysł IT powinien zmniejszyć swoją zależność od rynku Stanów Zjednoczonych i Wielkiej Brytanii. Innymi słowy, powinien poszukiwać nowych rynków zarówno krajowych, jak też zagranicznych, np. w Unii

Europejskiej, Australii i w gospodarkach wschodzących, gdzie rynki IT wydają się być obiecujące. Aby utrzymać indyjską solidną pozycję globalną w długim okresie, rząd indyjski powinien odgrywać kluczową rolę w zapewnianiu światowej klasy infrastruktury i urządzeń telekomunikacyjnych w przemyśle IT. Co więcej, rząd indyjski musi zracjonalizować i uprościć istniejące indyjskie prawo pracy, aby ułatwić aktywność ekonomiczną w przemyśle IT. Przeróżni interesariusze wraz z rządem powinni włożyć niezbędny wysiłek w rozwój krajowego rynku IT, które jest pełen możliwości.

Słowa kluczowe: przemysł technologii informacyjnych, metoda obwiedni danych, indeks produktywności Malmquista, model efektów losowych, całkowita produktywność czynników produkcji, catch-up, frontier-shift, Indie

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FISCAL PERFORMANCE BENCHMARKING OF INDIAN STATES - A ROBUST FRONTIER APPROACH

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Abstract:

Aim: The objective of the paper is to construct an index of fiscal performance of Indian states using DEA. The reason behind using non-parametric methods for the purpose of construction of index is that the traditional ratio approach is incapable of handling multiple input and output indicators.

Design / Research methods: The present study uses a two stage approach. In the first stage, DEA is deployed to evaluate the performance of Indian states for five consecutive years. The input and output indicators used for DEA have been selected on the basis of a simple theoretical model. Further, in order to tackle the problem of estimation bias (due to sampling variations) bootstrapped DEA is applied. In the second stage ,impact of indebtedness on the performance of the states has been assessed using a censored regression framework.

Conclusions / findings: The major outcome of the study is the construction of a fiscal performance index based on multiple indicators. Moreover, the second stage results indicate that state performance is significantly influenced by their degree of indebtedness.

Originality / value of the article: The present study is perhaps the first attempt to assess the performance of sub-national units in terms of both convex and non-convex mathematical programming methods.

Implications of the research (if applicable): The approach (with suitable modifications) can be effectively used to benchmark state performance which can serve as a basis for resource transfer from the central government to the states.

Keywords: robust frontier, Indian states, non-parametric approach

JEL: H 17 , D 21, C 61

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1. Introduction

In spite of the existence of a federal structure of administration (in which the financial powers and responsibilities are shared between the Centre and the State), it is commonly agreed that Indian states enjoy relatively much less administrative and financial power compared to the Central government. In this context, reexamination of Centre-State financial relations and possible initiation of reforms in the relationship are undoubtedly of interest to the researchers and policy makers. The primary motivation for the present paper, however, emanates from a different source- the unevenness in financial performance of Indian states. While it is generally agreed upon that the States require more authority in the matter of mobilization of financial resources and perhaps, more generous attitude of the Central government regarding transfer of funds from the Centre to the States, analysis of the internal strength and weaknesses of the States is also equally important. In the past one decade, the central government also linked its assistance to the state governments with the accomplishment of institutional reforms in area of fiscal operations. Against this backdrop, the present study benchmarks the performance of non-special category states (these are the states which do not enjoy any special tax concession or additional central assistance) for the years 2009-10 to 2013-14 using data envelopment and also tries to assess the impact of indebtedness on the efficiency performance of the states.

The paper is organized in to five sections and proceeds as follows. Section 2 provides an overview of state finances in India. Section 3 discusses the received literature relating the evaluation of fiscal performance of Indian states. Section 4 discusses the methodological issues connected with benchmarking of performance in a non-parametric setting and assessment of the impact of contextual variable on the efficiency scores. Section 5 presents and discusses the results. Finally, section 6 concludes.

2. Fiscal scenario of Indian states

While both the central and the state governments in India have independent revenue raising and spending powers, there are inherent asymmetries in the federal structure resulting in both vertical and horizontal fiscal imbalances. The vertical fiscal imbalances exist because compared to the centre, the state governments in India have limited power to mobilise resources through taxes. The central government retains the entire tax revenue collected from important sources like corporate income or customs. The states have limited opportunities to mobilise direct taxes. Although due to the more liberal sharing of tax collection with the state governments, their share has increased over the last few decades, the central government share in the combined revenue is still about 43%. Table 1 provides the trend relating to the relative share of the central government and the states in the combined revenue between 1990-91 and 2013-14.

Table 1. Relatives tax shares of central and state governments in the combined tax revenue

Category	1990-91	2000-01	2005-06	2009-10	2013-14
Central Government Share (after devolution of state share)	49.06	44.8	45.98	48.3	43.08
State Government Share	50.94	55.2	54.02	51.7	56.92

Source: Indian Public Financial Statistics, various years, Ministry of Finance.

With limited resources at their disposal, the state governments have to have to shoulder a significant burden of expenditure relating to the social sector. In particular, education and provision of medical services and public health are the important social sector activities taken up by the state governments. Table 2 provides the trend in social sector expenditure incurred by the state governments for the span 2009-10 to 2013-14.

Table 2. Social sector expenditures of Indian states (2009-10 to 2013-14) (Amount in Rs billion)

State Category	2009-10	2010-11	2011-12	2012-13	2013-14
Non-Special Category States	3,558.2	4,106.3	4,763.7	5,518.2	6,208.5
Special Category States	371.3	412.9	472.2	511.4	583.6
Total	3,929.4	4,519.4	5,235.7	6,029.4	6,792.0

Source: State Finances – A Study of Budgets of 2015-16, RBI, Mumbai.

The Indian constitution provides for the transfer of resources from the Central to the state governments to bridge the gap between resources required by states to meet their assigned responsibilities and their own resources. Effectively, the transfer system is a three tier transfer system: the Indian central government transfers funds via Finance Commission, Planning Commission and various union ministries and agencies (discretionary transfers). Recently, the Planning Commission has been replaced by the Niti Ayog (The National Institution for Transforming India – policy think tank established by the Central Government). Table 3 provides a snapshot view of the transfer of resources from the Centre to the states.

Table 3. Devolution & transfer of resources from the Central government (Amount in Rs billion)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
States' share in central taxes	1650.1	2194.9	2555.9	2915.3	3182.7
Grants from the Centre	1509.7	1635	1864.2	1886.3	2059.7
Gross Loans from the Centre	81.1	94.8	99	112	108.7
Total (Gross Transfer)	3240.9	3924.8	4519.1	4914.2	5351

Source: State Finances – A Study of Budgets of 2015-16, RBI, Mumbai.

In spite of the financial support from the Central Government (beyond the sharing of taxes), conditions of state finances in India deteriorated sharply from the eighties and this condition persisted for two decades. In order to ensure better fiscal governance, 28 states have passed Fiscal Responsibility and Budgetary Management (FRBM) Acts between 2003-2010 aiming at phased and time bound reductions in revenue and fiscal deficits (as a percentage of GSDP) to prudent levels and putting ceilings on total outstanding liabilities (as a percentage of GSDP).

In the post-FRBM phase, fiscal indicators have improved for the states in general. However, substantial inter-state variations in fiscal scenario continue to exist across the states due to variations in revenue mobilisation capacity, composition and quality of expenditure and outstanding liablities. There are also many idiosyncratic factors at play. For example, two states may have similar GSDP (Gross Domestic State Product) levels. Yet the potential and actual revenue mobilisation may differ widely between them depending on the relative presence of the organised manufacturing and service sectors in them. States also differ considerable in terms of outstanding liabilities. The objective of the present study is to focus on this horizontal imbalance in the post-FRBM phase.

3. Fiscal performance of Indian states-a review of literature and research gaps

3.1 Literature Review

Several research studies attempted to assess the fiscal performance of Indian states in the context of intergovernmental transfer of resources. The present section includes the important studies undertaken in Indian context which had a sub-national perspective.

Rao and Singh (1998) examined the fiscal situation of Indian states for the period 1955-56 to 1993-94 in terms of vertical and horizontal fiscal imbalances. As indicated earlier, vertical fiscal imbalance prevails due to the gap between expenditures and revenues at different levels of government while horizontal/lateral fiscal imbalance exists due to the gap between revenue and expenditure levels within a particular level of government.

Bajpai and Sachs (1999) reviewed the deteriorating fiscal position of the Indian states in the nineties and identified several reasons for the worsening position: a stagnating tax-GDP ratio, increasing proportion of non-development expenditure in the total expenditure, large quantum of clandestine subsidies, rising financial burdens of state enterprises and rising demand for public services.

Coondoo et al. (2001) considered the comparative tax performance of 16 states in India (as measured by tax/SDP ratio) for the period 1986-87 to 1996-97 using a quantile regression approach. On the basis of their study they classified the in-sample states in to four categories: best, medium, declining and worst.

Rao (2002) reviewed the situation of Indian state finances for the period 1980-2000. The study noticed worsening scenario in state finances during the nineties – as evidenced by sharp upswings in primary, revenue and fiscal deficits, growth in indebtedness and contingent liabilities, and downward trends in capital and maintenance expenditures. Low buoyancy of fiscal transfers from the central government and the contagion effect of central pay revisions had an adverse bearing on state finances. However, the own fiscal performance of the relative states has also seen sharp decline especially due to their failure to increase the tax base.

Dholakia (2005) provided an alternative to the Fiscal Self Reliance and Improvement Index recommended by the Eleventh and Twelfth Finance Commissions for measuring fiscal discipline of the Indian states. She developed a composite index of performance which she termed as Fiscal Performance Index which was constructed out of three indices-a Deficit Index, an Own Revenue Effort Index and an Expenditure and Debt Servicing Index. Dholakia used the Fiscal Performance Index to rank the performance of Indian states for the period 1990-91 to 2002-03.

Roy and Roy Chowdhury (2009) used a theoretical model to determine optimum fiscal policy of the state governments in India and then compared the actual revenue and expenditures with the optimum policy for 1981-2001. The comparison of actual own revenue and expenditure policies of the observed states to the optimum policy shows that states are spending at a higher level than estimated optimum level and collecting lesser revenue relative to the optimum.

Chakraborty and Dash (2013) considered the impact of introduction of fiscal rules by the states via Fiscal Responsibility Acts (FRBM). While they found that the introduction of fiscal rules have prompted the states to reduce revenue and fiscal deficits in the post-FRBM phase, inter-state disparities in per capita expenditure has increased during the recent years. Further, it was evidenced that fiscal targets under FRBM were achieved through cut backs in discretionary development spending.

Mundle et al. (2016) compared the governance performance of major Indian states for the years 2001-02 and 2011-12 from the stand points of services, infrastructure, social services, fiscal performance, justice, law and order and quality of legislature. For judging fiscal performance, two indicators were considered: proportion of development expenditure to total expenditure and the ratio of own tax revenue to total tax revenue. They found three high income states (Gujarat, Tamil Nadu and Haryana), two middle income states (Karnataka and Andhra Pradesh) and one low income state (Chattisgarh) as the best performers in the area of fiscal performance.

3.2 Research gaps and objective of the study

The existing literature relating to the comparative fiscal performance of Indian states mostly used weighted ratio approach. Only one study used the quantile regression methodology. The objective of the present study is to provide an alternative approach for constructing a comprehensive fiscal performance index based on robust methodology. For constructing the index, Data Envelopment Analysis (DEA) has been used. The composite indices developed as proxies for fiscal performance of states in studies like Dholakia (2005) used a priori and researcher assigned weights. Compared to this, DEA is a data driven approach which assigns weights to inputs and outputs in manner such that the units under observation are evaluated in the most favourable manner. Thus the approach used in the present study is more scientific than the weighted ratio based indices introduced earlier.

Another important advantage of the present study is the computation of interval estimates of performance through bootstrap which was not possible under the conventional methodology. For each in-sample year, we have only 16 observations. For small samples, DEA estimates of efficiency contain upward bias which can be corrected through bootstrap. The objective of performing bootstrap DEA is to obtain unbiased efficiency estimates.

Further, it is a known fact that the Indian states are dependent on borrowings for financing their activities to a significant extent. Thus in the second stage, the present study performs censored regression for exploring the influence of outstanding liability ratio (in terms of gross state domestic product) on point and bias corrected estimates of efficiency.

4. Performance benchmarking: the conceptual and methodological issues

4.1 A brief outline of the conceptual framework

In the present day context, a state has an important role to play in promoting economic growth and development. In order to see how economic growth is related to state finances, let us consider a very simple static macroeconomic framework. Consider a hypothetical state with the following income and budgetary identities:

$$Y_t = C_t + X_t + I_t + G_t \qquad (1)$$

$$G_t = R_t + F_t - rB_t \qquad (2)$$

Where Y_t stands for GSDP (Gross Domestic State Product), C_t for private aggregate consumption, X_t for net exports to other regions/states, I_t for private investment and G_t for government spending. R_t represents the total non-debt resources of the state and includes four components: own tax revenues,non-tax revenues share of central government taxes and transfers from central government under various heads. Bt stands for the outstanding debt in period t. Finally, r represents the rate of interest payable on the borrowed amount.

We further assume that It is dependent on government development spending: $It = mGt\ d$, 0<m<1. Finally, $Ft = f\ t$, f stands for the incremental debt-GSDP ratio. From equations (1) and (2) we get the following relationship:

$$Y_t = \frac{C_t + X_t + mG_t^d + R_t - (rB_t + G_t^n)}{[1-f]} \qquad (3)$$

Where 0<f<1.

Equation (3) shows that apart from, consumption expenditure and exports to other regions, the level of income (and its growth rate) depends positively on (non-debt)resources mobilized, government development spending. Since a state do not have discretionary power over other sources of revenue, own tax revenue (mobilized by the state) is an important variable from the perspective of the state. Similarly, development spending is also a facilitator for income generation and growth.

4.2 Evaluation of performance-the distance function approach

In the present study we follow a multi-criteria approach for performance evaluation. In this context, Shephard's (1953, 1970) distance function approach gives a sound theoretical basis for the derivation of performance evaluation rules. The idea emanates from a multi-input multi-output production system where distance function provide a functional interpretation of the production technology. The production technology encompasses an input and an output set. The input set is characterized by the input distance function. The output set is characterized by the output distance function. The efficiency of a productive unit is defined as a distance between the quantity of observed input and output and the quantity of input and output required for the best practice frontier.

In order to explain the concept of input and distance function, we consider a technology T_g utilizing a nonnegative vector of inputs $X=(x_1,x_2,......,x_n)\in R^n{}_+$ to produce a nonnegative vector of outputs $Y=(y_1,y_2,......,y_m)\in R^m{}_+$. They can be functionally related as: Y=P(X) and X=L(Y). These two functions relates inputs and outputs from the output and input perspectives respectively. P(X) refers to the output set (set of all output vectors) and L(Y) refers to the input requirement set (set of all combinations of inputs that will produce y).

An input distance function can thus be defined as D_{input}= Max[λ:X/λ $\in$ L(Y)].Intuitively speaking, an input distance function gives the maximum amount by which the producer's input vector can be radially contracted and yet remain feasible for the output vector it produces. The reciprocal of the input distance function can be considered as the radial measure of input-oriented technical efficiency.

In an analogous fashion, the output distance function is defined as: D_{output}= Min[μ:Y/μ $\in$ P(X)]. Intuitively speaking, an output distance function gives the minimum amount by which the producer's output vector can be deflated and yet remain feasible for a given input vector. The radial measure of output-oriented technical efficiency coincides with the output distance function

4.3 Estimation of the distance function

While both parametric and non-parametric methods can be used for the estimation of distance function, we prefer the non-parametric approach because of the following reasons:

(i) non-parametric methods can easily handle multiple outputs which is not the case for parametric approaches.

(ii) non-parametric methods do not require knowledge about the parametric functional specification of the relationship between input and output indicators.

As mentioned earlier, DEA has been used in the present study for estimating efficiency. DEA is a non-parametric method based on mathematical programming. DEA is frequently used for comparing the relative performances of economic units with two prior assumption on input-output relation: free disposability of inputs and outputs and convexity. The DEA approach constructs a convex efficiency frontier of productive units. Efficiency can be computed from both input perspective (input-oriented model) and output perspective. In the input-oriented model (under the assumption of variable returns to scale), the linear program for efficiency estimation is:

Min θ

Subject to $\theta x \geq \lambda X, y \leq \lambda Y, \lambda \geq 0, \sum \lambda = 1$

Efficiency= θ

Similarly, in the output-oriented model, the relative linear program is

Max θ

Subject to $x \geq \lambda X, \mu y \leq \lambda Y, \lambda \geq 0, \sum \lambda = 1$

Efficiency= $1/\theta$

4.4 The purpose of undertaking bootstrap

Banker (1993), while providing a formal statistical foundation for DEA, showed that DEA estimators of the best practice monotone increasing and concave production function would be maximum likelihood estimators if the deviation of actual output from the efficient output is regarded as a stochastic variable with a monotone decreasing probability density function. However, For a finite sample size, the best practice frontier estimator would lie below the theoretical frontier implying the existence of an upward bias in the constructed frontier. In practical application of DEA, statistical estimators of the frontier are obtained from finite samples. Consequently, the corresponding efficiency estimates are sensitive to the sampling variations of the obtained frontier. Korostelev et al. (1995a, 1995b) have shown that DEA estimators satisfy consistency property under very weak general conditions. However, the obtained rates of convergence are very slow. Bootstrap analysis facilitates the correction of such upward bias.

4.5 Bootstrap efficiency estimation:

Efron (1979) introduced the concept of bootstrap which involves resampling from an original sample of data via computer-based simulations to getting the sampling properties of random variables. The beginning of any bootstrap procedure is a sample of observed data points X = $\{x_1, x_2, \ldots, x_n\}$ randomly drawn from a population with an probability distribution f (unknown). The premise of the bootstrap method is that the random sample actually drawn "mimics" its parent population.

The sample statistic $\hat{\theta} = \theta(X)$ computed from this state of observed values is merely an estimate of the corresponding population parameter $\theta = \theta(f)$. Since the researcher has access to only one sample rather than multiple samples drawn from the same population, it is not possible to get sampling distribution of the statistic. Under the circumstances, if one draws a random sample with replacement from the observed values in the original sample, it can be treated like a sample drawn from the underlying population.

The bootstrap method suggested by Efron (1979) involves drawing of sample (with replacement) directly from the observed data and is known as naive bootstrap. In this case the bootstrap sample is effectively drawn from a discrete population which fails to recognize the fact that the underlying population density function f is continuous. Simar and Wilson (1998) suggested that the problem could be overcome by resorting to smoothed bootstrap which involves resampling via a fitted model. The smoothed bootstrap methodology involves the use of Kernel estimators as weight functions. If we write the naive bootstrap sample as $X_{nbs} = \{x_1^*, x_2^*, \ldots\ldots, x_n^*\}$

and the smoothed bootstrap sample as X_{sbs} =$\{x_1^{**}, x_2^{**},......, x_n^{**}\}$ then the elements of the two are related to each other in the following manner: $x_i^{**}=x_i^{*}+h\epsilon$ ~f, where h is the smoothing parameter for the density function while x_i^* and x_i^{**} represent the i^{th} elements of the naive and smoothed bootstrap samples.

In case of bootstrapping, every time when we replicate the bootstrap sample, we get a different sample X**, we will also get a different estimate of $\theta^* = \theta(X^{**})$. Thus, we need to select a large number of bootstrap samples, B, in order to extract as many combinations of x_j (j = 1, 2, . . . , n) as possible. The steps followed in bootstrapping are briefly as follows:

(a) Compute the technical efficiency θ from the observed sample X.

(b) Select r^{th} (r = 1, 2, . . . ,B) independent bootstrap sample X^*_r, which comprises of n data values drawn with replacement from the observed sample X. From this, compute the naïve bootstrap.

(c) Compute the statistic $\theta_{sb} = \theta(X^{**}_{sb})$ from the rth bootstrap sample X^{**}_b

(d) Construct pseudo-data from the smoothed bootstrap efficiency scores and compute technical efficiency

(e) Repeat steps (b),(c) and (d) a large number of times (say, N times).

(f) Calculate the average of the bootstrap estimate (θ_e).

4.6 Computation of bias corrected efficiency

One important objective for applying bootstrap analysis in the context of small samples is to get rid of the upward bias existing in the estimated frontier. The bias correction procedure is now spelt out in brief:

A measure of the accuracy of an estimator θ_e of the parameter θ is the bias measure $E(\hat{\theta})-\theta$. The bias-corrected estimator is: $\theta_{bc}=\hat{\theta}$-bias. In our case, we compute bias $=\theta_e-\theta$.

Thus the bias corrected estimated technical efficiency is :$\theta_{bc}=2\hat{\theta}-\theta_e$

However, as Simar and Wilson (2000) pointed out, this bias correction might generate additional noise. To check for this, the sample variances of the bootstrap values (σ_{bs}^2) are to be calculated. Bias correction is to be made only if : bias/σ_{bs} $>\sqrt{3}$.

4.7 Impact of contextual variable on the performance scores

An important objective of the study is to assess the influence of contextual/environmental variable on the efficiency estimates and this is done in terms of econometric analysis. However, since the efficiency scores are bounded (the lower and upper bounds being 0 and 1), ordinary least square method can not be applied without any kind of data transformation. In the present study, censored regression has been used in lieu of data transformation.The censored regression model is effectually an extension of the standard Tobit model. The dependent variable can be either left-censored, right-censored, or both left-censored and right-censored, where the lower or upper limit of the dependent variable can be any number. The censored regression model can be represented as:

$$y^{*}=x'\beta+u$$

$$y=c \text{ if } y^{*}\leq 0, y=y^{*} \text{ if } c<y^{*}<d \text{ and } y=d \text{ if } y^{*}\geq 0$$

Where y* is a latent (unobserved) variable and y is the observed variable. x is a vector of explanatory variables. c and d are the lower and upper limits of the dependent variable. β is a vector of unknown parameters and u represents the disturbance term.

Censored regression models are usually estimated by the Maximum Likelihood method. Under the assumption that the disturbance term u is normally distributed with expectation 0 and variance σ^2, the log-likelihood function may be written as:

$$LogL=\sum[Ia\log\varphi(\frac{a-x'\beta}{\sigma})+Ib\log\varphi(\frac{x'\beta-b}{\sigma})+(1\text{-}Ia\text{-}Ib)\{\log\theta(\frac{y-x'\beta}{\sigma})\text{-}\log\sigma\}]$$

where $\varphi(.)$ and $\theta(.)$ denote the cumulative distribution and probability density function respectively of the standard normal distribution and Ia & Ib are the indicator functions with Ia=1 if y=a and Ia=0 if y>a and Ib=1 if y=b and Ib=0 if y>b.

5. Framework of study, results and discussion

5.1 Inputs and outputs and model orientation

Benchmarking of state performance requires specification of input and output indicators. In the previous section, a simple framework of analysis was used which showed that the level of income is positively related to government revenue, government spending and the revenue-spending ratio. Taking cue from this, we now make use of three output indicators and one input indicator for the purpose of multi-criteria performance evaluation (Table 4). On the output side, two indicators are taken: Own Tax Revenue and Development Spending Mobilization of own tax resources is an important indicator of the intention to have fiscal discipline. The quality of spending, on the other hand, is found to be an important facilitator of growth and development and consequently development expenditure has been taken as a proxy for the quality of expenditure undertaken by the states. On the input side, Gross State Domestic Product is considered. Estimation of efficiency is made using the output-oriented approach. DEA efficiency scores were computed under variable returns to scale. Computations were made using ‘R’.

Table 4. Input and output indicators (and contextual variable) for performance benchmarking

Particulars	Variables
Input	Gross state domestic product
Output	Own tax revenue, development spending
Contextual variable	Level of indebtedness

Source: Author’s own elaboration.

5.2 Period of analysis, sample observations and data source

The present study is based on observations relating to 16 non-special category States for the period 2009-10 to 2013-14. In India, there are two categories of states: special and non-special. Out of the 29 states in India, eleven are special category states which have not been included in the present analysis because they enjoy special benefits in terms of tax concessions and Additional Central (Government) Assistance. Out of the 18 non-special category states, two small states (Delhi and Goa were excluded).The period has been chosen out of the interest to compare the states for the post-FRBM phase only. Data relating to the variables included in the study have been collected from the RBI and Government of India reports. To be specific, data relating to the output and input indicators have been collected from various sources including Report on State Finances (R.B.I.) and Economic Survey (Government of India).

5.3 Results and discussion

Table 5 presents the descriptive statistics of technical efficiency scores for the period 2009-10 to 2013-14. The state wise mean technical efficiency scores and standard deviation of efficiency scores are provided in appendix tables (A2 through A6). Table 5 indicates an alternating trend in mean efficiency scores across the time period.

Table 5. Mean Technical Efficiency scores of the in-sample states (2009-10 to 2013-14)

Particulars	2009-10	2010-11	2011-12	2012-13	2013-14
Mean Efficiency	0.8726	0.8528	0.8265	0.8419	0.8096
Standard Deviation	0.1624	0.1868	0.1850	0.1734	0.1997

Source: Author's own elaboration.

5.3.1. Bootstrap based interval estimates of performance:

In case of small samples point DEA estimates of efficiency contain upward bias. Table 6 provides the bias corrected mean efficiency scores, mean lower and upper bounds of efficiency relative to the in-sample states for the period under observation. The state wise such scores are provided in appendix tables A2 through A7. Kindly note that the tables contain upper bounds of efficiency scores (as reported by the software) which are greater than 1. These may be truncated to 1.

Table 6. Bootstrap DEA Estimates

Descriptive Statistics	2009-10	2010-11	2011-12	2012-13	2013-14
Mean Bias Corrected Technical Efficiency	0.7780	0.6342	0.6082	0.6455	0.5804
Mean Lower Limit of Confidence Interval	0.6991	0.4943	0.4758	0.5198	0.4407
Mean Upper Limit of Confidence Interval	0.9566	0.8469	0.8173	0.8518	0.8015

Source: Author's own elaboration.

5.3.2. Estimation of returns to scale

It is of interest to have information about the returns to scale characteristics of the in-sample states for the five year period. Table 7 presented below provides the summary information regarding the returns to scale. The table shows that most of the states exhibited decreasing returns to scale after 2009-10. Appendix Table A 7 provides the state wise information about returns to scale.

Table 7. Returns to scale

Descriptive Statistics	2009-10	2010-11	2011-12	2012-13	2013-14
No states exhibiting constant returns to scale	9	5	3	4	5
No states exhibiting increasing returns to scale	1	2	0	0	1
No states exhibiting decreasing returns to scale	6	9	13	12	10

Source: Author's own elaboration.

5.3.3. Efficiency variations across income groups

In the present study, performance of sixteen non-special category Indian states has been evaluated for 2009-10 to 2013-14 from the stand point of fiscal management. The efficiency score corresponding to a state is a composite index of efficiency. Now, for understanding the difference in efficiency performance across the affluent and not so affluent states, the in sample states have been categorized in to three categories on the basis of per capita Gross State Domestic Product The sixteen states include four high income states (Maharashtra, Gujarat, Haryana and Tamil Nadu), five middle income states (Kerala, Punjab, Karnataka, Andhra Pradesh and West Bengal) and seven low income states (Rajasthan, Jharkhand, Chhattisgarh, Madhya Pradesh, Odisha, Uttar Pradesh and Bihar). Table 8 represent the average performances across the three groups for the observed years. The categorization provides some interesting results. In the first two years under observation, high income states produced below average performance while the other two categories had above average result. However, there was a role reversal in the subsequent three years.

Table 8. Mean DEA efficiency across income groups

State	2009-10	2010-11	2011-12	2012-13	2013-14
High Income States	0.7537	0.7557	0.8311	0.9487	0.8248
Middle Income States	0.8728	0.8989	0.7397	0.7733	0.7530
Low Income States	0.9404	0.8754	0.8857	0.8298	0.8413
Overall	0.8726	0.8528	0.8265	0.8419	0.8096

Source: Author's own elaboration.

5.3.4. Impact of indebtedness

As indicated earlier, the influence of indebtedness of the Indian states on their efficiency performance is estimated using a censored regression framework. The DEA efficiency is taken as the dependent variable and the total outstanding liabilities to GSDP ratio (proxy for indebtedness) is taken as the independent variable. The year wise outstanding liability ratios for the in-sample states for the five year period are provided in appendix Table A 8. The results presented in Table 8 show that the influence of the outstanding liability ratio is significant provided we consider the point estimates of efficiency.

Table 8. DEA efficiency and Outstanding Liability-GSDP ratio

Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of Type I Error
Intercept	1.3487	0.1668	8.0860	<0.00001
Outstanding Liability-GSDP ratio	-0.0123	0.0048	-2.5960	0.0094
Cross-section dummy	-0.0028	0.0063	-0.4485	0.6538
Time series dummy	-0.0276	0.0221	-1.2480	0.2120

Source: Author's own elaboration.

However, if we consider the bias corrected scores (refer Table 9), then this linkage is not supported by empirical evidence. This is quite an interesting result: the states which are relatively more indebted may not have done that badly in terms of current performance. In fact, high degree of indebtedness is a legacy of the past.

With the on set of FRBM regulations, states have been compelled to restrict their borrowings for maintaining the FRBM upper limits.

Table 9. Bias corrected efficiency and Outstanding Liability-GSDP ratio

Particulars	Coefficient	Standard Error	Coefficient/ Standard Error	Probability of Type I Error
Intercept	0.8158	0.0802	10.1722	<0.00001
Outstanding Liability-GSDP ratio	-0.0017	0.0025	-0.6685	0.5038
Cross-section dummy	-0.0002	0.0034	-0.0731	0.9417
Time series dummy	-0.0402	0.0110	-3.6570	0.0003

Source: Author's own elaboration.

6. Conclusions

The present study attempts to provide robust estimates of fiscal performance indices based on non-parametric tools for five consecutive financial years. If we look at the DEA results, then we find that mean technical efficiency had an alternating trend. Mean efficiency improved in 2010-11 and then experienced a decline in 2011-12, further picked up in 2012-13 and declined again in 2013-214. This alternating trend is likely because of instability in the mobilization of own tax revenues and undertaking development spending. As mentioned earlier, middle and low per capita income states have performed better than the high income states during 2009-10 and 2010-11 but the trend was reversed during 2011-12 to 2013-14. For inefficient states, inefficiency can arise due to shortfalls in performance relative to the benchmark in respect of own tax revenue, development expenditure or index of fiscal discipline. Decomposition of inefficiency shows that the inefficiency of high and middle income states is mainly due to shortfalls in development expenditure. On the other hand, the low income states mainly lagged on account of poor mobilization of own tax revenues. Further, the alleged inverse linkage between indebtedness and efficiency performance does not hold good if we remove biases in efficiency estimates.

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Appendix: State wise efficiency scores

Table A1. State wise efficiency Scores (2009-10 to 2013-14)

State	2009-10	2010-11	2011-12	2012-13	2013-14
Andhra Pradesh	1.0000	1.0000	1.0000	1.0000	1.0000
Bihar	0.8872	0.6348	0.9438	0.7933	0.9145
Chhattisgarh	1.0000	1.0000	1.0000	1.0000	1.0000
Gujarat	0.6004	0.6234	0.7433	0.8647	0.8579
Haryana	0.5061	0.4635	0.5811	1.0000	0.4658
Jharkhand	0.9171	0.7420	1.0000	1.0000	1.0000
Karnataka	0.9855	1.0000	0.8238	1.0000	1.0000
Kerala	0.8934	0.9001	0.6061	0.7419	0.6066
Madhya Pradesh	1.0000	1.0000	1.0000	0.7626	0.6454
Maharashtra	1.0000	1.0000	1.0000	1.0000	1.0000
Odisha	0.9534	1.0000	0.7287	0.6348	0.6957
Punjab	0.8949	1.0000	0.6240	0.5709	0.6207
Rajasthan	0.8249	0.7513	0.5277	0.6182	0.6336
Tamil Nadu	0.9082	0.9359	1.0000	0.9300	0.9754
Uttar Pradesh	1.0000	1.0000	1.0000	1.0000	1.0000
West Bengal	0.5901	0.5943	0.6446	0.5538	0.5379

Source: Author's own elaboration.

Table A2. Bootstrap efficiency scores (2009-10)

State	Bias corrected mean efficiency	Lower limit (2.5%)	Upper limit (97.5%)
Andhra Pradesh	0.8648	0.7474	1.0319
Bihar	0.8339	0.7958	0.8969
Chhattisgarh	0.7553	0.5301	1.4544
Gujarat	0.5390	0.4894	0.6605
Haryana	0.4649	0.4324	0.5234
Jharkhand	0.8139	0.7254	1.2113
Karnataka	0.8996	0.8298	1.0336
Kerala	0.8365	0.7958	0.9019
Madhya Pradesh	0.9285	0.8760	1.0141
Maharashtra	0.8068	0.6317	1.2490
Odisha	0.8686	0.8032	0.9959
Punjab	0.8323	0.7865	0.9051
Rajasthan	0.7687	0.7280	0.8440
Tamil Nadu	0.8318	0.7722	0.9381
Uttar Pradesh	0.8664	0.7498	1.0318
West Bengal	0.5363	0.4930	0.6143

Source: Author's own elaboration.

Table A3. Bootstrap efficiency score (2010-11)

State	Bias corrected mean efficiency	Lower limit (2.5%)	Upper limit (97.5%)
Andhra Pradesh	0.7285	0.5517	0.9199
Bihar	0.5096	0.4410	0.6106
Chhattisgarh	0.6232	0.3372	1.2354
Gujarat	0.4736	0.3807	0.6166
Haryana	0.3701	0.3195	0.4485
Jharkhand	0.5617	0.4479	0.7736
Karnataka	0.7874	0.6698	0.9656
Kerala	0.7356	0.6559	0.8548
Madhya Pradesh	0.7372	0.5639	0.9298
Maharashtra	0.6468	0.3869	1.0705
Odisha	0.6721	0.4350	1.0141
Punjab	0.7481	0.5924	0.9280
Rajasthan	0.5959	0.5115	0.7293
Tamil Nadu	0.7366	0.6224	0.9051
Uttar Pradesh	0.7488	0.5896	0.9649
West Bengal	0.4723	0.4037	0.5833

Source: Author's own elaboration.

Table A4. Bootstrap efficiency score (2011-12)

State	Bias corrected mean efficiency	Lower limit (2.5%)	Upper limit (97.5%)
Andhra Pradesh	0.6713	0.4477	0.9490
Bihar	0.7462	0.6437	0.9128
Chhattisgarh	0.6268	0.3558	1.0890
Gujarat	0.5999	0.5323	0.7140
Haryana	0.4419	0.3641	0.5616
Jharkhand	0.6241	0.3526	1.1671
Karnataka	0.6284	0.5192	0.7885
Kerala	0.4627	0.3825	0.5898
Madhya Pradesh	0.7548	0.6122	0.9401
Maharashtra	0.6304	0.3675	1.0435
Odisha	0.5631	0.4741	0.6921
Punjab	0.4902	0.4222	0.6144
Rajasthan	0.4085	0.3446	0.5059
Tamil Nadu	0.7833	0.6684	0.9493
Uttar Pradesh	0.7818	0.6664	0.9432
West Bengal	0.5186	0.4597	0.6166

Source: Author's own elaboration.

Table A5. Bootstrap efficiency score (2012-13)

State	Bias corrected mean efficiency	Lower limit (2.5%)	Upper limit (97.5%)
Andhra Pradesh	0.7059	0.4957	0.9903
Bihar	0.6607	0.5923	0.7871
Chhattisgarh	0.7353	0.5531	1.0102
Gujarat	0.7112	0.6302	0.8419
Haryana	0.6719	0.4288	1.0504
Jharkhand	0.6599	0.4055	1.1726
Karnataka	0.8018	0.6876	0.9684
Kerala	0.5925	0.5055	0.7440
Madhya Pradesh	0.6103	0.5206	0.7716
Maharashtra	0.6813	0.4466	1.0405
Odisha	0.5248	0.4677	0.6218
Punjab	0.4570	0.3916	0.5670
Rajasthan	0.4944	0.4229	0.6122
Tamil Nadu	0.7599	0.6688	0.9211
Uttar Pradesh	0.8108	0.7041	0.9886
West Bengal	0.4512	0.3962	0.5411

Source: Author's own elaboration.

Table A6. Bootstrap efficiency score (2013-14)

State	Bias corrected mean efficiency	Lower limit (2.5%)	Upper limit (97.5%)
Andhra Pradesh	0.6416	0.3961	0.9506
Bihar	0.7150	0.6155	0.8820
Chhattisgarh	0.6237	0.3558	1.0221
Gujarat	0.6696	0.5738	0.8283
Haryana	0.3440	0.2717	0.4612
Jharkhand	0.5646	0.2422	1.1839
Karnataka	0.7610	0.6320	0.9593
Kerala	0.4644	0.3881	0.6074
Madhya Pradesh	0.4794	0.3825	0.6463
Maharashtra	0.6085	0.3294	0.9659
Odisha	0.5291	0.4403	0.6579
Punjab	0.4830	0.4133	0.6128
Rajasthan	0.4774	0.3918	0.6251
Tamil Nadu	0.7517	0.6368	0.9396
Uttar Pradesh	0.7663	0.6450	0.9696
West Bengal	0.4069	0.3362	0.5114

Source: Author's own elaboration.

Table A 7. Returns to scale (State wise results)

State	2009-10	2010-11	2011-12	2012-13	2013-14
Andhra Pradesh	Constant	Constant	Constant	Constant	Constant
Bihar	Increasing	Decreasing	Decreasing	Decreasing	Constant
Chhattisgarh	Constant	Constant	Constant	Constant	Constant
Gujarat	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
Haryana	Decreasing	Decreasing	Decreasing	Constant	Decreasing
Jharkhand	Constant	Decreasing	Constant	Constant	Increasing
Karnataka	Constant	Constant	Decreasing	Decreasing	Decreasing
Kerala	Constant	Increasing	Decreasing	Decreasing	Decreasing
Madhya Pradesh	Constant	Constant	Decreasing	Decreasing	Decreasing
Maharashtra	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
Odisha	Constant	Constant	Decreasing	Decreasing	Constant
Punjab	Constant	Increasing	Decreasing	Decreasing	Constant
Rajasthan	Constant	Decreasing	Decreasing	Decreasing	Decreasing
Tamil Nadu	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
Uttar Pradesh	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing
West Bengal	Decreasing	Decreasing	Decreasing	Decreasing	Decreasing

Source: Author's own elaboration.

Table A 8. Indebtedness of Indian states: outstanding liabilities to GSDP ratio (%)

State	2009-10	2010-11	2011-12	2012-13	2013-14
Andhra Pradesh	25.9	23.9	22.5	23.0	22.9
Bihar	36.5	31.2	27.9	26.4	25.8
Chhattisgarh	16.4	14.3	12.4	13.0	14.0
Gujarat	28.6	27.4	25.3	25.7	24.6
Haryana	18.3	17.8	19.0	19.8	20.5
Jharkhand	26.8	22.2	23.1	23.1	21.9
Karnataka	25.0	22.8	23.3	21.6	22.6
Kerala	32.5	31.8	30.3	31.6	31.7
Madhya Pradesh	29.8	28.7	26.5	24.8	22.2
Maharashtra	23.8	22.0	21.0	21.3	20.5
Odisha	28.1	23.8	21.7	19.6	18.5
Punjab	34.3	33.1	32.3	32.4	32.2
Rajasthan	34.5	29.4	25.7	25.2	24.8
Tamil Nadu	21.2	19.6	19.6	20.5	21.0
Uttar Pradesh	39.4	38.3	35.6	31.3	30.9
West Bengal	44.0	41.9	40.4	39.1	36.7

Source: Author's own elaboration.

Benchmarking kondycji fiskalnej indyjskich stanów – podejście oparte na odporności granicy

Streszczenie

Cel: Artykuł ma na celu skonstruowanie indeksu kondycji fiskalnej indyjskich stanów w oparciu o metodę DEA. Uzasadnieniem wykorzystania metod nieparametrycznych w celu opracowania indeksu jest niezdolność tradycyjnego podejścia współczynnikowego do uwzględnienia wskaźników wielokrotnych nakładów i wyników.

Metodyka badań: Badanie oparto na dwuetapowym podejściu. W pierwszym etapie wykorzystano metodę DEA do oceny kondycji indyjskich stanów w pięciu kolejnych latach. Wskaźniki nakładów i wyników użyte w DEA ostały wybrane na podstawie prostego modelu teoretycznego. Następnie, aby rozwiązać problem błędu szacunkowego (ze względu na wariacje doboru próby), zastosowano samoczynną DEA. W drugim etapie oceniono wpływ zadłużenia na kondycję stanów, wykorzystując cenzurowane modele regresji.

Wnioski: The major outcome of the study is the construction of a fiscal performance index based on multiple indicators. Moreover, the second stage results indicate that state performance is significantly influenced by their degree of indebtedness.

Wartość artykułu: Głównym wynikiem badań jest opracowanie indeksu kondycji fiskalnej opartym na wielokrotnych wskaźnikach. Co więcej, wyniki z drugiego etapu badań wskazują, że kondycja stanów znajduje się pod istotnym oddziaływaniem stopnia ich zadłużenia.

Ograniczenia: Niniejsze badanie to prawdopodobnie pierwsza próba oceny kondycji jednostek subnarodowych pod względem zarówno wypukłych, jak i niewypukłych metod programowania matematycznego.

Implikacje: Zaprezentowane podejście (z odpowiednimi modyfikacjami) może być z powodzeniem stosowane do benchmarkingu kondycji stanów, co może służyć jako podstawa transferu zasobów od rządu centralnego do stanów.

Słowa kluczowe: odporność granicy, indyjskie stany, metoda nieparametryczna

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