



A Literature Study of Public Spending Efficiency Using DEA Approach

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A Literature Study on Public Spending Efficiency Using DEA and SFA

자료포락분석 (DEA)와 확률프런티어분석을 이용한 공공지출효율성에 관한 기존연구 분석

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Abstract

The purpose of the paper is to survey and review the recent literature in the study of efficiency of public spending using the two most recognized methodologies, Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA). This paper not only surveys the previous literature and introduces some new techniques such as the Bootstrap and Three-stage method, but also analyzes the comparability of two different methodologies. The findings support the facts that first, the environmental variables affecting the efficiency of public spending are equally significant in both analyses, although SFA measures an ‘absolute’ efficiency and DEA estimates ‘relative’ efficiency. Second, both SFA and DEA are not comparable but complementary to each other in both static and dynamic analyses. The results from both methodologies are significantly different, especially, when the dynamic behavior of the efficiency in over time is considered.

Key Words: Stochastic Frontier Approach (SFA), Data Envelopment Analysis (DEA), efficiency and effectiveness of public spending, public policy, and bootstrap method

JEL Codes: C14, E62, H51, H52, H54, H75

I. Introduction

Ever since Keynes wrote ‘The General Theory’ in 1936, much controversy surrounding the public (central and local governments) spending on economic growth has existed. In the 1990s, Barro (1990) initiated discussions on the effects of government expenditures. He discovered that an increase in resources devoted to non-productive (but possibly utility-enhancing) government services are associated with lower per capita growth.

There are various types of literature on this issue: The first type of literature includes the analysis of the relationship between government spending and economic growth with both time-series and cross-sectional data. The second type of literature shows the efficiency analysis of public spending since recently, the focus has shifted from estimating the movement of the key variables such as consumption and real wage by public spending to the efficiency and effectiveness of the spending. The areas of a government spending include R&D, education, health care, welfare, national security, and general public administration. Furthermore, the two most recognized methodologies on these issues have been found in the literature: the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA).

Thus, the purpose of this paper is to survey the burgeoning literature on the efficiency of public spending, not only for the future research but for comparing the results made by different methods whether they are substitutable or complementary to each other.

The second chapter describes the concepts of public spending and efficiency. The third chapter surveys the literature in methodology: SFA, DEA, and comparison of SFA with DEA. There will be some concluding remarks in the last chapter.

II. Basic concepts of public spending and efficiency

1. Public Spending (Government Purchases/Government Expenditure)

Public (Government) spending or expenditure includes all government consumption, investment, and transfer payments. The change in government spending is a major component of fiscal policy used to stabilize the macroeconomic business cycle.¹⁾

1) Wikipedia, 「Public Spending」.

In 2016, according to the Office of Management and Budget of United States (OMB), the estimated total US government spending is \$6.7 trillion: \$4.0, -\$0.7, \$1.6, and \$1.8 trillion for federal, inter-governments, state, and local governments, respectively.²⁾ The areas (or functions) that the US Government planned to spend are health care (20.9%), pensions (19.4%), education (14.9%), defense (11.9%), welfare (7.4%), and remainder including environment (23.9%).

According to Eurostat (2017), the total government spending by EU's 28 countries is divided into the sectors of general public service (13.1%), defence (2.9%), public order and safety (3.7%), economic affairs (9.0%), environmental protection (1.7%), housing and community amenities (1.2%), health (15.2%), recreation, culture and religion (2.2%), education (10.3%), and social protection (40.6%). The numbers in the parenthesis indicate the percentage of total government expenditure.

Ramey (2013) makes the distinctions between government spending on private goods and government value-added output. According to the US's NIPA (National Income and Product Accounts), government purchases include:

- (a) government purchases of goods from the private sector such as aircraft carriers,
- (b) government value-added, which is comprised of compensation of government employees, such as payments to military and civilian personnel, and
- (c) consumption of government capital.

Finn (1998) also found that there was an opposite effect of government purchases on private sector output, employment, and investment. Cavallo (2005), Pappa (2009), and Gomes(2010) had similar results on this issue. On consumption of government capital, the empirical results are rather mixed.

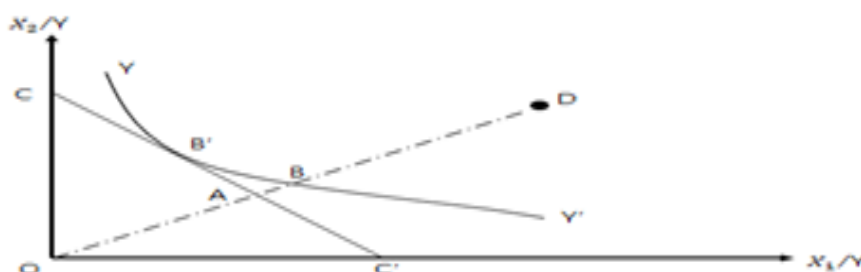
2. Meaning of Efficiency in DEA

Why do governments spend money on education, health, military purchasing, and stimulating economies especially in recessions? Every government in the world spends money to achieve a high economic growth as possible. There are a few steps between the initial public spending stage and final economic growth stage. Suppose that US government spent \$1 billion on public healthcare programs. This

2) usgovernmentspending.com

spending becomes an input to produce output such as increased numbers of doctors and beds in hospitals (measurable) and solutions to traffic congestions (unmeasurable). Thus, producing the maximum output with the least input is called ‘efficiency.’

In production frontier analysis, Farrell (1957) characterized ‘efficiency’ in different ways, ways in which a productive unit can be ‘inefficient’ by: (1) obtaining less than the maximum output available from a determined group of inputs, which is called technically inefficient, (2) not purchasing the best package of inputs given their prices and marginal productivities, which is called ‘allocative inefficient’. Figure 1 depicts these inefficiencies.



<Figure 1> Technical and Allocative (in)Efficiencies

In Figure 1, according to Murillo-Zamorano (2004), Farrell assumed a constant returns to scale (CRS) in input-oriented scheme: unit isoquant YY' (CC' is a slope of the isocost line), where X axis is a ratio of input X_1 to output Y , and Y axis is a ratio of input X_2 to output Y , captures the minimum combination of inputs per unit of output needed to produce a unit of output. Farrell noted that every set of inputs along the unit isoquant is considered as technically efficient while any one else such as point D is technically inefficient. The distance BD along the ray OD measures the technical inefficiency of producer located at point D . This distance represents the amount by which all inputs can be divided without decreasing the amount of output. Thus, the ratio BD/OD measures the technical inefficiency of DMU_0 (Decision Making Unit of 0), while $(1-BD/OD)=(OB/OD)$ then measures the efficiency of DMU_0 .

Conversely, a unit is Pareto-efficient when an attempt to improve on any of its inputs or outputs will adversely affect some other inputs or outputs. Formally, Charnes et al. (1981) considered a DMU to be 100% efficient only when ‘none of its inputs can be decreased without either (i) decreasing some of its outputs, or (ii) increasing some of its other inputs, and none of its outputs can be increased without either increasing one or more of its inputs or decreasing some of its other

outputs'. Since the condition for Pareto-efficiency is that a DMU's efficiency score is 1, efficiency and Pareto-efficiency are synonymous. [Charnes et al.(1981)]

Within the context of DEA, Cooper, Seiford and Tone (2007)³⁾ explains the concepts of Farrell vs. Pareto-Koopmans' efficiencies as following: We have been dealing with pairs of positive input and output vectors (x_j, y_j) ($j=1, \dots, n$) of n DMUs. All data are assumed to be non-negative but at least one component of every input and output vector is positive. (and for all $j=1, \dots, n$) (With $m+s$ dimensional linear vector space where m and s refer to the number of dimensions required to express inputs and outputs respectively.) ($x \in R^m, y \in R^s$) With a production possibility set P ,

$$P = \{(x, y) \mid (x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0)\} \quad (1)$$

where, $X = (x_j)$, $Y = (y_j)$, and λ is a semi-positive vector in R^n , the CCR (Charnes, Cooper, and Rhodes (1978)) model was formulated as an LP (linear Programing) problem with row vector, for input multipliers and row vector as output multipliers. These multipliers are treated as variables in the following LP problem (Multiplier form):

(LP_0) $\max_{v,u}$	uy_0
Subject to	$vx_0 = 1$ $-vX + uY \leq 0$ $v \geq 0, u \leq 0$

(2)

The dual problem of (LP_0) is expressed with a real variable and a non-negative vector $\lambda = (\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_n)$ of variables as follows (Envelopment Form)

(DLP_0) $\min_{\theta, \lambda}$	uy_0
Subject to	$\theta x_0 - X\lambda \geq 0$ $Y\lambda \geq y_0$ $\lambda \geq 0$

(3)

Here, (DLP_0) has a feasible solution $\theta=1, \lambda_0=1, \lambda_j=0$ ($j \neq 0$), hence the optimal θ , denoted by θ^* is not greater than 1, and the second condition above forces λ to be nonzero so that $0 < \theta^* \leq 1$. Then, we define the input excesses $s^- \in R^m$ and output shortfalls $s^+ \in R^s$, and identify them as 'slack' vector by⁴⁾ :

3) Cooper, Seiford and Tone (2007), pp.43-46.

$$s^- \theta x_0 = -X\lambda, \quad s^+ = Y\lambda - y_0 \quad (4)$$

with $s^- \geq 0, s^+ \geq 0$ for any feasible solution (θ, λ) of (DLP_0) . Solving for θ^* gives the optimal objective value of LP_0 and is the CCR-efficiency value, also called 'Farrell Efficiency.' That is, DMU_0 is called CCR-efficient if

(a) $\theta^* = 1$

(b) All slacks are zero

The two conditions must be satisfied if full efficiency is to be attained. Thus, since the Farrell efficiency only satisfies the first condition, it is called 'weak efficiency.' On the other hand, a DMU is full efficient if and only if it is not possible to improve any input or output without worsening some other input or output, it is called 'Pareto-Koopmans efficiency.'

Koopmans adopted the concept from Pareto in production. He altered the test of vector optimum with reference to whether it was possible to increase any output without worsening some other output under conditions allowed by available resources such as labor, capital, and raw materials in his 'Activity analysis of production and allocation.'

III. Survey of literature

In this paper, we are interested in surveying the literature on public spending efficiency on R&D, healthcare, education sectors, and in a more aggregated sense, the impact of general government spending for the promotion of economic growth.

1. SFA (Stochastic Frontier Approach)

Researchers such as Kumbhakar and Lovell (2004) initiated discussions on the concept of 'stochastic' rather than 'deterministic' analysis in the area of efficiency and effectiveness of many issues including public spending.

SFA has become a popular methodology for estimating 'efficiency' matters after the introduction of two pioneering papers by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broek (1977). Both papers suggested adding a two-sided error term to the one-sided error term normally used in the production function

4) Slacks - The additional improvement (increase in outputs and/or decrease in inputs) needed for a unit to become efficient.

approach. Their model is based on the fact that a firm's real output (q_i) may be lower than that the production function enables. The reasons may be a random supply shock, and is expressed in composite error terms in a production function with a random noise and asymmetric inefficiency such that,

$$\ln q_i = \beta_0 + \beta_1 \ln x_i + v_i + u_i \quad (5)$$

where, q_i are inputs or dependent environmental variables, $v_i \sim N(0, \sigma_v^2)$ is a random (white) noise and u_i is a technical inefficiency. Inefficiency shows the deviation, by which the actual production differs from the ideal. In the case of $\sigma_v^2 = 0$, the result is a deterministic frontier, while in the case of $\sigma_u^2 = 0$, the result is a stochastic frontier.

There are many possible probability distributions for the asymmetric error term: (1) Exponential, (2) half-normal, (3) truncated-normal, and (4) gamma distributions as proposed by Coelli et al. (2005) and various papers by Greene (2010, 2005a, 2005b, 2004a, 2004b, 2003, 1994, 1990, and 1980). Also, Greene's various works probability distributions for solving econometrics problems such as heteroscedasticity, autocorrelation, and multicollinearity, it enhanced the econometric estimations in a stochastic sense. Greene (2005) further analyzed the types of distributions⁵⁾ :

- (a) Stochastic frontier: normal-half normal [Aigner et al. (1977)]
- (b) Normal – truncated normal [Stevenson (1980)]
- (c) Heteroscedastic normal [Singly or Dubly, Hadri (1999)]
- (d) Scaling (truncation and heteroscedasticity models can be combined and permuted) [Albarez et al. (2005)]
- (e) Latent class [Greene (2004b)]

The pioneering work done by Battese and Coelli (1995) has affected many researchers in this area of study of analyzing models for technical inefficiency: The concept of 'inefficiency' in public spending model, for instance, emerged in the literature, and replaced the concept of estimation from 'deterministic' to 'stochastic.' In the 1990s, this method became more popular.

First, on the issue of public (and private) R&D's efficiency literature, Liik, Masso, and Ukrainski (2014) analyzed the efficiency and effectiveness of R&D using 25 OECD countries with two-digit (ISIC) industry level panel data in 1987–2009. In

5) See Greene (2005), p. 85 for econometric information in detail.

their works, the following Cobb–Douglas production function, which is similar to the equation (5), was used:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 RND_{it} + \sigma_i \ln Z_{it} + v_{it} + u_{it} \quad (6)$$

where, Y_{it} is value-added per employee, K_{it} is physical capital per employee, RND_{it} is R&D capital stock per employee, t is time trend for Hicks-neutral technical change, Z_{it} is efficiency covariates (external factors), v_{it} is random noise, and u_{it} is time-varying inefficiency. Their findings suggest that the R&D capital productivity enhanced as the level of technology increases, while physical capital shows the opposite effect.

Hu, Yang, & Chen (2014) used a translog distant function approach, and a modified-SFA to avoid some econometric problems, for 24 countries in 1998–2005. On the issue of public (government) R&D, Hu, Yang, & Chen (2014) used a variable SGRD, a ratio of government R&D to total national R&D expenditures, it determined a positive sign on efficiency scores, even if it does not have statistical significance. This finding supports Guellec and van Pottelsberghe de la Potterie (2004)’s view that the government R&D could be efficient, since it generally focuses on basic research and public missions to enhance the stock of knowledge for the society. However, this finding is quite different from the results of Wang (2007) in that government budget outlays are usually used less efficiently than the funds appropriated by the private sector due to the interference of bureaucratic red tapes. (See Table 2 for the details of the equation.)

Wang and Wong (2012) utilized the data from 77 countries in 1986–2007 and showed an impact of foreign R&D (both public and private) on domestic economy’s technical efficiency. First, they estimated the efficiency with a translog-production function for 77 countries. In the inefficiency function, the inefficiency scores are regressed with many environmental variables such as country’s openness, urbanization, political stability, and international R&D transferred by inward FDI or imports into the country. Their findings demonstrate some striking facts, that foreign (both public and private) country’s R&D is a critical factor for the increase of the technical efficiency of the domestic economy.

Fritsch and Slavtchev (2007) studied the German economy for the purpose of establishing what determines the technical efficiency of the regional innovation system in 1995–2000. They employed both quasi-deterministic and the stochastic frontier approach. With many variables on regression, the study concluded that both

knowledge spillovers within the private sector and public sector have a positive impact on the efficiency on the regional innovative system.

Wang (2007) also employed SFA incorporating a translog production function in his study of DEA. He introduced the following SFA incorporating translog specification:

$$\ln y = b_0 + \sum b_i (\ln x_i) + \sum b_{ii} (\ln x_i)^2 + \sum \sum b_{ij} (\ln x_i) (\ln x_j) \quad (7)$$

where y is output volume, x_i and x_j are inputs i and j . This provides a basis for testing the maintained hypothesis of the cross-country function approach, that there is a single aggregate R&D production function for all the countries. His findings showed that, after the controlling of the operating environment factor is included, the means of efficiency scores increased to about 0.85. Furthermore, R&D performance indices show a positive correlation with income level.

Zhang, Zhang, and Zhao (2003) used 8,341 Chinese firms to measure the R&D (both total and public) efficiencies. They used a basic R&D production function similar to Bae (2009) used with a different inefficiency function to see if the ownership and infrastructure have affected the (in)efficiency level:

$$\mu_i = \delta_0 + \sum \delta_j \text{ownership}_{ij} + \sum \delta_k \text{infrastructure}_{ik} \quad (8)$$

That is, inefficiency is specially analyzed by different ownership types, state and non-state, and three different levels of infrastructure types. The state sector faces significantly lower efficiency levels in both R&D and productive activities than the non-state sector.

There is a massive amount of literature on measuring the effects of public expenditures on the healthcare and education sectors. First, Ogloblin (2011) did extensive work on 78 countries for pooled data of 2000, 2003, and 2007. He used a health production function with various inputs and outputs, and a production inefficiency function with a truncated normal distribution was also included. The findings are: First, the inefficiency of national healthcare systems is inversely related to per capita income and directly related to income inequality. Second, healthcare systems are more efficient when greater shares of total healthcare expenditure come from public sources and out of pocket, rather than from private insurance coverage.

Pereira and Moreira (2007) also measured the efficiency of public spending on secondary education in Portugal municipalities. The Cobb-Douglas educational

production function, identical to Battese and Coelli (1988)'s, with the normal-truncated normal model, has been utilized. The determinants of 'inefficiency' are the following: teacher seniority, school size, private management, and the location of the schools. The closer to the main cities, the higher the efficiency scores.

Perhaps, one of the most extensive works done in terms of developing countries' health and education was performed by Hereira and Pang (2005). With the Cobb-Douglas health and education production functions and an assumption of the half-normal distribution on the inefficiency functions, their findings include: First, a positive relationship between expenditure and the level of economic development has been found. It supports the Balassa-Samuelson effect, the price levels in wealthier countries tend to be higher than those in poorer countries. It depends on inter-country differences in the relative productivity of the tradable and non-tradable sectors. Second, urbanization and income inequality are positively and negatively correlated with efficiency, respectively.

Greene (2005b) measured the efficiency of public spending in developing countries with the SFA method. He used the same data as Herrera and Pang (2005), and regressed the education spending with various school enrollment rates (primary and secondary), youth literacy rates, primary and secondary completion rates, and average years of schooling yields the followings : Adult literacy rates and aid revenue are used as control variables. The author took 1975-1995 and 1996-2002 averages and estimated a two-period panel with an assumption of a normal-truncated normal distribution, and found the regression coefficients are better behaved.

Jayasuriya and Wondon (2003) also used an educational production function which is identical to the function used by Battese and Coelli (1988). Controlling for changes over time, neither education expenditure nor regional differences have a statistically significant impact on net primary enrollment.

In the economic growth literature, not many works have employed SFA to analyze the public spending efficiency. Yabbar (2013) used a similar type of Cobb-Douglas production function as used in Battese and Coelli (1988) to measure the impact of efficiencies on economic growth and the level of poverty. To solve the simultaneity in growth and poverty equations (9) and (10) following the Three- stage least squares (3SLS) model has been employed.

$$\text{Grt} = f(\text{eff}_i) \quad (9)$$

$$\text{Kms} = f(\text{eff}_i, \text{Grt}) \quad (10)$$

where Grt is economic growth, eff_i is efficiency score of budget management, Kms is poverty percentage of total population, and i is education, health, and infrastructure sector, respectively.

Recently, Baldacci (2017) estimated the relationship between government spending on health care and education and selected social indicators, with samples of data for developing countries and transition economies. Baldacci (2017) found that the latent variable approach yields better estimates of a social production function than the traditional approach, with higher elasticities of social indicators with respect to income and spending, therefore providing stronger evidence that increases in public spending do have a positive impact on social outcomes.

2. DEA (Data Envelopment Analysis)

Voluminous literature on utilizing the DEA to measure the efficiency of government spending, either total spending or spending in specific policy areas, in attaining a range of socio-economic objectives such as health and education outcomes can be found.

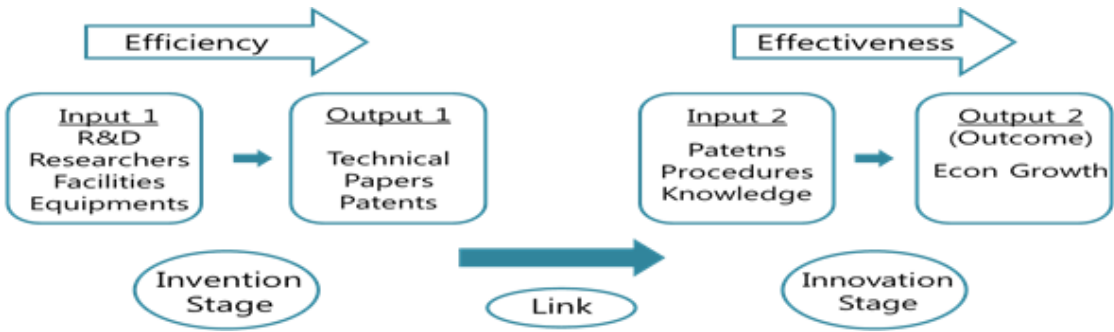
On the DEA literature, most of the papers used the two-stage method: First, the efficiency scores are estimated by using relative inputs and outputs. Second, a regression analysis such as Tobit or truncated Tobit analysis is employed to identify the factors affecting the (in)efficiency.

First, on the R&D literature, Bae (2012) employed a network DEA model which makes multi-stage analysis possible: Figure 4 illustrates that the total procedure of R&D, from the initial R&D expenditures to outcome, has been divided into two stages: The first stage, invention stage, explains the procedure inputs such as R&D expenditures, the number of researchers, and facilities and equipment become the outputs such as technical papers and patents. The efficiency is estimated by how well the inputs change to outputs. However, this is not the main reason that a government or a firm invests. Indeed, the final goal of a firm is to create new products, new procedures, and hence new markets eventually, while governments are eager to have a high economic growth. This has been designed as a second stage, innovation stage. The outcome is a by-product of effectiveness. In between

the efficiency and effectiveness stages, or invention and innovation stages, there is a 'link variable': patents. The number of patents could be output from input 1, and they could be another input producing outcome such as a high economic growth.

Bae (2012) found that the three types of efficiencies, efficiency in the first stage, effectiveness of the second stage, and overall efficiency, are scored quite differently. According to the results, the cities and provinces with high efficiency in the first-stage do not necessary, or automatically have higher effectiveness in the second stage: It explains the city-specific or province-specific efficiency and effectiveness in R&D investment. Thus, unlike the previous works which do not allow the multi-stage analysis, Bae (2012) suggests more specific benchmarking for each stage.

Bae (2010) also employed a dynamic DEA model of the R&D efficiency for 16 Korean major cities and provinces with variable returns to scale (VRS) assumption in 2005-09. In this study, Bae (2010) supported the fact that the cities including Seoul and Daejeon are the most efficient cities and provinces. Compared to the previous static models used, the dynamic DEA model can show that the actual average efficiency level of R&D investment is relatively lower than the static models. It implies that the efficiency scores in R&D investment are lower than we have thought with previous static models, thus they are over-estimated: Improving the level of efficiency in both public and private R&D is a big task that the Korean Government and firms face in the future.



<Figure 2> Two-stages in R&D efficiency analysis

Bogetoft et al. (2009) employed a dynamic Network DEA model to estimate the optimal public and private R&D investment paths in US manufacturing sector at state-level. According to Bogetoft et al. (2009), the following perpetual inventory method which estimates the net capital stocks in each state for period t was employed:

$$N_{tj} = \sum_{i=1}^t I_{ij} \left(1 - \frac{\delta_j}{2}\right) (1 - \delta_j)^{t-i} \quad (11)$$

where, $t \geq 1$, N_{tj} , is the net capital stock of asset type j , I_{tj} is real investment in year i , and δ_j is the annual geometric rate of depreciation for asset of type j .

Their findings are: First of all, there is too little investment in the public sector relative to private manufacturing capital in the the US. Second, their findings suggest that public spending on infrastructure crowded out private sector capital, and furthermore, it discouraged private sector job growth during the late 1980s and most of the 1990s.

Sharma and Thomas (2008) used gross domestic expenditure on R&D and the number of researchers as inputs, while the patents granted were used as the output measure. Utilizing both CRS and VRS models, their findings show that under CRS (Constant Returns to Scale), Japan, the Republic of Korea and China are found to be efficient, whereas under the VRS (Variable Returns to Scale) framework, some more countries such as India, Slovenia and Hungary are also included in the most efficient group of countries. The inefficiency in the countries' R&D resource usage indicates the underlying potential for development and is urged to be developed to increase the growth of nations.

S. Rousseau and R. Rousseau (1997 and 1998) are perhaps one of the pioneers in this field for estimating R&D efficiencies. Using DEA with CRS assumption for 18 countries (14 European), their findings suggested that Switzerland was the most efficient and effective country in Europe in 1993, and DEA can be used as a tool to construct performance indicators for governments.

On the healthcare and education literature, Brini and Jemmali (2015) analyzed the efficiency of general administration, health, education and infrastructure. The study covers the areas of the Middle East and North Africa (MENA) using panel data of 1996–2011. For the modelling of efficiency, political stability, voice and accountability, democracy, trade, money growth, growth domestic product are regressed with the Tobit analysis: The results indicate that (1) Jordan is the most efficient in public spending on administration, education, and health, while Libya, Algeria, and Yemen are relatively less efficient in public spending on administration and the health sector. (2) According to the Tobit regression analysis, the variables such as political stability, trade freedom, and economic growth have a positive effect on public spending efficiency. (3) However, voice and accountability

negatively affect the efficiency of public spending.

Hsu (2013) used the DEA with a Censored-Tobit approach to avoid the environmental variable effects: First, technical efficiency (TE) scores are calculated in the DEA scheme. Second, using the Censored-Tobit model, efficiency scores are regressed (Tobit) on environmental variables such as population density, GDP, hospital beds, average years of primary schooling, and regional dummies. The findings suggest that the increased hospital beds and primary schooling affected the efficiency score positively, while the countries in Europe performed a higher efficiency.

Hauner and Kyobe (2009) also had a DEA analysis on education efficiency with various inputs and outputs. In the first stage, three types of scores are estimated: (1) public sector performance (PSP), (2) public sector efficiency (PSE), and (3) DEA scores. As a result of the second stage by the fixed and random effects and system GMM estimators, Hauner and Kyobe (2008) supported the fact that higher government expenditure relative to GDP tends to be associated with lower efficiency in the respective sector.

Using 63 developing countries with a similar income level, Rayp and Van De Sijpe (2007) supports the fact that there is a negative relationship between the optimal size of government expenditure and economic growth. The first stage of DEA with the second stage estimation by the non-linear least squares instrumental variables (NLSIV) method resulted that government expenditure efficiency lowers the optimal size of government expenditure required to maximize the economic growth.

Afonso and Hernandes (2005) utilized 51 Portuguese municipals from the RLVT region to measure the efficiencies in many areas including education and healthcare sector. After the first stage of DEA estimation, the output efficiency scores are regressed by many environmental variables in each area, such as the purchasing power level, educational level, geographical distance, and population by means of the Tobit analysis in the second-stage. Their results showed a low level of efficiency for most of the municipalities in Portugal, and they could achieve, on average, the same level of output using fewer resources, and improve performance without necessarily increasing municipal spending. Inefficiency scores are afterwards explained using a Tobit analysis with a set of relevant explanatory variables playing the role of non-discretionary inputs.

Loikkanen and Susiluoto (2005) measured the efficiency level in the healthcare

sector and education sectors in Finland. In the second stage of the OLS regression, regressing the cost efficiency scores with the variables of size-related factors, location and physical structure, producer of services and age of employees resulted in (1) there were considerable cost efficiency differences between the municipalities: The most efficient municipalities were rather small and mostly located in southern Finland, while the least efficient ones were in the peripheral northern parts. (2) The biggest cities showed a rather varying performance. (3) The variables such as the peripheral location, high-income level (high wages), large population, high unemployment, diverse service structure and a big share of services bought from other municipalities tend to reduce the efficiency of municipal service provision.

On the literature of general government spending on economic growth, Moreno and Rozano (2016) used the most recent model in DEA, a super SBI dynamic network DEA model, to estimate the efficiency of general government spending for both allocations of the public budget and transformation of government expenditures into services to the people. The link variables, or the carryovers such as financial assets, debt, and employment are used for networking and dynamic activity in the model.

It is interesting to find that not only high-deficit European countries but also financially sound countries such as Germany and France have also performed poorly. By the Slack-based measure of inefficiency (SBI) metrics, they suggested feasible reductions in taxes and debt issuances, along with feasible targets for government expenditure.

Kyriacou et. al (2015) analyzed the redistributive efficiency of public spending and taxation in a panel of both advanced and developing economies during the last three decades (1984–2012). To explore how redistribution is achieved through fiscal policies, a two-stage approach is applied. As a result, first, Kyriacou et. al (2015) identified higher efficiency levels in the Nordic and Central European countries, while the southern Europe and other countries display much lower levels and consequently a greater scope for improvement. Second, the differences in economic development, the quality of institutions, and the country's population structure by the redistributive education spending, health expenditures, and old age pensions affected the redistributive efficiency.

Bae (2015) employed a combination of the DEA and the Granger-causality test for 16 Korean major cities and provinces in 2006–12. In the first DEA stage, Jeju-do

showed the highest efficiency score in both technical and pure technical efficiencies, while Incheon City scored the lowest. In the second stage, the Granger-causality tests illustrate that there exist no Granger-causes between economic growth and public expenditures in various sectors, but a strong and positive relationship exists between economic growth and efficiencies measured in the DEA stage.

Ziolo (2013) also studied the impact of general government spending on macroeconomic conditions of the economy for 12 OECD countries in 2000–2011. He reached a conclusion that the countries with the poorest DEA efficiency have excessive deficit and debt problems very often. Some of the countries were bailed out recently, while the most efficient OECD states were characterized by the adjustments made to the Maastricht criteria deficit and debt level.

Wang and Alvi (2011) tried to compare the efficiency results of Asian countries with those of OECD countries. Two main tasks were undertaken in this study: The Extreme Bounds Analysis (EBA) approach in association with the truncated Tobit regression was adopted to carry out in the second-stage. The results of Wang and Alvi (2011) showed that (1) the United States, New Zealand and Germany are the countries having the highest efficiency scores in the OECD sample; and Japan is the one with the highest score in the Asian group. (2) The EBA method in association with Tobit regression indicates that private sector activities exhibit a robust negative relationship with government inefficiency, which means that increasing the share of private activities in the economy helps reduce the inefficiency of public spending.

Recently, researchers started employing several new methods such as ‘bootstrap’ and ‘three-stage’ techniques since the previous DEA models incorporated only discretionary inputs, those of which quantities of DMUs can be changed. They also do not take into account the presence of environmental variables or factors, known as non-discretionary inputs.

‘Bootstrapping’ is a method for estimating the sampling distribution of an estimator by resampling it with a replacement from the original sample. The Bootstrap technique was invented by Efron (1979) and further developed by Efron and Tibshirani (1994).

Dufrechou (2016) used the Bootstrap method insisting that DEA analysis should consider a truncated model, to respect the bounded domain of efficiency scores

since many efficiency scores of DMUs are 1. A score of 1 is just an estimated bound for the true (unobserved) efficiency, as even the best producers have room for improvement. He analyzed the educational efficiency in 35 Latin American countries with educational spending as an input and various outputs such as average schooling years and population with secondary level as highest attainment. He employed an inefficiency regression as following:

$$\widehat{\delta}_i = \alpha + z_{jt}\beta + \varepsilon_{jt} \quad (12)$$

where, $\widehat{\delta}_i$ is an estimated inefficiency scores, variables are real GDP per capita, regional dummy, democracy index, globalization, and their lagged variables.

Dutu (2016) also studied the areas of education, healthcare, transportation, and agriculture in Switzerland in 2009–2012. His findings support the fact that fiscal equalization and public procurement enhance the allocative efficiency of public spending in Switzerland. Furthermore, he used the Bootstrapping method to prevent his outcomes from biasedness.

Cullmann et. al (2009) tested the hypothesis that regulation (on R&D spending) reduces competition by raising barriers to entry, thereby lowering competitive pressure and the incentives to innovate efficiently. He used a two-stage including the Bootstrap method for OECD countries. Sweden, Germany, and the US belong to the best performing countries in the first stage of DEA. Then, some regulatory variables are regressed. The results suggest that the low-level indicators on communication and implication of rules and procedures, antitrust exemptions and sector specific burdens have a significant impact.

Afonso and Aubyn (2006) also argued that the DEA output scores are likely to be biased due to environmental influences which affect the efficiencies, and the environmental variables are correlated to output and input variables.⁶⁾ Thus, they used a usual DEA with Tobit analysis corrected by a single and double bootstrap procedure originally suggested by Simar and Wilson (2004) for analyzing 25 countries' secondary education efficiency.

Unlike others, Hsu and Hsueh (2009) used a three-stage DEA analysis on the efficiency of Taiwan's government-sponsored R&D projects (GSP). In the first stage, DEA analysis with inputs such as project R&D staffing, government subsidy

6) Afonso and Aubyn (2006), p. 477.

to GSP projects, and GSP budget from recipient firm, post-project period and two outputs: (1) Intermediate outputs : publication articles, patent stocks, and final outputs : innovative commercialization, profited commercialization for each stage. In the second stage, from the following equation (15), the input slacks of GSP are regressed on some of the uncontrollable environmental variables including firm size, industry, R&D intensity, technology novelty, and ratio of GSP subsidy to total firm R&D budget.

$$IS_{j,i} = f_i(Z_{j,i}, \beta_j, \epsilon_j) \quad (13)$$

where, $IS_{j,i}$ is input slack j for GSP, $Z_{j,i}$ is a vector of external variables, β_j is parameter vector, and ϵ_j is disturbance term.

Among these variables, it is found that firm size, industry, and ratio of public subsidy on R&D budget of recipient firm significantly influenced the technical efficiency of GSP in Taiwan. In the third stage, the estimated coefficients in the Tobit regressions were employed to forecast the total input slack for each input and each R&D project based on associated environmental variables. The predicted values of $IS_{j,i}$ in the equation (10) were employed to adjust the primary input data.

Wang and Huang (2007) had a similar method as Hsu and Hsueh (2009) to analyze the R&D efficiency for 20 countries in 1997–2002. In the first stage, a standard DEA was performed with inputs of R&D net capital stock, researchers, and technicians, and outputs of patents granted and publication counts. Then, in the second stage, the efficiency scores are regressed with some of the environmental variables which might influence the R&D efficiency: PC density, economic freedom index, % of R&D performed by the government. In the last stage, with the adjusted data, DEA was reemployed. At this stage, the estimated coefficients from the Tobit regressions are used to predict the total input slack for each input and each country based on its environmental variables.

3. Comparison of SFA with DEA

1) Strengths and weaknesses of SFA and DEA

As we have discussed earlier (in Figure 3), there are two major methodologies in measuring the efficiency: Frontier and non-frontier approaches. The production frontier characterizes the minimum input bundles required to produce various outputs, or the maximum output producible with various input bundles, and a given technology. On the other hand, cost frontier characterizes the minimum expenditure

required to produce a given bundle of outputs, given the prices of the inputs used in its production and given the technology in place (Kumbhakar and Lovell [2004]). Then, both the Frontier and non-frontier approaches have two estimation techniques: parametric and non-parametric estimations. There are several estimation methods in Frontier-parametric estimation, SFA and Bayesian estimation, while there are DEA and FHD in Frontier non-parametric estimation.

Recently, many researchers have argued whether SFA and DEA are complementary or substitutionary to each other, that is, whether they are good enough to be an independent methodology (substitutes) or not. It depends on the similarity of the results and strengths/weaknesses of both methodologies. <Table 1> reports the strengths and weaknesses of DEA and SFA.

<Table 1> Strengths and Weaknesses of DEA and SFA

Method	Strengths	Weaknesses
	Data Envelopment Analysis (DEA)	
	<ul style="list-style-type: none"> • Allow one to compare the efficiency of countries directly (ranking) • No need to define the relative importance of the various inputs employed and output produced (due to the absence of weights or prices attached to each outcome) • No need to specify a functional relationship between inputs and outputs • Not subject to simultaneous bias and/or specification errors • Allow to deal with the simultaneous occurrence of multiple inputs and outputs 	<ul style="list-style-type: none"> • Heavy reliance on the accuracy of the data • Difficult to distinguish between output and outcomes • Efficiency scores attributed to inputs while other factors may also contribute • Frontier depends on the set of countries considered (Inefficiencies can be under-estimated)
	Stochastic Frontier Analysis (SFA)	
	<ul style="list-style-type: none"> • Error term with two components: conventional error term + term representing deviation from Frontier (relative inefficiency) • Allow for hypothesis testing, confidence interval • Allow to explain inefficiency • Allow to handle appropriately measurement problems and other stochastic influences • With respect to cross-country data, SFA provides a means of accommodating unmeasured but surely substantial cross-country heterogeneity 	<ul style="list-style-type: none"> • Assume irrational functional form for the production function • Assume distributional form of the technical efficiency term • Single output dimension • Frontier depends on the set of countries considered (Inefficiencies can be under-estimated)

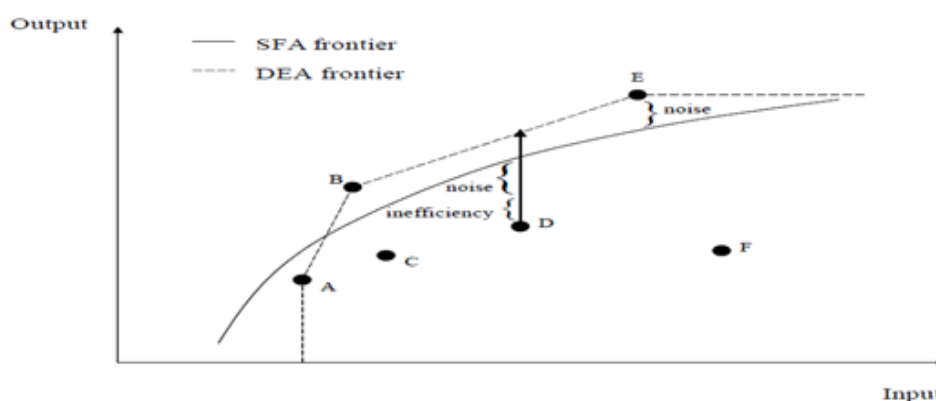
(Sources: Cincera et. al (2009) and Greene(2005))

Cincera et al. (2009) summarised the strengths and weaknesses of both SFA and DEA. SFA defines and divides the efficiency (or inefficiency) easily: It allows for the error term to be divided into two components: conventional error term (white noise) and the term representing a deviation from Frontier (relative inefficiency). Since SFA is an econometrical estimation process, it allows for hypothesis testing and confidence interval, while DEA does not. However, it needs to establish the

functional forms for the production functions, which are subject to be estimated: It can have significant effects on the efficiency rankings and absolute efficiency measures generated

DEA allows one to compare the relative efficiency of DMUs in ranking directly. DEA is not subject to simultaneous bias and/or specification errors by the occurrence of the simultaneity by the multiple inputs and outputs. Perhaps, one of the biggest strengths of DEA is that it does not have to assume irrational functional forms as well as unknown distributions for the production functions, where SFA often does. DEA also has many inputs and outputs utilized comparing to the SFA with a single output dimension. However, DEA has a very critical weakness. That is, it is a very sensitive method when outliers exist in the data. It also heavily relied on the accuracy of the data and is difficult to distinguish between output and outcomes. The efficiency scores produced by DEA attributed to inputs, while other environmental factors may also contribute. The last weakness of DEA is that frontier depends on the set of countries considered. That is, inefficiencies can be under-estimated.

Some papers include both SAF and DEA methods on our issue of public spending. Perhaps, a critical difference which results in the different estimation is shown in Figure 5. It shows that SFA allows for the two types of error terms as discussed before. For instance, DMU D shows a fall in output than other DMUs such as B and E. SFA recognizes this error term with two deviations, one is statistical white noise, and the other is inefficiency, while DEA defines it as a total white noise or inefficiency. DEA is also very sensitive to mismeasurement. For example, in Figure 5, if the output of DMU E were inaccurately recorded and overstated, the inclusion of E in the frontier would mean that the Frontier itself was measured incorrectly and that the inefficiency of DMU such as F would be overestimated.



<Figure 3> Estimations by SFA and DEA

2. Comparability of the Results in SFA and DEA

This section analyzes efficiency in public spending by reviewing the papers that employed both SFA and DEA with short-term period data (such as two or three years of time span) or a cross-sectional country or local government data. Most of the works deal with the static concepts of efficiency including Cincera, Czarnitzki, and Thorwarth (2009). They had extensive work on R&D activities of EU member states and some OECD countries between (1981–2004). With output-oriented DEA and variable returns to scale, the two-stage Tobit regression analysis was performed for explaining the determinants of the (in)efficiency. The study found that the countries with the best performance in terms of innovative activities are also the ones that exhibit the highest efficiencies of their public R&D support, while higher government expenditures in a percentage of total consumption are associated with the lower performance of efficiency.

They further analyzed and concluded that the different results from both the SFA and DEA are partly due to the different assumptions underlying the estimations. According to their work, it seems there is a positive relationship between SFA and DEA results at first glance: The top performance group includes the Australia, Finland, and the US, while less efficient countries are Romania, Russia, and China.

However, the authors grouped the data into the world regions such as internal market and Euroland, and GDP per capita, and measured the efficiency scores. It seems that the SFA estimation showed more statistically significant variables than DEA, and there appears to be no comparability.

Second, the outputs, the dependent variables are R&D expenditures and R&D personnel, and they have been regressed with some of the environmental variables such as the size of government, legal structure, access to sound money, freedom to trade, and regulation. With the exception of the legal structure variable, both SFA and DEA estimations do not result in comparability, again.

Bae (2009) also compared the results of the SFA with the DEA in estimating the efficiency of public R&D investment for Korean major cities and provinces. Some provinces such as Gwangju and Ulsan are found to be the most efficient areas, and similar results were found by both methods. The cities and provinces such as Seoul and Gyeonggi-do need to increase the level of efficiency so that it would enhance the national level of efficiency in public R&D. According to Bae (2009), it seems that there is a high correlation in between SFA and output-oriented DEA

estimation, which is greater than 0.500, when the number of patents is used as output for both SFA and both-oriented DEA estimation.

On the educational issues, Aubyn et al. (2009) studied the efficiency and effectiveness of public spending on tertiary education in Europe, Japan, and the US. They employed SFA and two different DEA models, one with some of the physically measured inputs (the DEA model 1), and the other with financially measured inputs (the DEA model 2). Some of the environmental variables are used in the second-stage DEA. (See Table 6 for detailed specification)

Their findings include: (1) Tertiary education systems in a core group of countries in Europe are clearly more efficient. (2) Tertiary education efficiency is related to institutional factors and also to the quality of secondary education. (3) Efficient spending matters for labor and total factor productivity (TFP). In their study, both SFA and DEA methods are used and conclude that UK and Japan were the best-practiced countries. It appears there is a positive relationship between both results of efficiency. However, Aubyn et. al. (2009) mentioned that the results are quite different due to some factors: (1) A production function approach is applied by DEA, while a cost minimization framework was used for SFA. (2) In the second-stage of DEA, the efficiency was measured by two different terms, physical or monetary units. However, in SFA estimation, the paper considered the cost with tertiary education institutions as the dependent variable in a regression and outputs as explanatory variables. This different formulation, by itself, may induce dissimilar results. (3) In DEA efficiency analysis, it represents “relative” efficiency, and there are many DMUs that could be the most efficient ones. However, this is a very rare case in SFA. (4) The SFA’s maximum likelihood estimation method allows for an unbalanced panel, while it is necessary to have a complete panel for DEA calculations.

Chakraborty et. al (2001) used the data of Utah’s 40 school districts for the academic year of 1992–1993. They employed both SFA and the two-stage DEA model. Although they did not compare the results from SFA and DEA directly, their findings suggested that there was a substantial variation in technical efficiency among the school districts observed. While it is invariant as to the distributional assumption (a half-normal or exponential) of the one-sided component of the error term in SFA, with a mean efficiency of 86.07 percent. On the other hand, the DEA analysis shows that the socioeconomic and environmental factors have a strong influence on student success.

De Borger & Kerstens (1996) utilized four different methodologies to examine social, economic and political characteristics of Belgian local municipalities. They found large differences in the mean efficiency scores, and rank correlations between the parametric and non-parametric measures were relatively low (0.59–0.83). It was reassuring to observe that with minor exceptions all parameters of the explanatory variables consistently had the same sign across the methods. Local tax rates and education were estimated to influence municipal efficiency positively, and the per capita block grant and average income affected efficiency in a negative way.

Let's turn our attention to the dynamic analysis. Zhongji (2014) used both DEA and SFA with Chinese panel data of R&D expenditures from 2002–2011. Since the period covered longer than ten years, using a dynamic DEA (with VRS) and SFA models (stochastic frontier model of transcendental logarithmic production function) fits better. The findings of Zhongji (2014) include: First, with the generally low level of R&D, Eastern region's efficiency is significantly higher than the Midwest areas. Second, both DEA and SFA showed significant differences, but the correlation is up to 68.1 percent. Finally, there seems no direct link between R&D efficiency intensity and the economic level: This is quite a different result from Bae (2015) that a positive relationship exists between economic growth and various efficiencies measured in DEA stage.

Of course, one cannot compare the results of DEA and SFA directly since efficiency scores in DEA measures the 'relative' efficiency, while the estimated efficiency scores in SFA refer to the 'absolute' measures. However, we may compare those results in this way: Figure 4 shows DEA and SFA averages and standard deviations from Zhongji's results. It seems that the DEA averages and standard deviations for the total period are higher than those of SFA.⁷⁾ One striking result from Figure 4 is that, on DEA estimation, the average efficiency score had been lowered, even though the standard deviation of the efficiency scores were changing overtime: They were decreasing until 2008, and was increasing since then. However, on the SFA estimation, Figure 9 illustrates the vice versa: While the standard deviation of efficiency scores has been rather steady at a certain point in time, the overall average score was improving.

Thus, this study shows a very critical difference in both methods, and it gives us a very important message: The comparison between the results of SFA and DEA

7) In DEA estimation, the mean of the efficiency for the whole period was 0.441, comparing to the 0.300 for SFA. The standard deviation was 0.231 for DEA and 0.169 for SFA.

should include the over-time effect, that is, the dynamic behavior of the efficiency. Finding a path of the efficiency fluctuation rather than a certain point in time provides more significant information for the study. In this respect, two methodologies are not comparable at all as long as the dynamic behavior of the efficiency in over time is concerned, however, they can be complementary each other such that: (1) The 'absolute' average efficiency of public spending was improving (SFA results), while 'relative' average efficiency of public spending was not enhancing. (2) The gap (standard deviation) between 'absolute' average efficiency did not change, while the 'relative' average efficiency was decreasing until 2008, and increased from 2008 to 2011.

Unfortunately, we cannot find many works dealing with dynamic SFA and DEA in the area of fiscal spending efficiency. However, as we have seen from Bae (2010)'s work, which compared the dynamic DEA model to the previous static one, he was able to demonstrate that the actual average efficiency level of R&D investment is relatively lower in the dynamic models. It implies that the efficiency scores in R&D investment are lower than we have thought. Thus, they were over-estimated in the previous static models.

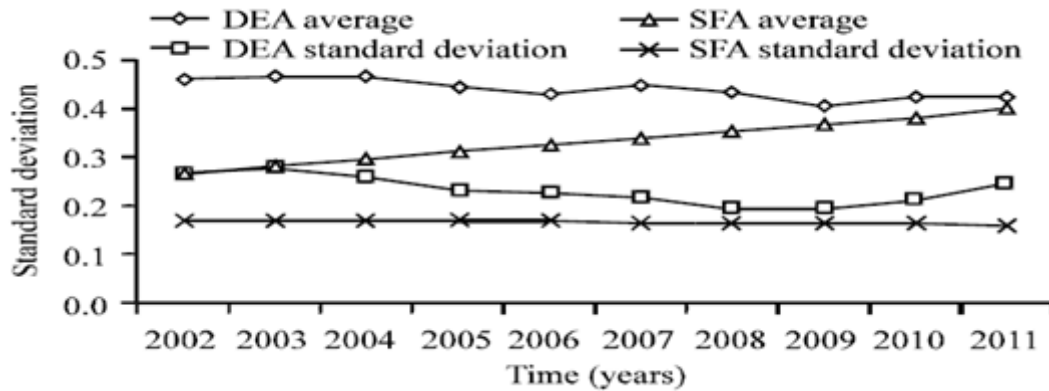


Figure 9. Averages and standard deviations of the efficiency scores for DEA and SFA (Source: Zhongji (2014))

IV. Concluding Remarks

An extensive literature survey of SFA (Stochastic Frontier Approach) and DEA (Data Envelopment Analysis), which contains more than one hundred research papers that introduced the methodologies, models, and empirical findings on the

efficiency of public spending in the areas of R&D, health care, education, and economic growth, has been reviewed in this paper. We shed light on the methodologies used – the two most recognized frontier methodologies, SFA and DEA. Both have methodological strengths and weaknesses, and the differences in empirical findings are critically analyzed in this paper.

Furthermore, this paper introduced the new techniques in DEA and SFA such as a dynamic network DEA model which combines dynamic aspects with the multi-stage analysis on the subject and three-stage method (DEA), and new techniques of econometrics such as the Bootstrap method (SFA). They are useful when a correlation exists between the dependent (or environmental) variables and the error term in the regression. Both methods resulted in unbiased estimates and produce a more robust estimation.

Our findings clearly demonstrates that SFA and DEA are not comparable, but they can be complementary each other. In comparisons of static and dynamic models, there are various theoretical, technical, and econometrical factors preventing consistency of the static results between the SFA and DEA: The estimation is biased as Bae (2010) insisted. The results from both methodologies are significantly different, especially when the dynamic behavior of the efficiency in over time is considered as it was shown in Jhongji (2014). That is, finding a path of the efficiency fluctuation rather than an efficiency score at a certain point in time provides more significant information for the study of efficiency.

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<국문초록>

본 논문의 목적은 정부의 공공지출에 있어서의 효율성을 주제로 주요 방법론인 확률프런티어 어프로치 (Stochastic Frontier Approach (SFA))와 자료포락분석 (Data Envelopment Analysis (DEA))의 범주에서 연구된 기존의 논문들을 리서치하여 비교·분석하는 것이다. 즉, 본 논문에서는 최근의 새로운 기법, 즉 부트스트랩 (bootstrap) 이나 3단계 방법 (Three-stage method)을 사용한 연구들의 모형과 측정 방법의 리뷰는 물론이며, SFA와 DEA 두 기법의 호환성에 대하여 논한다. 100여개가 넘는 논문들을 기초로, 본 논문에서 발견된 결론은 다음과 같다. 첫째, SFA 기법이 절대적 효율성을 측정하고 DEA는 상대적 효율성을 측정하는 기법이지만 공공지출의 효율성에 영향을 주는 환경변수들이 두 기법 모두에서 중요성을 보였다. 둘째로, SFA와 DEA 기법의 결과물은 비록 측정된 효율성의 순위 (ranks)에서는 비교적 높은 상관관계를 보였으나, 기존의 정학분석이나 최근의 동학분석 모두에서 서로 호환될 수 없음을 보여주었다. 더욱이 두 기법은 시간의 개념이 포함된 효율성의 동학적 분석에서 가장 두드러지게 대체적이지 못한 것을 보였다.

국문주제어: 확률프런티어 어프로치, 자료포락분석, 공공지출의 효율성, 부트스트랩 기법

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