Public Sector Efficiency on Education and Health; Evidence from East Java

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Abstract

In this paper we analyze public sector efficiency in the East Java Regions. After a corceptual discussion of expenditure efficiency measurement issues, we compute efficiency scores and rankings by applying a range of measurement techniques that is DEA (Data Envelopment Analysis). Another method that we used in this paper to measure the efficiency is the Stochastic Frontier Analysis (SFA). The study finds that expenditure efficiency on education and health across regions in East Java member states is rather diverse especially as compared to the group of top performing emerging markets in Indonesia. SFA model applied both time invariant and time varying decay. The estimation process yields differences on the education and health sector. In the education sector model, per capita expenditure on education doesn't significant in the education SFA model but per capita expenditure on health has significant impact on percentage of health people as a output in the SFA model. The estimation for DEA scores yields different in significant parameter and estimation technique (fixed or random) to get the best parameter.

Keywords: Public Sector, efficiency, Stochastic Frontier Analysis, Technical Efficiency, Data Envelopment Analysis, Expenditure on Education and Health.

JEL: I18, I21, I28, H51, H52, C14, C1, C14

I. Introduction

Basic education and health as well as social and cultural services are provided by the public sector in all of countries in the world. In some cases the public sector not only finances most of the costs of these services, but also acts as the producer. In other ones, the private or non-profit sector is the main producer. Also, the level of government at which key provision/production decisions are made, can vary from a centrally organized service system to a highly decentralized system (Loikkanen and Susiluoto, 2005). For instance in France, health services in hospitals are provided by the national health system, which has a regional structure and its hospitals cover the whole country. Basic health services, however, are supplied by private doctors, whose customers' expenses are typically covered by insurance. Municipalities in France do not produce or provide health services, and the same is true for basic education. In Indonesia, since the decentralization era begins, regions such as municipals and districts have to make decision related to management of their public finance by themselves.

Indonesia has been going through a major change in its intergovernmental system since 2001 by adopting a much more decentralized regime, widely termed fiscal decentralization. Local governments now have more responsibility to provide public goods and services that were previously provided primarily by the central government through its de concentrated ministries or agencies. On the other side, local governments also have greater power, at least in theory, to manage and collect their own revenues, especially taxes. It should be noted that the central government must still give some subsidies or grants to local governments when the primary objective is that of redistribution. The grants, however, are to be distributed based on a new formula that is especially designed to support the fiscal decentralization program. In the basic law of the Indonesian Government said that government has to allocate 20% of the budget for education sector, but this is almost impossible to do at central or regional government. Health and education as basic services always be attention by the society.

In recent years there has been much research focusing on effectiveness and efficiency of public sector activities (see Afonso, Schuknecht and Tanzi (2005) for a brief overview and references). Results suggest that there is ample scope to reduce public spending. However, the literature also stresses that for significant efficiency gains to materialize it is necessary to enact deep changes in public sector management and to transfer activities to the private sector. Economic efficiency of the public sector is a permanent topic of research and debate (Loikkanen and Susiluoto, 2004).

The debate over spending efficiency of local governments has been renewed with the implementation of decentralization policies designed to refocus public decision making from central to municipal levels of government. The theoretical rational behind this decentralization supports that higher participation of local governments, in choosing the use of public resources, allows for a better match between public services provision and the needs and preferences of a heterogeneous citizenry. This type of outcome additionally favors .efforts to make government both more efficient and more democratic and a more effective control of the overall growth of government (see Marlow (1988) and Rowland (2001)).

The importance of the efficient use of public resources and high-quality fiscal policies for economic growth and stability and for individual well-being has been brought to the forefront by a number of developments over the past decades. Macroeconomic constraints limit countries' scope for expenditure increases.

Governments of developing countries typically spend resources equivalent to between 15 and 30 percent of GDP. Hence, small changes in the efficiency of public spending could have a significant impact on GDP and on the attainment of the government's objectives whichever these are (Harrera and Pang, 2005). The first challenge faced by stakeholders is measuring and scoring efficiency. This paper tries to investigate case studies of efficiency scores of two public sectors, which are education and health sector in 37 district and municipal at East Java, Indonesia. East Java has interesting aspect to be analyzed, since the development visions of the east java government were measured by several indicators. For instance, government has strategies to achieve some education performance such as increasing schooling participation at basic and high school, decreasing illiteracy rate and etc. For health sector, government had fixed the achievement such as expectancy of life and mortality rate of the baby was born and etc. Two methods were applied in this paper, parametric approach such as Data Envelopment Analysis (DEA) and non parametric approach such as Stochastic Frontier Analysis (SFA). This paper provide how efficient of the regions in East Java in spending to the basic services.

The paper has four chapters following this Introduction. The first one presents the methodology that defines efficiency as the distance from the observed input-output combinations to an efficient frontier. This frontier, defined as the maximum attainable output for a given input level, is estimated using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) techniques. The exercise focuses on health and education expenditure because they absorb the largest share of most countries' budgets, and because of lack of data availability for international comparisons in other types of expenditures. This chapter also explores the previous studies about public sector efficiency.

The next chapter estimates the efficiency frontiers for three education output indicators and two health output indicators, based on a sample of 37 municipals and districts and data for 1998-2002. Both parametric and non parametric approach applied and compared each other. This chapter explores how expenditure efficiency has changed over time.

The last part of the paper explains the limitation of some methodologies that are used in this paper. This chapter discusses the context within which such models are deployed; their underlying assumptions and their usefulness for a regulator of public services. Four specific model building issues are discussed: the weights that are attached to public service outputs; the specification of the statistical model; the treatment of environmental influences on performance; the treatment of dynamic effects. In this chapter also seeks to identify empirical regularities that explain cross-regions variation in the efficiency scores. Using a panel approach, this chapter shows whether higher expenditure levels are generally associated with lower efficiency scores. Three other variables that explain the cross regions variation in efficiency scores are the degree of income disparities as Gini ratio showed. The others variable are literacy, and poverty as well as the dependency ratio. The fourth chapter deals with the results of the model both DEA and SFA also regression results of factors determining the technical efficiencies score. The last chapter concludes with recommendations for policy makers and researchers on the development and use of efficiency measurement techniques.

II. Review of the Methodology

This section first compares two different ways of deriving factor productivity change: stochastic-frontier analysis (SFA), and DEA by Forstner and Isaksson (2002). Efficiency measurement naturally requires the definition of a frontier as a benchmark indicating efficiency. Usually a measure reflecting the distance of a data point to the frontier indicates the level of efficiency. One of the crucial characteristics to distinguish efficiency measurement tools is the way in which they construct the frontier.

One way to circumvent the averaging problem is to rely on SFA. The approach is attractive in that it constructs a frontier of efficient observations, which envelops the relatively inefficient observations. An important advantage of the method is that it is able to handle outliers and that hypotheses can be tested in the usual (econometric) way. However, there are several important drawbacks as well. The production function is assumed to be valid for all observations and technological change is the same for all observations.

Whether technological change is continuous and smooth and common to all observations can be questioned. It is also somewhat disturbing that a distributional form of the error term as well as a functional form of the production function has to be assumed.

By contrast, DEA does not require any assumption about the functional form of the production function or economic agents' behavior. Furthermore, there is no need to assume any specific distributional form of an "error term" (there is none!) and there is also no need to assume perfect factor markets or optimal resource allocation. A disadvantage of DEA is, of course, that it cannot handle noisy data in a satisfactory manner. Hence, in a dataset with many outliers or serious measurement errors, DEA may not be the best method to apply. On balance, in view of a dataset comprised of industrial data, the present study considers DEA to be a more flexible and appropriate tool for the task at hand than the other methods outlined above.

2.1. Data Envelopment Analysis (DEA)

The Data Envelopment Analysis is a multivariate technique for monitoring productivity and providing some insights on possible directions of improvements of the status quo, when inefficient. In particular, DEA is a non-parametric technique, i.e. it can compare input/output data making no prior assumptions about the probability distribution under study.

Data Envelopment Analysis (DEA) is receiving importance as a tool for evaluating and improving the performance of manufacturing and service operations. It has been extensively applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc.(Charnes, 1994). DEA is a multi-factor productivity analysis model for measuring the relative efficiencies of a homogenous set of decision making units (DMUs). The efficiency score in the presence of multiple input and output factors is defined as:

$$efficiency = \frac{weighted\_sum\_of\_outputs}{weighted\_sum\_of\_inputs} \qquad (1)$$

Assuming that there are n DMUs, each with m inputs and s outputs, the relative efficiency score of a test DMU p is obtained by solving the following model proposed by Charnes et al. (1978):

$$\max \frac{\sum_{K=1}^{s} V_K Y_{Kp}}{\sum_{j=1}^{m} \mu_j X_{jp}}$$

$$s.t \frac{\sum_{K=1}^{s} V_K Y_{Ki}}{\sum_{j=1}^{m} \mu_j X_{ji}} \leq 1 \qquad \forall i \qquad (2)$$

$$v_k, u_j \geq 0 \qquad \forall k, j$$

Where

k = 1 to s,

j = 1 to m,

i = 1 to n,

yki = amount of output k produced by DMU i,

Xji = amount of input j utilized by DMU i,

vk = weight given to output k,

uj = weight given to input j

The fractional program shown as (2) can be converted to a linear program as shown in (3). For more details on model development see Charnes et al. (1978).

$$
\begin{aligned}
&\max \sum_{k=1}^{s} V_k y_{kp} \\
&s.t \sum_{j=1}^{m} u_j X_{jp} = 1 \\
&\sum_{k=1}^{s} V_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \le 0 \qquad \forall i \\
&v_k, u_j \ge 0 \qquad \forall k, j
\end{aligned} \tag{3}
$$

The above problem is run n times in identifying the relative efficiency scores of all the DMUs. Each DMU selects input and output weights that maximize its efficiency score. In general, a DMU is considered to be efficient if it obtains a score of 1 and a score of less than 1 implies that it is inefficient.

Benchmarking in DEA

For every inefficient DMU, DEA identifies a set of corresponding efficient units that can be utilized as benchmarks for improvement. The benchmarks can be obtained from the dual problem shown as (4).

min θ

$$s.t\sum_{i=1}^{n}\lambda_i x_{ji} - \theta x_{jp} \leq 0 \quad \forall j$$

$$\sum_{i=1}^{n}\lambda_i y_{ki} - y_{kp} \geq 0 \qquad \forall k$$

$$\lambda_i \geq 0 \qquad \forall i \tag{4}$$

Where

θ = efficiency score, and

λs = duals variables

Based on problem (4), a test DMU is inefficient if a composite DMU (linear combination of units in the set) can be identified which utilizes less input than the test DMU while maintaining at least the same output levels. The units involved in the construction of the composite DMU can be utilized as benchmarks for improving the inefficient test DMU. DEA also allows for computing the necessary improvements required in the inefficient unit's inputs and outputs to make it efficient. It should be noted that DEA is primarily a diagnostic tool and does not prescribe any reengineering strategies to make inefficient units efficient. Such improvement strategies must be studied and implemented by managers by understanding then operations of the efficient units.

Although benchmarking in DEA allows for the identification of targets for improvements, it has certain limitations. A difficulty addressed in the literature regarding this process is that an inefficient DMU and its benchmarks may not be inherently similar in their operating practices. This is primarily due to the fact that the composite DMU that dominates inefficient DMU does not exist in reality. To overcome these problems researcher utilized performance-based clustering methods for identifying more appropriate benchmarks (Doyle and Green, 1994; Talluri and Sarkis, 1997). These methods cluster is utilized as benchmark by other DMUs in the same cluster.

2.2 Stochastic Frontier Analysis (SFA)

Stochastic frontier models date back to Aigner, Lovell and Schmidt (1977) and Meesen and van den Broek (1977), who independently proposed a stochastic frontier production, function with a two-part 'composed' error term. In the production context, where its use is most common4, this error is composed of a standard random error term, representing measurement error and other random factors, and a one-sided random variable representing what Farrell (1957) called 'technical inefficiency', the distance of the observation from the production frontier. This notion of technical efficiency reflects the ability of a firm, country or university to obtain maximal output from a given set of inputs. It is measured by the output of the firm relative to that which it could attain if it were 100 % efficient, if it lay on the frontier itself, and is therefore bound between zero and one. When one combines this with allocative efficiency, the ability of the firm etc to use the inputs in optimal proportions, given their respective prices, one has a measure of total *economic efficiency*.

Let's review the nature of the stochastic frontier problem. Suppose that producer has production function $f(z_{it},..,\beta)$. In a world without error or inefficiency, in time t, the *ith* institution would produce

$$q_{it} = f(z_{it}, \beta) \tag{5}$$

A fundamental element of stochastic frontier analysis is that each institution potentially produces less than it might due to degree of inefficiency. Specifically,

$$q_{it} = f(z_{it}, \beta)\xi_{it} \tag{6}$$

Where ξ_{it} is the level of efficiency for firm I at time t; ξ_{it} must be in the interval (0,1]. If $\xi_{it} = 1$, then the firm is achieving the optimal output with the technology embodied in the production function $f(z_{it},.., \beta)$. Since the output is assumed to be strictly positive (i.e.,qit >0), the degree of technical efficiency is assumed to be strictly positive (i.e.,qit ξ_{it} > 0).

Output is also assumed to be subject to random shocks, implying that

$$q_{it} = f(z_{it}, \beta)\xi_{it} \exp(v_{it}) \tag{7}$$

Taking the natural log of both sides yields

$$\ln(q_{it}) = \ln\{f(z_{it}, \beta)\} + \ln(\xi_{it}) + v_{it} \tag{8}$$

Assuming that there are k inputs and the production function is linear in logs, defining $u_{it} = -\ln(\xi_{it})$ yields

$$\ln(q_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(z_{jit}) + v_{it} - u_{it} \tag{9}$$

Since *uit* is subtracted from ln (qit), restricting $u_{it} \geq 0$ implies that $0 < \xi_{it} \leq 1$ as specified above.

Kumbakar and Lovell (2000) provide a detailed version of the above derivation, and they show that performing an analogous derivation in the dual-cost function problem allows one to specify the problem as

$$\ln(c_{it}) = \beta_0 + \beta_q \ln(q_{it}) + \sum_{j=1}^{k} \beta_j \ln(p_{jit}) + v_{it} - su_{it} \tag{10}$$

Where qit is output, the zjit are input quantities, cit is cost, and the pjit are input prices, and

S = 1 for production function and -1 for cost function. The model that frontier in panel data analysis is of the form:

$$y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j x_{jit} + v_{it} - u_{it} \tag{11}$$

So, in the context of the discussion above, $y_{it} = \ln(q_{it})$ and $x_{jit} = \ln(z_{jit})$ for production function and for a cost function, $y_{it} = \ln(c_{it})$, the x_{jit} are the $\ln(p_{jit})$ and $\ln(q_{it})$. It is incumbent upon the user to perform the natural logarithm transformation of the data prior to estimation if the estimation results are to be correctly interpreted in the context of stochastic frontier production or cost model.

2.3 Previous Research

There is abundant literature measuring productive efficiency of diverse types of decision making units. For instance, there are papers measuring efficiency of museums (Bishopand Brand, 2003), container terminals (Cullinane and Song, 2003), electric generation plants (Cherchye and Post 2001), banks (Wheelock and Wilson, 2003), schools (Worthington, 2001) and hospitals (Bergess and Wilson, 1998), among others. Few papers, however, analyze aggregate public sector spending efficiency using cross-country data. These are the direct precursors of this paper and are the focus of this section's survey.

Gupta and Verhoeven (2001) employ the input-oriented FDH approach to assess the efficiency of government spending on education and health in 37 African countries in

1984-1995. Using several output indicators for health and education, they construct efficiency frontiers for each of the indicators and for each of the time periods they considered. That is, they used a single input-single output for each time period. They find that, on average, African countries are inefficient in providing education and health services relative to both Asian and the Western Hemisphere counties. They also report, however, an increase in the productivity of spending through time, as they document outward shifts in the efficiency frontier. Finally the authors report a negative relationship between the input efficiency scores and the level of public spending, which leads them to conclude that higher educational attainment and health output requires efficiency improvement more than increased budgetary allocations.

Evans and Tandon (2000) adopt a parametric approach to measure efficiency of national health systems for the World Health Organization, by estimating a fixed effects panel of 191 countries for the period 1993-1997. Health output was measured by the disability adjusted life expectancy (DALE) index, while health expenditures (public and private aggregated) and the average years of schooling of the adult population were considered as inputs. The output-efficiency score is defined as the ratio of actual performance above the potential maximum. The authors also introduce the square of the inputs (average years of schooling and expenditure), arguing it's a second-order Taylor-series approximation to an unknown functional form. The fact that the quadratic terms are significant may be an indication of the importance of non-linearity, but may also reflect neglected dynamics or heterogeneity in the sample (Haque, Pesaran and Sharma, 1999), given that both developed and developing nations were included. An interesting contribution of the paper is a construction of a confidence interval for the efficiency estimates through a Monte-Carlo procedure. These authors document a positive relationship between their efficiency scores and the level of spending. The more efficient health systems are those of Oman, Chile and Costa Rica. The more inefficient countries are all African: Zimabawe, Zambia, Namibia, Botswana, Malawi and Lesotho.

Greene (2003) combines the previous two papers in the sense he concentrated on health efficiency only using the WHO panel data and explained inefficiency scores variation across the sample of counties. Greene's stochastic frontier estimation is much more general and flexible, as it allows for time variation of the coefficients and heterogeneity in the countries' sensitivity to the explanatory variables. The author first estimates a health production function using expenditure (public and private together) and education as inputs, and then explains inefficiency with a set of explanatory variables of which the only significant ones are the income inequality measure, GDP per capita and a dummy variable for tropical location.

Afonso, Schuknecht and Tanzi (2003) examine the efficiency of public spending using a non-parametric approach. First, they construct composite indicators of public sector performance for 23 OECD countries, using variables that capture quality of administrative functions, educational and health attainment, and the quality of infrastructure. Taking the performance indicator as the output, and total public spending as the input, they perform single-input, single-output FDH to rank the expenditure efficiency of the sample. Their results show that countries with small public sectors exhibit the highest overall performance.

Afonso and St. Aubyn (2004) address the efficiency of expenditure in education and health for a sample of OECD countries applying both DEA and FDH. This paper presents detailed results by comparing input-oriented and output-oriented efficiency measurements. The small overlap of the samples limits the comparability of these results with those presented in the next section. An apparently strange result, reported in earlier drafts of the paper, was the inclusion of Mexico as one of the benchmark countries (on the efficiency frontier). The result is strange given that the sample is the OECD countries, and it counterintuitive. This is the result of Mexico having very low spending and low education attainment results, hence it cam be considered as the "origin" of the efficiency frontier. The next chapter discusses this topic and reports similar counterintuitive results but for other countries.

III. The Data, Input-Output Indicators and Limitation

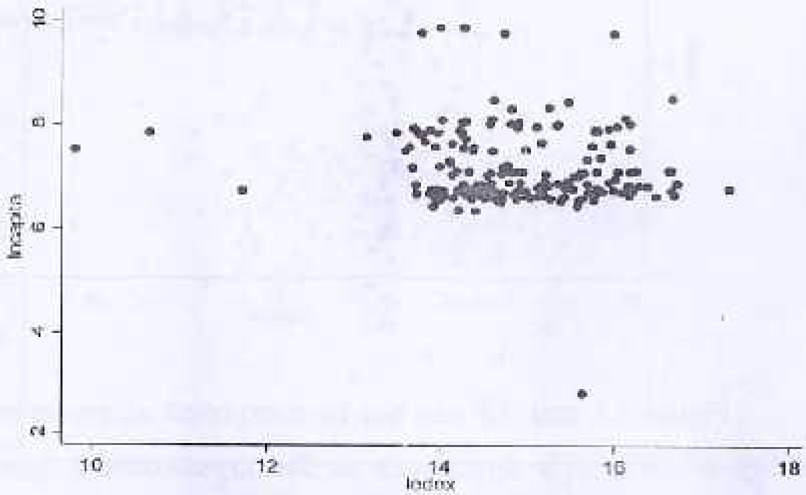
3.1 The Data Description

The data set used in this analysis come from BPS (Badan Pusat Statistik/Center Bureau of Statistic) and Finance Department at the

Regional Public Finance Information system. The Data also from the National Welfare Survey (SUSENAS).The full data set is a panel of data observed for 37 regions (district and municipal) in East Java from 1998 to 2002.

As a first step of our quantitative analysis, we will provide some stylized facts i) about development (education and health) expenditure levels and level of development indicator (per capita income), and ii) about the relation between education and health expenditure and the level of economic development such as education and health performances. This will help gauge the situation of the regions in East Java Province.

Figure 3.1
Education Spending and GRDP (Gross Regional Domestic Bruto) per capita



Positive association between expenditure and the level of economic development (as measured by per-capita-GDP) may be explained by several reasons (Harrera and Pang, 2005). One of them could be the Balassa-Samuelson effect, according to which price levels in wealthier regions tend to be higher than in poorer regions. This applies to both final goods and factor prices. Thus price of the same service (health or education, for instance) will be higher in the country with higher GDP. Similarly, wages in the relatively richer counties are higher, given the higher marginal productivity of labor, which will tend to increase costs, especially in labor-intensive activities as health and education. In figure 3.1 and 3.2 unfortunately, the form of the scatter is undefined.

Figure 3.2
Health Spending and GRDP (Gross Regional Domestic Bruto) per capita

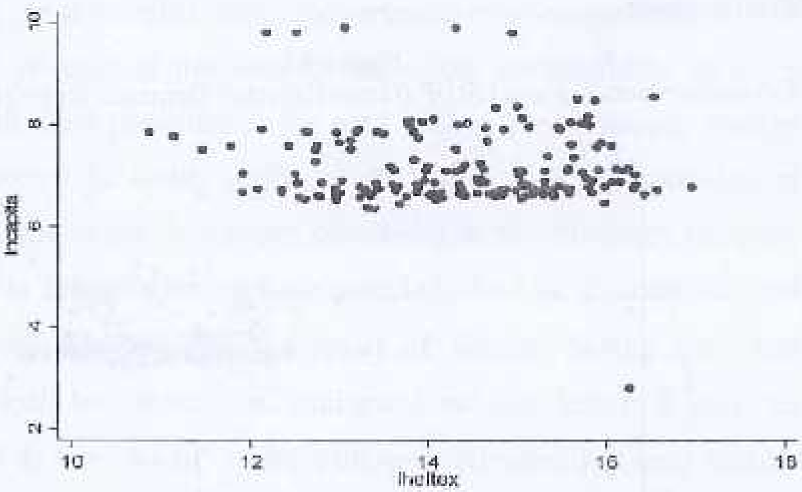


Figure 3.1 and 3.2 can not be interpreted as evidence of the validity of Wagner's hypothesis at the cross-country level. This hypothesis, postulates that there is a tendency for governments to increase their activities as economic activity increases. Since 1890 Wagner postulated that economic development implied rising complexities that required more governmental activity, or that the elasticity of demand for publicly provided services, in particular

education was greater than one. This hypothesis has been tested econometrically (Chang, 2002) in time series and cross-country settings, showing that this is nothing particular of the series used for the present study.

Figure 3.3 shows us relationship between per capita public expenditure on health and ratio of health person and sick. Cross regions and time varying analysis in figure 3.3 does not interpret anything because it has no pattern. In figure 3.4 shows us the education scatter plot between the education public expenditure and the ratio of the schooling children 7 until 12 years old. this fact will be explored in the next section.

Figure 3.3
Per Capita Public Expenditure on Health and Ratio Health of Sick

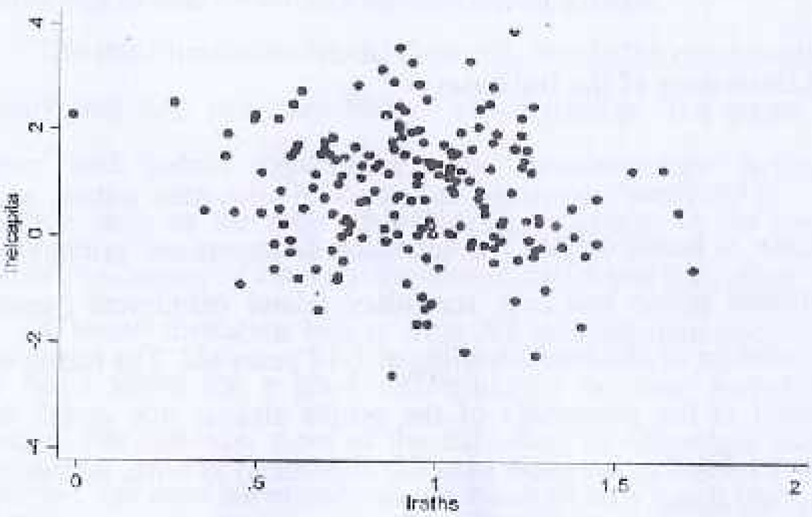
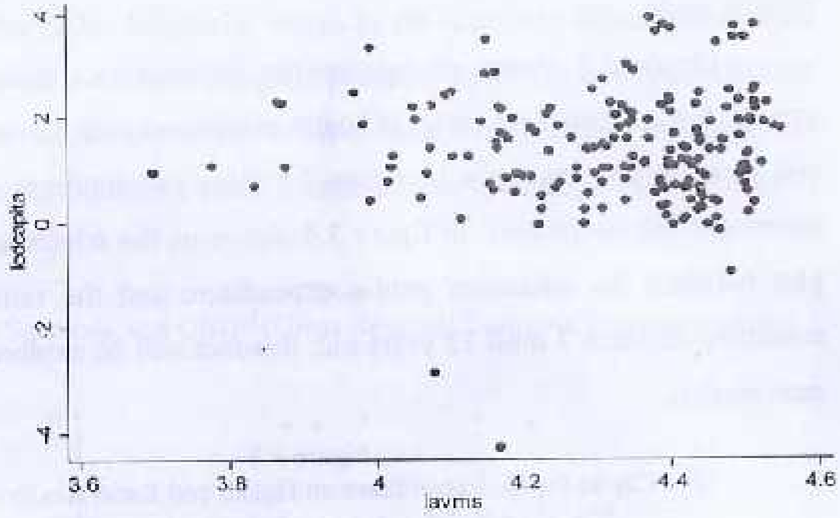


Figure 3.4
Per Capita Public Expenditure on Education and Percentage of Schooling Children 7-12 years old



3.2 Limitations of the Indicators

This paper uses three indicators of education output and one indicator of health output. The education indicators are: primary school enrollment (gross and net), secondary school enrollment (gross and net), average of children schooling at 7-18 years old. The health output indicator is the percentage of the people sick at one month before surveyed. Most of the paper used life expectancy at birth, immunization (DPT and measles), and the disability-adjusted life expectancy (DALE) but this is difficult to get those data for this research, in SFA analysis, outputs for education was composed by made it averaged, because SFA requires single output for analysis. Education inputs consist of public spending at education for young generation, national cultural, and belief in almighty God, and ratio of the pupils per teachers. At the health side, inputs consist of public spending on health, social welfare, population and family planning.

Determination of the input and output in this paper has several limitations. First, the paper uses aggregate public spending on health and education, while using disaggregate measures of output, such as primary enrollment or secondary enrollment. Ideally the input should be using separately public spending in primary and secondary education. Similarly, health care spending could be disaggregated into primary care level care and secondary level. The data can be disaggregated even further, by analyzing efficiency at the school or hospital levels. Second, there are omitted factors of production. This is especially true in education, as the paper did not consider private spending due to data constraints for developing nations.

The third limitation arising from the data is the combination of monetary and non monetary factors of production. The paper uses together with public expenditure, other non-monetary factors of production such as the ratio of teachers to students, in the case of education, or literacy of adults in the case of health and education.

A fourth limitation arising from the selected indicators is that these don't allow for a good differentiation between outputs and outcomes. For instance, most of the indicators of education, such as completion and enrollment rates do not measure how much learning is taking place in a particular country. In education, this paper advances by considering the percentage of number children have age 7 until 12 years. But in health, outcomes such as the number of sick-day leaves or the number of missed-school days because of health-related causes could be better reflections of outcomes (Harrera and Pang, 2005). In this paper we use this indicator.

IV. Empirical Results

4.1 DEA Results

Table 4.1 shows some aggregate figures of the estimated DEA models. Different models give different variation ranges for the results, as could be expected. In empirical application DEA models related cost efficiency scores of districts and municipalities were calculated for each year during 1998-2002 assuming constant returns to scale (CRS) for the efficiency frontiers. In the table 4.1 we see that Units of efficiency was written with 1, 2, 3, 4, 5, this means that 1 is the initial time of observation, 2 is the second time observation of the panel data, and so on. The results of calculation of efficiency score are various. At education sector the interval of the scores between 11.65% until 100%. The average of efficiency score is 65.19%. The lowest score is Pamekasan (1998) and followed by Sampang (1998), Bangkalan (1998), Probolinggo (1998) and Sumenep (1998), which have score 13.50%, 19.32%, 20.31%, and 23, 36% and the regions which have the highest efficiency score is Pasuruan (1998), kota Mojokerto (1999), Jember (1999), and Madiun (2000) with 100% of efficiency score. The details rank can be explored at table 4.1.

Table 4.2 shows that the number of efficient municipalities (on frontier) varied annually from 1998-2002 on health sectors the average of efficiency score of the panel data is 41.72%. The lowest efficiency score at Surabaya (2000, 1999, and 1998) and Kota Malang those are below 12%. The highest efficiency score is at Kota Pasuruan (2002) and Sumenep (1999) with 100% efficiency. Averages of annual median efficiency scores ranged from 0.856 to 0.898 suggesting that on average 10-15 % more output could be produced with given resources, if all municipalities were fully efficient (on the frontier). On the other hand, a good amount of efficiency variation is still left in the results.

Figure 4.1
Panel Trend of Education Efficiency Score

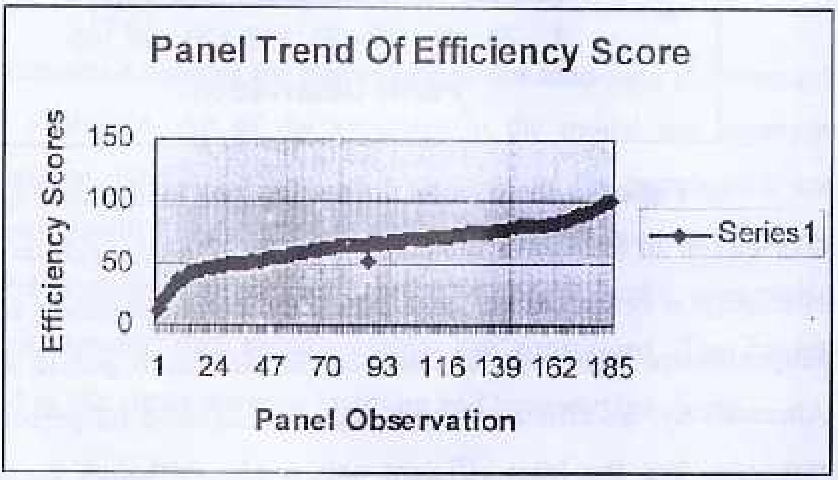
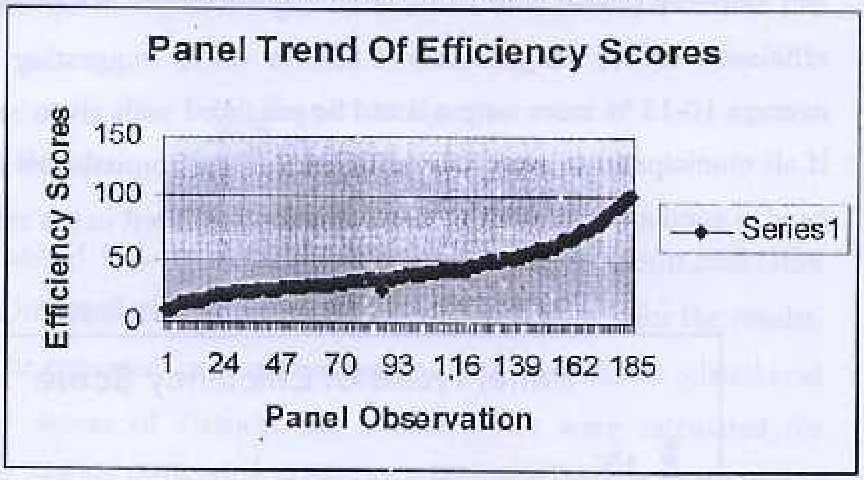


Figure 4.1 shows a Salter diagram of efficiency scores (from low to high values) for all the 353 Finnish municipalities included in the study. There are found municipalities are fully efficient during all of the years from 1998 to 2002, several of them have the score one (100 per cent) in education public sector for the whole research period. However, a few municipalities get very close to this, and a group of four top performers is found.

Figure 4.2
Panel Trend of Health Efficiency Score



In Figure 2 there is an increasing tail in the cost efficiency distribution of East Java municipalities. In 37 municipalities average efficiency is below 70 per cent. Not only in the education sector are fully efficient scores found, but also in the health public spending. Alternatively, an efficient municipality would need 62 percent of the resources that the least efficient unit needs. Although these results indicate differences across municipalities, they cannot be taken too literally. One must bear in mind that when applying DEA, the variation of resulting efficiency rates depends among other things, inversely on the number of variables in the model and the assumption concerning the efficiency frontier (here CRS) (Loikkanen and Susiluoto, 2005).

4.2 SFA Results

In this paper, education and health public sector spending are analyzed by two approaches, parametric (SFA) and non parametric (DEA) as mentioned above. This part provides to explore the SFA results. The tables in this part will report the estimation of the models in chapter 2, both education and health public spending. The model of the of the estimation for education and health are below

Education = f (public expenditure on Education, Ratio of the Pupils per Teachers) + vit-uit

(4.1)

Health = f (public expenditure on health, Total health facility) + vit-uit

(4.2)

Education denotes the percentage of the schooling children at 7 until 18 years old. All of the variables in the model are logarithm transformation. Health denotes the percentage of the people sick and total health facility consist of number of hospitals, center of public health and workers in those facilities including the medic, paramedic, and administration, then those variables are considered. The models estimated in this paper are time invariant and time varying decay.

Table 4.1
Estimation Time Invariant Model for Education

Ln CS	Coef	Std. Err	z	P>|z|	[95% Conf.	Interval
ledcapita	-.0010294	.0038191	-0.27	0.788	-.0085146	.0064559
lavT\Pupils	-.0772509	.0143688	-5.38	0.000	-.1054133	-.0490885
_cons	4.738556	.0445774	106.30	0.000	4.651186	4.825926
/mu	-.1369153	.4101918	-0.33	0.739	-.9408764	.6670458
/lnsigma2	-2.398031	.8815389	-2.72	0.007	-4.125815	-.6702462
/ilgtgamma	3.794463	.9076134	4.18	0.000	2.015574	5.573353
sigma2	.0908968	.080129			.0161503	.5115826
gamma	.9779999	.0195283			.8824225	.9962166

sigma_u2	.088897	.0801264			-.0681479	.245942
sigma_v2	.0019997	.0002315			.001546	.0024535

In addition to the coefficients, the output reports estimates for the parameters and sigma_v2, sigma_u2, gamma, sigma2, ilgtgamma, lnsigma2, and mu. Sigma_v2 is estimate of σv^2, sigma_u2 is the estimate of σu^2. Gamma is the estimate of $\frac{\sigma_u^2}{\sigma_s^2}$, sigma2 is the estimate of $\sigma_S^2 = \sigma_v^2 + \sigma_u^2$. Since γ must be between 0 and 1, the optimization is parameterized in terms of the inverse logit of γ, and this estimate is reported as ilgtgamma. Since σ_s^2 must be positive, the optimization is parameterized in terms of $\ln(\sigma_s^2)$, whose estimate is reported as lnsigma2. Finally, mu is the estimate of u.

Table 4.2
Estimation Time Varying Decay Model for Education

Ln CS	Coef	Std. Err	z	P>|z|	[95% Conf.	Interval
ledcapita	-.0551506	.0198027	-2.79	0.005	-.0939632	-.016338
lavT\Pupils	-.0045153	.0043585	-1.04	0.300	-.0130578	.0040271
_cons	4.682047	.0561693	83.36	0.000	4.571957	4.792137
/mu	-.1317574	.3926406	-0.34	0.737	-.9013189	.6378041
/eta	.0236089	.0144682	1.63	0.103	-.0047482	.051966
/lnsigma2	-2.471952	.8773146	-2.82	0.005	-4.191457	-.7524467
/ilgtgamma	3.743252	.9042464	4.14	0.000	1.970962	5.515543
sigma2	.0844199	.0740628			.0151242	.4712122
gamma	.9768707	.0204309			.8777144	.9959924
sigma_u2	.0824674	.0740628			-.0626876	.2276223
sigma_v2	.0019526	.0002263			.0015091	.0023961

Table 4.3
Estimation Time Invariant Model for Health

lraths	Coef	Std. Err	z	P>|z|	[95% Conf.	Interval
ltotalhealth	.0252389	.0575572	0.44	0.661	-.0875711	.138049
lhelcapita	-.0288182	.012255	-2.35	0.019	-.0528375	-.0047988
_cons	1.227299	.4314249	2.84	0.004	.3817223	2.072877
/mu	.4201871	.2101532	2.00	0.046	.0082944	.8320797
/lnsigma2	-2.531377	.4296518	-10.06	0.000	-3.024349	-2.038405
/ilgtgamma	.3883294	.4296518	0.90	0.366	-.4537727	-2.038405
sigma2	.0795494	.0200083			.0485894	.1302362
gamma	.5958805	.1034631			.3884641	.7738941
sigma_u2	.0474019	.0196296			.0089287	.0858751
sigma_v2	.0321475	.0037608			.0247764	.0395185

Table 4.4
Estimation Time Varying Decay Model for Health

lraths	Coef	Std. Err	z	P>|z	[95% Conf.	Interval
ltotalhealth	.0209484	.0573154	0.37	0.715	-.0913877	.1332844
lhelcapita	- .0216609	.0156881	-1.38	0.167	-.0524089	.0090872
_cons	1.253515	.4287476	2.92	0.003	.4131847	2.093844
/mu	.4393028	.2171406	2.02	0.043	.0137149	.8648906
/eta	- .0192089	.0268224	-0.72	0.474	-.0717799	.0333621
/lnsigma2	- 2.486966	.2738105	-9.08	0.000	-3.023625	- 1.950308
/ilgtgamma	.4687554	.4527863	0.003	0.301	-.4186894	1.3562
sigma2	- 2.486966	.0227706			.0486246	.1422303
gamma	.6150891	.1071992			.3968304	.7951414
sigma_u2	-	.0224273			.0071952	.0951087

	2.486966					
sigma_v2	.0320099	.0037454			.0246692	.0393507

Table 4.1 presents estimation results for education stochastic frontier model for model time invariant. The table shows that public spending per capita doesn't significant impact to efficiency accounting but the other condition is absolute difference in time varying estimation at table 4.2, public spending has strong impact in the model. For the health sector, time invariant estimation (table 4.3) shows that public spending per capita (lhelcapita) statistically significant but not significant for time varying estimation (table 4.4). Efficiency scores are reported at in the table 4.11 that shows us technical efficiency. Once of the model is estimated, inefficiency measures are calculated using the residuals. Thus, the technical efficiency (TE) can be captured by decomposing the error term in to parts as follows,

$$\varepsilon_i = \upsilon_i + \mu_i \qquad (4.1)$$

Where the first component, vi is a normal error term with vi ~ N $(0,\sigma^2)$ representing pure randomness, and ui is non positive error term exponentially or half normally distributed which represents technical efficiency (Jondrow, 1982). In the table 4.6 we will see the technical efficiency scores per districts and municipals in East Java at 2002.

After investigated the efficiency scores, then we try to explore factors determining efficiency scores both from DEA and SFA in education and health as well as time invariant and time varying model of SFA. Variables are used in this paper that affecting efficiency scores are dependency ratio, income disparity in Gini ratio, number of population, number of literacy, number of unemployment, and income per capita. All of the variables in the regression models in form of natural logarithm transformation. Efficiency scores of SFA are estimated by FGLS technique, which is the best technique after simulations of several techniques. The lower panel of Table 4.5-4.8 presents a second step analysis of the estimated inefficiencies from the two models. They suggest that income and the distribution of income are both significant in explaining variation in efficiency. Since u_i is in proportional terms, the absolute magnitudes of the coefficients give the proportional impacts. It appears that the most important determinant is the distribution of income, with larger values of the gini coefficient (less equal income distribution) having a major negative impact on health outcomes however measured. (Increases in u_i imply lower efficiency.) The second largest determinant is per capita income, which works in the expected direction – higher income is associated with more efficient delivery of health care and achievement of higher life expectancy. (These results are not interpretable as direct impacts on the health outcomes.)

Table 4.5
Education Technical Efficiency Score Outcome Regression from Time Invariant Model

TE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
lunemploy	0.03517	0.011096	3.17	0.002	0.013421	0.056918
lncapita	0.018851	0.008602	2.19	0.028	0.001991	0.035711
ldepend	0.136395	0.051341	2.66	0.008	0.035768	0.237021
lpop	1.013827	0.083105	12.2	0	0.850944	1.17671
lgini	0.07969	0.046156	1.73	0.084	-0.01077	0.170153
lliteracy	-1.02882	0.074725	-13.77	0	-1.17528	-0.88237
cons	-0.74679	0.255112	-2.93	0.003	-1.2468	-0.24678

Table 4.6
Education Technical Efficiency Score Outcome Regression from Time Varying Model

TE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
lpop	0.971829	0.079819	12.18	0	0.815387	1.128271
ldepend	0.137566	0.049311	2.79	0.005	0.040919	0.234213
lunemploy	0.034768	0.010658	3.26	0.001	0.01388	0.055657
lncapita	0.018846	0.008262	2.28	0.023	0.002652	0.035039
lliteracy	-0.98538	0.071769	-13.73	0	-1.12604	-0.84471
lgini	0.08115	0.04433	1.83	0.067	-0.00574	0.168036
_cons	-0.76336	0.245023	-3.12	0.002	-1.24359	-0.28312

Table 4.7
Health Technical Efficiency Score Outcome Regression from Time Invariant Model

TE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
ldepend	-0.02261	0.124788	-0.18	0.856	-0.26719	0.221967
lunemploy	0.066878	0.026971	2.48	0.013	0.014017	0.119739
lncapita	0.052146	0.020909	2.49	0.013	0.011166	0.093127
lpop	-0.45068	0.201993	-2.23	0.026	-0.84658	-0.05478
lliteracy	0.363857	0.181623	2	0.045	0.007883	0.719832
lgini	0.324518	0.112185	2.89	0.004	0.10464	0.544395
_cons	1.081807	0.620066	1.74	0.081	-0.1335	2.297114

Table 4.8
Health Technical Efficiency Score Outcome Regression from Time Varying Model

TE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
ldepend	-0.0608	0.128936	-0.47	0.637	-0.31351	0.191905
lunemploy	0.068485	0.027867	2.46	0.014	0.013866	0.123103
lncapita	0.052123	0.021604	2.41	0.016	0.00978	0.094465
lgini	0.329264	0.115914	2.84	0.005	0.102077	0.556451
lliteracy	0.342926	0.187661	1.83	0.068	-0.02488	0.710735
lpop	-0.43693	0.208708	-2.09	0.036	-0.84599	-0.02787
_cons	1.332535	0.640679	2.08	0.038	0.076827	2.588244

In the results of DEA scores estimation, there is difference estimation model between education and health scores. For education, the best model is random effect model after applied the Hausman test for specification. On the other side, health efficiency scores are estimated by random effect model. Table 4.9 and 4.10 below show us the estimation results.

Table 4.8
Education Technical Efficiency Score Outcome Regression Random Effect

Efficiency	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
lpop	-59.775	18.45251	-3.24	0.001	-95.94127	-23.6088
ldepend	-29.1016	10.57302	-2.75	0.006	-49.82433	-8.37884
lunemploy	-2.38054	2.477937	-0.96	0.337	-7.237209	2.476127
lncapita	-3.04751	1.815508	-1.68	0.093	-6.605839	0.510822
lliteracy	62.49759	16.55852	3.77	0	30.04349	94.95169
lgini	32.4241	8.534437	3.8	0	15.69691	49.15129
_cons	247.8039	52.92902	4.68	0	144.0649	351.5429

Table 4.8
Health Technical Efficiency Score Outcome Regression Fixed Effect

healthdea	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
lliteracy	-69.5442	25.28005	-2.75	0.006	-119.0922	-19.9963
lgini	-25.3987	10.68797	-2.38	0.017	-46.34679	-4.4507
lpop	57.6217	28.23223	2.04	0.041	2.287542	112.9559
ldepend	14.88523	14.59424	1.02	0.308	-13.71895	43.48941
lunemploy	-3.15103	3.821839	-0.82	0.41	-10.64169	4.339641
lncapita	1.993263	2.590777	0.77	0.442	-3.084566	7.071092
_cons	118.4349	74.57661	1.59	0.112	-27.7326	264.6023

4.3 Discussion of the Techniques

In this section we discuss four of the most important issues that arise when seeking to use productivity models in the public services: the weights that are used to indicate the values of different outputs, how the efficiency models are constructed, and the treatment of environmental nuances on performance and dynamic aspects of productivity. Smith and Street (2004) explained the problems related to both of method that commonly used in public sector efficiency.

4.3.1 Output Weights

There are important questions relating to the objectives that are encompassed by any index of efficiency. Is it legitimate for the central policy maker to attach a uniform set of *objectives* to all organizations? If so, is it further legitimate to apply a uniform set of *weights* to these objectives? If so, how should they be chosen? If not, what is the extent of legitimate variation, and who should choose? These are fundamental issues, the answers to which determine whether or not creating a single measure of organizational performance is warranted. In our view, organizations can be ranked in this way only if the policy maker may legitimately

(a) Set objectives and

(b) Attach weights to those objectives.

The set of weights w ought to reflect societal values. However, it is not simple to derive such weights, particularly when organizations face multiple objectives and there is disagreement about organizational priorities. Ultimately the selection of objectives in the public services is a job for the politicians who are charged with reconciling conflicting claims on public resources. The main role for analysts is to clarify the choices that are required of policy makers, to provide evidence on popular preferences and to develop measurement instruments that most faithfully reflect the chosen objectives. Note that policy makers are effectively attaching a zero weight to any output that is excluded from the efficiency index.

4.3.2 Modeling the Production Process

Having decided on what objectives are to be considered, and their relative importance, the next problem concerns how to model the process by which these may be achieved and the constraints that limit levels of attainment.

The research interest in productivity models is predominantly in the structure and determinants of the production process rather than specific efficiency estimates for individual organizations. Countless research questions present themselves. For example: what is the marginal productivity of a factor of production? How do returns to scale vary? What influence do external environmental factors have on efficiency? What is the aggregate level of inefficiency in the sector? These are all important questions with potentially important policy implications. However, they all fit into the traditional empirical research model in that they seek to identify aggregate (or sample average) patterns within the data. Modeling is usually a means to the end of securing a more satisfactory aggregate model with which to address the research questions.

In contrast, the managerial or policy interest is in the estimate of efficiency for individual organizations. This estimate is derived from the residual or organization-specific effect, and the model parameters are no longer the main interest. This switch of attention turns the statistical model on its head. We believe that this may require a fundamental rethink in modeling methodology.

4.3.3 Environmental constraints

In addition to difficulties in specifying the production process, the measurement of efficiency of public service organizations is further complicated by the need to take account of influences on performance that lie outside organizational control. Numerous classes of factors may influence measured levels of organizational attainment. These include the following:

(a) Differences in the characteristics of citizens being served;
(b) The external environment—e.g. geography, climate and culture;
(c) The activities of other related agencies, both within and outside the public services;
(d) The quality of resources being used, including the capital stock;
(e) Different accounting treatments;
(f) Errors in data;
(g) Random (or idiosyncratic) fluctuation;
(h) Different organizational priorities;
(i) Differences in efficiency.

In the short run, many of these factors are outside the control of the organizations that are under scrutiny. We call these 'environmental' variables. In the longer term a broader set of factors is potentially under the control of the organizations, but the extent and nature of this control will vary depending on the nature of the context. So, for example, the short run efficiency of a hospital should be judged in the light of the capital configuration that it has available. Yet in the longer run we might expect the hospital to reconfigure its capital resources when this is likely to lead (say) to lower unit costs.

In whatever way the uncontrollable environment is defined, usually some organizations operate in more adverse environments than others, in the sense that external circumstances make the achievement of a given level of attainment more difficult. This means that—for a given level of expenditure—the production possibility frontiers of different organizations will not be identical. The frontiers for organizations operating in difficult environments will lie inside those of more favorably endowed organizations, and the environmental influences on organizational outputs should therefore be incorporated in statistical models of efficiency.

4.3.4 Dynamic effects

One of the most problematic issues in productivity analysis is the treatment of dynamic effects. Generally, organizations operate within a historical context, drawing on past inheritances and making investments towards future performance. This implies that the production process should be modeled in a dynamic fashion, in which contemporary performance is to some extent dependent on previous investment, and contemporary inputs are to some extent invested for future outputs.

Therefore, the correct production model for examining current performance should include among its inputs the endowment that is bequeathed to current management by previous organizational efforts. This is a fiercely complex issue, as many such organizational endowments defy satisfactory measurement. For example, the current performance of police forces in terms of crime rates and detection rates may reflect previous efforts in crime prevention. In some senses this can be considered an uncontrollable 'environmental' influence on current managerial performance.

Yet in general we have no concrete way of quantifying this potentially important input, and most studies ignore such factors. Equally, some elements of current effort may be directed towards future attainment. For example, investment in health promotion activities may not yield discernible achievements until years after the activities have been completed. Again, in principle, we should include such endowments as an output from the current period. In practice, they are extremely difficult to capture in assessments of efficiency, especially as the investment effort may itself contain an element of inefficiency.

V. Conclusions

Research efforts in productivity analysis have burgeoned in recent decades. Much of this research effort is to be applauded, and further research should be encouraged. However, our intention in this paper has been to point out the poor understanding of the role that productivity analysis might have for policy purposes. In this paper view, both researchers and policy makers should seek to improve this understanding.

The cost efficiency of welfare service production in East Java municipalities 1998-2002 was studied in this paper. A two-stage procedure was applied. At the first stage, annual relative efficiency scores were estimated for 37 municipalities with the DEA method and SFA. The alternative constant returns to scale models were used. The outputs consisted of several most important services in the health, social and educational sector, and combined production costs of these services were used as the input. Considerable differences exist between municipalities.

From the DEA results we see that several regions have perfect efficient and also in SFA results also found that several regions have a perfect inefficiency. Our results strongly suggest that efficiency in spending in these two economic sectors where public provision is usually very important is not an issue to be neglected. In the results of both methods vary across regions as shown in the table 4.5 and 4.6.

Finally we examine via econometric analysis the influence of non-discretionary factors, notably non-fiscal variables, on expenditure efficiency. The study shows that per-capita income, dependency ratio, unemployment, income disparity, population, and literacy of adult have significant impact on technical efficiency. Several differences in the estimation results were found in the significant of those variables in the time variant and time varying model of SFA.

In terms of policy implications, it is vital to differentiate between the technically efficient level and the optimal or desired spending level. Even if a region is identified as an" efficient" benchmark region, it may very well still need to expand its public spending levels to achieve a target level of educational or health attainment indicators. Such is the case of countries with low spending levels and low attainment indicators, close to the origin of the efficient frontier. The important thing is that countries expand their scale of operation along the efficient frontier.

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