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Assessing Hospital Performance in Indonesia: An Application of Frontier Analysis Techniques

*Firdaus Hafidz [1,2], Tim Ensor[1], Sandy Tubeuf[1]

AFFILIATIONS

(1) University of Leeds
(2) Universitas Gadjah Mada

*CORRESPONDING AUTHOR CONTACT DETAILS:
Firdaus Hafidz - Leeds Institute of Health Science, University of Leeds, Worsley Building,Leeds, LS2 9LJ - +44 (0) 113 343 6354 - Email: umfhas@leeds.ac.uk

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Worsley Building
University of Leeds
Leeds, United Kingdom
LS2 9JT

http://medhealth.leeds.ac.uk/lihs

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Abstract

Despite increased national health expenditure in health facilities in Indonesia, health outcomes remain poor. The aim of our study is to examine the factors determining the relative efficiency of hospitals. Using linked national data sources from facility-, households, and village-based surveys, we measure the efficiency of 200 hospitals across fifteen provinces in Indonesia with output oriented data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Inputs include the number of doctors, nurses and midwives, other staff, and beds while outputs are the number of outpatient visits and bed-days. We run truncated regression in second stage DEA and one stage SFA analysis to assess contextual characteristics influencing health facilities performance. Our results indicate a wide variation in efficiency between health facilities. High-performing hospitals are in deprived areas. Hospitals located in less concentrated health facilities, in Java and Bali Island, high coverage of insurance scheme for the poor perform better than in other geographical location. We find an inconclusive impact of quality of care, and ownership on efficiency. This paper concludes by highlighting the characteristics of hospitals that have the potential to increase efficiency.

Key words: Efficiency, hospitals, frontier analysis, data envelopment analysis, stochastic frontier analysis, Indonesia

1. Introduction

Hospitals represent the largest share of healthcare spending. Indonesian hospitals account for 55 percent of total public health expenditures (CHEPS *et al.*, 2016). Between 2005 and 2014, the share of hospitals' expenditures increased by 22% point (Soewondo *et al.*, 2011; CHEPS *et al.*, 2016). However, the average hospital bed occupancy rate (total number of inpatient days in a year over the number of beds) in Indonesia is just above 60 percent, which is lower than the recommended occupancy levels of 85%–90% (Mahendradhata *et al.*, 2017; Chisholm & Evans, 2010).

Inappropriate health facility size including the number of beds which exceeds the capacity of human resources, medical equipment, and the high cost of drugs and medical supplies were found to be the main causes of inefficiency in health facilities (Sari, 1999; Chalidyanto, 2013). A study by Chalidyanto (2013) found that less than 35% of hospitals in Indonesia were fully technically efficient, and the average technical efficiency score was 80%. Another efficiency measurement study conducted in East Java province showed only one out of 39 hospitals to be efficient (Cahyani *et al.*, 2012).

This study aims to investigate the level of efficiency and possible causes for the variations in the efficiency. Frontier analysis was then conducted to provide benchmark of hospital efficiency as well as determine the functional relationships between between efficiency and the possible contextual factors.

2. Hospitals in Indonesia

Hospitals in Indonesia mainly focus on curative and rehabilitative services, including inpatient, outpatient, and emergency services. It is categorised by the capacity of services (Class A to D), and ownership (public or private) (Kemenkes, 2014a). By its capacity of services, hospitals in Class A are the largest, mainly served as national referral (2.42%), followed by Class B (14.11%), Class C (41.25%), and Class D (21.07%) (Kemenkes, 2017). Public hospitals are managed by the government, including the Army and Police. There were 2,601 hospitals in 2016, 35% of them were in the public sector (Kemenkes, 2017). Meanwhile, private hospitals are managed by profit-organisations, including enterprises and state-owned companies, as well as non-profir organisation.

Hospitals were far less accessible than the primary care. PODES report showed only 67.3% of population have access to hospital as secondary care (Sparrow & Vothknecht, 2011). The number of hospitals increased by 16.74% between 2013 to 2016, and nationally, the hospital bed ratio was 1.12 per 1,000 people which was higher than the WHO standard of 1 bed per 1,000 people (Kemenkes, 2017). However, there were still seven provinces having less than 1 bed per 1,000 people: Banten (0.82), East Nusa Tenggara (0.80), West Java (0.79), Lampung (0.77), West Sulawesi (0.77), West Kalimantan (0.77), and West Nusa Tenggara (0.65). The highest hospitals bed ratio were in Jakarta (2.23), North Sulawesi (2.05), and Yogyakarta (1.80) (Kemenkes, 2017).

In 2015, there were 322,607 health workers in hospitals, including 147,264 nurses, 30,561 midwives 47,605 medical specialists and non-specialist physicians. On average, there are 16 specialists, ten general practitioners, two dentists, 74 nurses, and 14 midwives per hospital (Kemenkes, 2014b).

To improve the availability and quality of human resources in accordance with the standard of health services, the Ministry of Health set the Ministry of Health Strategic Plan indicator for 2015-2019 where at least 35% of C class hospital should met the minimum requirement of having at least four basic medical specialists, and three supporting specialists including radiology, anesthesiology, and clinical pathology. By 2016 there were 45.22% of class C public hospitals in Indonesia reporting that they have met the required number of specialists (Kemenkes, 2017). However, 19% of public hospitals in Indonesia did not have internists, 20% did not have a surgeon, 25% did not have paediatricians, and 17% did not have obstetrics and gynaecology specialists (Kemenkes, 2012a). The total number specialists working in hospitals in Indonesia in 2016 amounted to 49,742 people. Basic medical specialists constitute the majority of specialists in hospitals (42.6%), followed by other medical specialists (37.04%), supporting medical specialists (16.97%), and dental specialists (3.37%). The highest number of medical specialists reside in West Java and Jakarta, while North Kalimantan and West Sulawesi have the lowest number of medical specialists (Kemenkes, 2017).

The Ministry of Health formed the hospital accreditation commission and started a hospital accreditation programme in 1996 in order to improve hospitals' quality of services. The accreditation aimed to increase the quality of services, patients safety, protection to the patients, community, human resources of the hospital and the hospital as an institution. The hospital needs to be accredited every three years to ensure their quality of services. Moreover the government also encouraged hospitals to proceed with international accreditation (Kemenkes, 2012b). The Ministry of Health aimed to have at least one accredited hospital in each district. However until 2016, accredited hospitals in Indonesia only amounted to 33.12% out of 2,500 hospitals. Provinces with the highest percentage of accredited hospitals were Bali, Jakarta and Lampung respectively by 69.09%, 53.30% and 52.94%. In North Kalimantan, all of the seven hospitals had not been accredited (Kemenkes, 2017). Challenges in hospital accreditation implementation were the accreditation bodies that are not yet integrated, lack of clarity on the role of provincial and district health offices, lack of accreditation guidelines, lack of engagement or support from clinical staff, and political pressure to provide licences to hospitals that do not satisfy the minimum licensing requirements (Hort *et al.*, 2013).

3. Methods

3.1. **Data.**

This study assesses the determinants of productivity in hospitals by analysing data from three different sources. The first is a survey of health facilities carried out by Indonesia's Ministry of Health (MoH) between October 2010 and September 2011. The survey collected data on resources (infrastructure, equipment, staff, pharmaceuticals, and medical supplies), and expenditures (e.g. office supplies, maintenance, and transport expenses) for 122 public hospitals (17%), and 78 private hospitals (17%). We used these data to estimate the relative efficiency of health facilities and identify internal factors determining efficiency. Second, we use data from the 2011 National Socioeconomic Survey (SUSENAS) that provides household characteristics at district levels such as the education levels of all adults in the household, health insurance coverage, and household expenditures. Third, we use data from the 2011 village potential statistics (PODES), which is a census providing information about village characteristics across Indonesia such as population size, type of jobs, availability of and access to health facilities, and death rate. We identify geographic and infrastructure characteristics, including the availability of healthcare services. We merged SUSENAS, PODES dataset and the MoH health facility survey data using districts identifiers for hospitals.

3.2. **Input and output variables.**

The efficiency analysis is based on a vector of inputs measuring labour and capital in hospitals. The choice of the inputs and outputs was guided by past efficiency measurement studies undertaken in hospitals, and included hospitals production inputs and outputs with the different roles of health workers and types of services (Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Varabyova & Schreyogg, 2013; Chowdhury *et al.*, 2014; Yang & Zeng, 2014). Six different inputs and seven outputs indicators are considered. Those six inputs are: (1) the number of doctors, (2) the number of nurses (3) the number of other staff, (4) the number full-time-equivalent (FTE) of non-specialist doctors, (5) the FTE of specialist doctors, and (6) number of beds. Meanwhile, the seven outputs considered are: (1) the number of outpatient visits, (2) the number of bed-days, (3) the adjusted number of admissions (adjusted by the admission death rate), (4) the number of surgeries, (5) the number of outpatient visits and bed-days, (6) the number of outpatient visits and the adjusted number of admissions, and (7) the number of outpatient visits,the adjusted number of admissions, and the number of surgeries (Table 1).

3.3. **Explanatory variable.**

The analysis examined factors beyond the control of health institutions and evaluated their impact on the efficiency level (Worthington, 2004). In our study, we selected the explanatory variables using previous empirical studies and according to the availability of data. Explanatory variables were grouped into two groups: (1) internal factors, elements within providers, which affect facility efficiency (e.g. size and capacity, ownership, and case-mix index); (2) external factors, outside the influence of a provider that can impact on facility efficiency (e.g. insurance coverage, education level, and geography) (Besstremyannaya, 2013; Cordero Ferrera *et al.*, 2014; Ding, 2014; Herr, 2008; Gok & Sezen, 2013; Heimeshoff *et al.*, 2014; Nedelea & Fannin, 2013; Matranga & Sapienzab, 2015; Kirigia & Asbu, 2013; Mitropoulos *et al.*, 2013; Mobley & Magnussen, 1998; Shreay *et al.*, 2014; Varabyova & Schreyogg, 2013; Yang & Zeng, 2014).

Our large dataset with many explanatory variables that are potentially highly correlated can lead to problems for multivariate regression techniques (Everitt & Hothorn, 2011). To address the issue, principal components analysis (PCA) was used to create a smaller number of new variables, which were uncorrelated (Jolliffe & Cadima, 2016). The Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy was used to verify the adequacy of PCA to reduce the number of variables. Components were extracted with eigenvalues less than one in the correlation matrix (Everitt & Hothorn, 2011). We thus transformed 21 variables into six new index variables: an index of disruption in health facilities, an index of less management, an index of household health expenditure, an index of household economy, an index of health facility access and an index of higher education. PCA results are presented in Table 2,

In addition to PCA variables, the initial general model contained all the identified explanatory variables: class of hospital, teaching status, ownership, type of patients, number of population in the district, geographical location, and health insurance coverage. We ran several models, checked for multicollinearity and finalised a vector of explanatory variables. All explanatory variables are available in Table 3.

3.4. **Measurement technique.**

To measure efficiency, we applied two approaches of frontier analysis: a non parametric approach, the data envelopment analysis (DEA) and a parametric approach, the stochastic frontier analysis (SFA), both of which estimate the production frontier from cross-sectional sample data. Many empirical studies have been increasingly employed both methods to measure relative efficiency in health care services (Hollingsworth, 2003, 2008).

3.4.1. *DEA.*

Data envelopment analysis (DEA) uses mathematical programming to construct a frontier line, as such that no observed point should lie outside (Giuffrida & Gravelle, 2001). This technique can employ multiple inputs and outputs and providing information on similar peer institution (Giuffrida & Gravelle, 2001; Hollingsworth, 2003; Worthington, 2004). However, it does not accommodate error, outliers, noise measurement, or a measure of the best fit frontier (Coelli *et al.*, 2005; Jacobs *et al.*, 2006).

We applied DEA to estimate the efficiency scores for each of the providers in the sample by benchmarking them to fully efficient health facilities lying at the frontier (Coelli *et al.*, 2005; Jacobs *et al.*, 2006) Variable returns-to-scale (VRS) were applied to run input and output-oriented models to estimate the individual hospital efficiency scores. Output-orientation was chosen to identify factors determining efficiency because healthcare resources as the inputs, including the workforce and capital investment, are mostly not within the control of the hospital managers, especially for public hospitals (Mahendradhata *et al.*, 2017) Therefore the aim of the hospital managers should be on how to maximise outputs with the available inputs. Under the assumption of output-oriented efficiency, each facility is required to maximise health care services while maintaining the amount of health care resources used constant.

$$
\begin{aligned}
&\max \quad \phi \\
&\text{subject to} \\
&\sum_{i=1}^{n} \lambda_i x_{ji} \leq x_{jo} \qquad j = 1, 2, .., m; \\
&\sum_{i=1}^{n} \lambda_i y_{ri} \geq \phi y_{ro} \qquad r = 1, 2, ..., s; \\
&\sum_{i=1}^{n} \lambda_i = 1 \\
&\lambda_i \geq 0 \qquad i = 1, 2, ..., n
\end{aligned} \tag{1}
$$

Where i = decision making unit (DMU); x_{ji} is the inputs of i-th, $j = 1, 2, .., m$ is the number of inputs; y_{ri} = outputs of i-th, $r = 1, 2, ..., s$ is the number of outputs; λ_i = set of weights, corresponding to each DMU$_i$, that the sum of λ equals to one; ϕ = represents the efficiency of DMU. The right hand side is one of the n DMUs that is un

While both input and output-oriented approaches use 1 to indicate fully efficient facilities, inefficiency in input-oriented models are indicated by score less than one while inefficiency in output-oriented models are indicated by score greater than one. Therefore to allow direct comparison between the input-oriented DEA models, we used the reciprocals of DEA output-oriented efficiency scores.

3.4.2. *SFA.*

Stochastic frontier analysis (SFA) differ from DEA as it estimates a best-practice frontier using the least-square method, requiring assumptions of cost or production frontier (Giuffrida & Gravelle, 2001). SFA decomposes the error into two components: random noise (unobserved heterogeneity) and true inefficiency component (Mutter *et al.*, 2013; Jacobs *et al.*, 2006). Thus, SFA is often preferred because it can better handle noise present in the data. However, it requires assumptions about functional form and error distribution. It is also vulnerable to small sample sizes (Coelli *et al.*, 2005; Giuffrida & Gravelle, 2001).

The stochastic frontier models combine the efficiency term u with the error term v. The base model is given as:

$$
\begin{gathered}
\ln y = \ln f(x) + v - u \\
\text{with } v \sim N(0, \sigma_v^2) \text{ and } u \sim N_+(0, \sigma_u^2)
\end{gathered} \tag{2}
$$

v represents the stochastic nature of the production process and possible measurement errors of the inputs x and output y, and the u term is the potential level of inefficiency of the provider. We assumed that the terms v and u are independent. If $u = 0$, the health facility is

100% efficient, and, if $u > 0$, then there is some inefficiency. N denotes a normal distribution, and N_+ denotes a half-normal distribution.

This study estimated technical inefficiency with four different SFA models: a Cobb-Douglas production function, a Translog, a distance function, and a Translog distance function. A single output Cobb-Douglas production function was initially estimated, represents the unitary elasticity of substitution and is written as follows:

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + (v_{i-}u_i) \tag{3}$$

Where j represents the number of independent variables, i the health facility, y_i the output of the i-th health facility, x_i the input j of the i-th health facility, β the parameters to be estimated, v_i a symmetric random error, to account for statistical noise, and u_i the non-negative random variable associated with technical inefficiency of health facility i.

The Cobb-Douglas form is restrictive since it assumes constant elasticity of substitution. Therefore we additionally estimated a Translog stochastic production frontier form model. The Translog function is a functional form providing a second order approximation and is written as follows

$$\log(y_i) = \beta + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + (v_i - u_i) \tag{4}$$

$\log x_{ji} \cdot \log x_{hi}$ represents the interaction of the corresponding inputs j and h of the i-th facility.

Both Cobb-Douglas and Translog forms in a standard SFA model were limited to only one output. The sum of the number of treated patients, y in (Eq. 3 and 4) might not be appropriate due to a different type of outputs. Therefore, a multi-output distance function and a Translog distance function were also estimated to anticipate that the sum of the number of treated patients in the Translog function might not be appropriate for our outputs. The multi-output distance function is written as follows

$$\log(\frac{1}{y_{ni}}) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \sum_{j=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \tag{5}$$

The multi-output Translog distance function is written as follows

$$\begin{aligned} \log(\frac{1}{y_{ni}}) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + \sum_{h=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}} \\ + \frac{1}{2} \sum_{j=1}^{k-1} \sum_{h=1}^{k-1} \beta_{jh} \log \frac{y_{hi}}{y_{ni}} \log \frac{y_{hi}}{y_{ni}} + \sum_{j=1}^{k} \sum_{h=1}^{k-1} \beta_{jh} \log x_{ji} \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \end{aligned} \tag{6}$$

The analysis eventually omitted the Translog distance function because it did not fit our data, with the model showing (nearly) perfect multicollinearity.

3.5. **Validity Testing.**

We tested the internal validity, focusing on the stability of the results within the method and their external validity, which addresses the stability of the results between DEA and SFA. Several alternative specifications with a different combination of input and output variables were used to test the changes in the efficiency estimates (Table 4).

Two-step internal validity testing was conducted in both DEA and SFA prior to the external validity test. With DEA, we first compared two model assumptions using the non-parametric Kruskal-Wallis test to see whether the difference was statistically significant by reducing the number of inputs and outputs. Second, we used a Spearman rank correlation test to estimate the correlation between DEA input and output-oriented models. With SFA, a likelihood ratio test was first performed and investigated under the null-hypothesis of no difference between SFA and ordinary least squares (OLS) models. The presence of inefficiency was confirmed by the high values of the contribution of the inefficiency (σ_u) to the total error (γ). However, the single-output Cobb-Douglass and translog models does not fit to our data, as they were not significantly different from the OLS models. Spearman rank correlation test was also used to estimate the correlation between the SFA models (i.e. Distance function, and Translog distance function). We found that the DEA results were more sensitive to changes in the specification of input and output variables than the SFA models, with the correlation between the DEA models ranging from -0.01 to 0.81, and between the SFA models from 0.78 to 0.97 (Table 5).

External validity was tested by comparing the correlation of efficiency scores estimated between DEA and SFA using the same set of input and output variables (Varabyova & Schreyogg, 2013). The Spearman rank correlation test was chosen due to the skewness of data distribution, although the Pearson correlations were used in previous research (Jacobs, 2001). Comparing all models, we found that the correlation between DEA output orientation and SFA efficiency ranged between 0.48 and 0.64. External validity correlation estimates suggesting that the aggregation of doctors and services increases the efficiency correlation. Finally, we included two models (models O3 and TD3) with high internal validity estimate and moderate external validity estimate. The preferred specification of the model included the aggregated total number of doctors, the number of nurses and midwives, the number of other staff and the number of beds among the inputs, and in the outputs the total number of outpatient visits and the number of bed-days.

3.6. **Quadrant score between DEA and SFA.**

Since the results of the DEA and SFA approaches were not always similar, it appeared important to identify the hospitals that were commonly efficient and inefficient in the two approaches (Jacobs *et al.*, 2006). For this purpose, we plotted the DEA and SFA scores of health facilities and divided the plot into four quadrants representing different levels of efficiency. Health facilities in the first quadrant (lower left) scored low in both DEA and SFA, health facilities in the second quadrant (upper left) scored low in DEA but high in SFA, health facilities in the third quadrant (upper right) scored high in both DEA and SFA, and health facilities in the fourth quadrant (lower right) scored high in DEA but low in SFA.

3.7. **Explanatory variable analysis.**

3.7.1. *DEA second stage analysis.*

Two-stage approach procedures have been widely implemented (Hollingsworth, 2008) to find factors determining efficiency. First, we use DEA to estimate the relative technical efficiency of health facilities. Then we use regression model predicting the efficiency scores according to a set of explanatory variables that are expected to influence the technical efficiency of health facilities. There is some debate about regression for this second stage analysis (Hoff, 2007; McDonald, 2009; Simar & Wilson, 2011). Since efficiency scores above 1 are not possible then it is reasonable to use truncated regression model as an appropriate technique to investigate the relationship between DEA efficiency scores computed in the first stage and a vector of contextual factors. The linear regression model is defined as follows

$$\theta = \beta_0 + \beta_1 z_1 + \cdots + \beta_n z_n + \varepsilon, \tag{7}$$

where the left-hand side variable θ is efficiency score said to be truncated, β is a parameter to be estimated, z is an explanatory variables and $\varepsilon \sim N(0, \sigma_u^2)$ is a random error.

3.7.2. *SFA one stage analysis.*

The two-step procedures in the SFA model has also been found to be biased because of misspecified or under-dispersed distribution (Battese & Coelli, 1995; Wang & Schmidt, 2002; Kumbhakar *et al.*, 2015). We applied a one-step procedure to study the determinants influencing the efficiency using the same vector of contextual variables as the second stage analysis in DEA (Battese & Coelli, 1995). The inefficiency term u follows a positive truncated normal distribution with constant scale parameter σ_u^2 and a location parameter μ that depends on additional explanatory variables:

$$u \sim N_+(\mu, \sigma_u^2) \text{ with } \mu = \delta z, \tag{8}$$

where δ is an additional parameter (vector) to be estimated.

3.8. **Data Management.**

Data were manipulated and merged in STATA 14 (Stata-Corp, College Station, TX, USA), then exported into R (http://cran.r-project.org) for analysis. The efficiency scores were obtained using different packages; we performed DEA using Benchmarking version 0.26 (Bogetoft & Otto, 2010), and SFA using frontier version 1.1-0 (Coelli & Henningsen, 2013). Truncated regression analysis was applied using the package truncreg version 0.2-4 (Henningsen & Toomet, 2011). While DEA efficiency scores are sensitive to the presence of outliers, we implemented the data cloud method to check outliers using the FEAR package (Frontier Efficiency Analysis) in R version 2.0.1 (Wilson, 2008). However, we did not find significant differences in efficiency scores with and without outliers. Therefore, we did not drop outliers detected to prevent the loss of valuable information.

Hospitals are assumed to have inputs and produce outputs according to the standardised figures provided by the Indonesian Ministry of Health (Kemenkes, 2014a). Therefore, we replaced zero values by missing. Complete data were available for 138 hospitals over a total of 200 hospitals (31% missing). These missing data cause potential bias in the results because of unrepresentativeness of the hospitals, and can lead to misinterpretation in policy conclusions (Marshall *et al.*, 2009). Tsikriktsis (2005) suggested regression imputation is an appropriate way when more than 20% of the data are missing. Missing data are assumed to be missing at random where probability of missing data depends on observed data. We imputed using chained equations technique with 'mice' library in R statistical software (Buuren & Groothuis-Oudshoorn, 2011). There is no statistical difference between complete and imputed data.

With regard to the minimum number of DEA observations, we applied the rule according to which the number of health facilities must exceed three times the sum of inputs and outputs, and must exceed the product of the number of inputs and outputs (Bowlin, 1998; Bogetoft & Otto, 2010), i.e. $K > 3 \cdot (m + n)$ and $K > m \cdot n$ where K is the number of health facilities, m the number of inputs and n the number of outputs. After the imputation, we had 200 facilities which exceeded the minimum sample of health facilities needed.

4. Results

4.1. **Hospital statistics.**

Table 6 presents characteristics and activities of hospitals. There was a wide variation in the number of outputs and inputs. Hospitals produced a median number of 34,690 outpatient visits, 27,136 bed-days, and 1,310 total surgeries. Hospitals produced these outputs using a median number of 35 doctors, 153 nurses and midwives, and 111 other staff.

4.2. **Technical efficiency.**

Table 7 shows summary statistics of efficiency between two models; smaller average scores imply lower facilities efficiency. The efficiency score in DEA was slightly lower than SFA, however the spread of DEA efficiency range was much larger than the spread in the SFA efficiency. There were 47 hospitals with a DEA efficiency of 1 (i.e. fully efficient) while the maximum efficiency of SFA was 0.93.

The output orientation efficiency is the maximal number of services (output) given the number of health workers (inputs). The average scores of 0.61 in DEA and 0.67 in SFA suggested that we could expand the outputs by 0.64 and 0.50 percentage points respectively without spending additional resources. In absolute terms, hospitals could expand between 35,700 and 45,101 outpatient visits, as well as 17,827 and 22,522 bed-days per year without increasing the number of health staff.

Figure 1 shows the scatter plot of hospitals; the vertical and horizontal lines represent the mean values of DEA and SFA. It appears that proportion of low (quadrant I) and high (quadrant

III)-performing hospitals with both techniques are similar (35%). A remaining 31% of health facilities are inconclusive (quadrant II and IV). Statistics of hospitals by quadrant scores between DEA and SFA are presented in Table 8. Even though there are substantial variations found across quadrants, in general, hospitals in the quadrant III have higher inputs and outputs on average compared to hospitals in other quadrants, especially quadrant I. The number of doctors and the number of other staff between each quadrant does not show significant differences. However, significant differences were found in the number of nurses and the number of beds. High-performing hospitals were found to have the highest mean number of nurses with 210 while the low-performing hospitals only had a mean number of 151 nurses. High-performing hospitals had 1.4 times the number of beds compared to low-performing hospitals. As for the outputs produced, both indicators used were found to have significantly different means between each quadrant. High-performing hospitals were found to have almost three times more outpatient visits and bed-days than low-performing hospitals. Also, the ratio of outpatients per health workers (i.e nurse and doctor) and bed-days per bed showed high-performing hospitals in quadrant III were double compared to low-performing hospitals, despite hospitals in both quadrant have similar capacity (i.e. health workers and beds).

The possible correlation between contextual characteristics with the efficiency scores are assessed in the following subsection.

4.3. **Contextual factors.**

The results of the two-stage DEA model, the one-step SFA, and the multilevel models are presented in Table 9. Generally, internal and external contextual factors were found to be significantly associated in the DEA models, and none were found in the SFA models. The direction of the association for the variables that are consistently significant through all DEA models are found to be the same in the SFA models.

For the internal factors, less monitoring, percentage of NCD patients, hospitals of class A or B, and whether the hospital was a teaching hospital are found to be significantly associated with the efficiency scores in the DEA models. Less monitoring and the status of teaching hospital are found to be negatively associated with efficiency, while positive associations are found with higher percentage of NCD patients and for hospitals of class A and B. The quality of the facilities were proxied by disruption index, and ownership of the hospital are not found to be significant.

Almost all external factors were found to be significantly associated through all DEA models except the population size. However, none of the regressors were significant in the SFA models. The health insurance scheme for the poor and health facilities in Java or Bali were found to be positively associated with efficiency in the DEA model. For a one-unit increase in the proportion of population with poor insurance scheme coverage, there was a 0.47 points increase in the predicted value of efficiency. A similar sign is observed in the SFA model, with a 2.87 points increase of the predicted value of efficiency with the proportion of population with poor insurance scheme coverage, however this association was not significant. Access to health facilities, wealth index, and higher education index were found to be negatively associated with efficiency. One-unit increase in the wealth index was associated with a 0.05 points decrease in the predicted efficiency on the DEA, and 0.39 points decrease on the SFA although it was found to be not significant.

5. Discussion

5.1. **Technical efficiency.**

Efficiency measurement is required for ensuring health resources for services are spent as intended. Given the advantages and disadvantages of each method, there is no consensus on which method is best to estimate efficiency. It is therefore important for several specifications to be developed and both methods to be applied in order to see whether the results are sensitive to the analytical methods used (Jacobs, 2001). The consistency of the results from both methods was helpful to find the best specification; we found as in previous studies (Xu *et al.*, 2015; Jacobs, 2001) that DEA results were more likely to changes with different input and output variables than SFA models.

Nevertheless, the correlation of efficiency scores within the model may show inconsistency in individual efficiency level as best or worst performers (Mathiyazhagan, 2007; Chirikos & Sear, 2000). The differences in efficiency scores may be due to many factors such as the nature of the environmental variables, measurement error, outlier, and other random noise (Jacobs, 2001; Katharakis *et al.*, 2014).

This study found that SFA efficiency score was higher than DEA. Previous studies carried out in China, Thailand, and the United Kingdom that applied both methods together also showed that average efficiency in SFA was higher than in DEA (Xu *et al.*, 2015; Jacobs, 2001). In contrast, international comparisons of technical efficiency measures found DEA corrected using bootstrap slightly higher than SFA (Varabyova & Schreyogg, 2013).

Hospitals as shown in Figure 1 can be grouped into three main groups. The first group consists of hospitals where the efficiency scores are sensitive to the technique used (quadrant II and quadrant IV), the second group consists of the health facilities that remain efficient on both techniques (quadrant III), and in the last group are the health facilities that remain inefficient using both techniques (quadrant I). Inferences should not be drawn from hospitals in the first group and the second group since they should be considered as outliers Jacobs *et al.* (2006). More critical scrutiny, such as performance assessment and determinants of the inefficiency, should be directed to the third group to improve their efficiency.

5.2. **Contextual variables affecting efficiency.**

Both DEA and SFA were applied to check for the robustness of the association between contextual variables with the estimated efficiency (Nedelea & Fannin, 2012). The study found that the two methods produced different results regarding factors determining efficiency, yet had the same direction. Although no factors were found significant in SFA analysis, second-stage of DEA showed high-performing hospitals were predominantly large, non-teaching hospitals, in deprived areas with a population more likely to be poor and less likely to be educated to secondary school standard. This difference might be due to a different interpretation of inefficiency, where SFA considers a random component in measurement (Varabyova & Schreyogg, 2013).

The size of the hospital was one of the internal factors found to be associated with efficiency. Study by Colombi *et al.* (2017) and Xenos *et al.* (2017) found that large-sized hospitals have higher efficiency than small-sized hospitals. Large size of health facilities was also found to have better utilisation and higher bed occupancy rate compared to small ones (Mobley & Magnussen, 1998). This result must be explained by the fact that larger hospitals tend to have better management and reallocation of human resources using performance target, and have information technology capability, innovations (Mitropoulos *et al.*, 2013; Shettian, 2017). However, Mitropoulos *et al.* (2013) found that both medium and large-scale hospitals had lower level of efficiency. These mixed results found in the previous studies might be explained by the argument that the effect of the size of the health facility was different depending on location with larger hospitals found to be more efficient in urban area while smaller hospitals were more efficient in a rural area (Asmild *et al.*, 2013).

In addition to size, teaching hospitals were found contributing negatively to efficiency. This occurs because health care services are not their only objective. Teaching hospitals are also responsible for teaching and research, thus treatment may last longer than medically required (Xenos *et al.*, 2017). These results agree with the findings of other studies in which teaching hospitals costs are higher compared to non-teaching hospitals because hospitals provide sub-specialised health care services, severe cases -referred from other hospitals-, and a large share of medical graduate training of residency (Medin *et al.*, 2011; López-Casasnovas & Saez, 1999). This result therefore needs to be interpreted with caution. Additional indicators need to be considered to assess teaching hospitals efficiency, such as teaching and research costs, number of citations, and publications (Medin *et al.*, 2011)

Contrary to expectations, this study found a positive association between the proportion of patients with non-communicable disease conditions and efficiency. Dealing with non-communicable diseases suggests that more health resource are demanded because of the complexity and severity of condition (Herr, 2008; Medin *et al.*, 2011). A possible explanation for these results might be due to the difference in the demand for health-care services for each condition (Cellini *et al.*, 2000). The prevalence of non-communicable diseases such as cardiovascular disease and diabetes is increasing. Most of them need regular follow-up visits and hospitalisation, therefore increasing utilisation in general (IHME, 2016; Khanal, 2017; Gonçalves *et al.*, 2015).

Ownership is a particularly important variable when examining efficiency (Hollingsworth, 2008). Findings of the current study are consistent with the review of Herrera *et al.* (2014) that found inconclusive results whether public or private hospitals have better performance. Although a recent study by Guerrini *et al.* (2017) showed private hospitals perform better than public hospitals in productivity and cost because private sectors have a flexibility to manage their health workers and purchasing medicine and medical equipment. Private hospitals also may offer salary structures below the market rate and part-time contract staff, allowing them to make savings Chatterjee *et al.* (2013); Ensor & Indradjaya (2012). In contrast to earlier findings, however, Herr (2008) found both private for-profit and non-profit ownership hospitals are less efficient than public hospitals in Germany. There are several possible explanations for this result. Public hospitals usually have more resources such as staff, beds, and medical technologies, and thus they can treat more patients compared to private hospitals (Asbu *et al.*, 2012; Lee *et al.*, 2008). Another explanation is that public hospitals have more room to reinvest their profits in capital, including high-tech medical equipment and training medical personnel, while private hospitals often pay higher salaries to recruit qualified personnel to pursue physician-attracting strategies (Lee *et al.*, 2008; Helmig & Lapsley, 2001). Moreover, differences between the efficiency of public and private hospitals might also be due to the differences in the payment mechanism. Study by Barbetta et al., 2007 found convergence in the efficiency of not-for-profit private hospitals and public hospitals after they employed a common DRG-based payment system.

With respect to external factors, the results on geography match those observed in earlier studies by Barnum & Kutzin (1993). Health facilities in Java island were more efficient compared to those on the other islands. These factors suggest that a better transport and health facility infrastructure is important to reduce physical barriers to health care access. However, negative association was observed in this study between access to health facility and efficiency. This study has been unable to demonstrate that access to primary health care facilitated more access to hospitals, perhaps through referrals and increased case detection (Silva & Powell-Jackson, 2017). This rather contradictory result may be due to the fact that areas with better access to primary care higher, namely urban areas, also have higher hospital concentration. This higher concentration leads to lower demand in each hospital, therefore decreasing technical efficiency Nedelea & Fannin (2013); Cellini *et al.* (2000) Difficulty in accessing primary care facilities and lack of trust of primary care facilities quality , patients often by-pass primary care services and directly access hospital emergency services (Gonçalves *et al.*, 2015; Yip & Hsiao, 2014). Another possible explanation for this is that avoidable hospital admissions decreases due to better access to primary care. A systematic review by Rosano *et al.* (2013) found a 75% inverse association between primary care access and hospitalisation.

Another important finding is the positive association between the health insurance coverage scheme for the poor and efficiency; this suggests that the scheme reduces financial barriers to health care access and increases the levels of utilisation. It is possible therefore that hospitals in deprived areas treat more patients with access to the insurance scheme for the poor. Another aspect to be considered is the fact that hospitalisation is positively associated with less education and lower economic classes, people who frequently face risk factors such as obesity, smoking and sedentary lifestyle (Gonçalves *et al.*, 2015). However, US published studies by (Nedelea & Fannin, 2013) and (Rosko & Mutter, 2010) found an inconclusive effect of Medicaid admission on efficiency. In addition, the Indonesian insurance scheme for the poor uses the prospective payment mechanism. In general, a prospective payment mechanism gives health providers strong incentives to operate efficiently by reducing the average lengths of stay and minimise cost (Hsu, 2010; Herr, 2008; Xenos *et al.*, 2017).

5.3. **Policy implications.**

Improving technical efficiency in hospitals is crucial because of hospitals represent a high share of overall health expenditure while providing key services to improve population health. To ensure resources are spent as intended, assessing efficiency is fundamental to decision-making process. There are different methods to measure efficiency and policymakers need to understand the advantages and disadvantages of these methods and integrate efficiency measurement into regular monitoring health system.

In the areas where health facilities are highly concentrated, there were found to be waste of excess health resources. Therefore, better reallocation of health care resources is expected to improve technical efficiency. However, public hospitals mostly have little autonomy because of bureaucratic and government regulations (Yip & Hsiao, 2014). Therefore, public hospitals need more flexibility in purchasing including hiring and firing decisions to ensure competition can lead to improvements in efficiency by meeting demand.

Although high performing hospitals were found in the area with less concentration of health facilities, the policy implication of this result should be interpreted with caution. This result might be due to poor primary care services in such area, leading to higher utilisation of hospitals as secondary care. Therefore strengthening and improving quality and quantity of primary care in rural areas, where availability of health services and basic equipment is often poor, is very much needed (Mahendradhata *et al.*, 2017). This will encourage patient to access primary care first before accessing hospitals, thus reducing unnecessary hospitalisation. Integration between hospital and primary care facilities is important to increase the overall efficiency of the health system in order to achieve universal health coverage.

Another policy implication of this study is the importance of universal health coverage in a country. One of the aims of universal health coverage is to protect people from catastrophic health expenditures, thus improving their access to health services. The expansion of UHC coverage is therefore expected to increase utilisation, leading to efficiency. Apart from population coverage, international experience has also shown that single-payer systems in UHC have the ability to become a strategic purchaser and control the health expenditure growth (Yip & Hsiao, 2014).

5.4. **Limitations.**

This study has some limitations due to the nature of the data and methods used. The study could be repeated using recent and longitudinal data, which would highlight changes in efficiency due to policy changes or interventions especially in implementation of national health insurance in 2014 in Indonesia. In addition, longitudinal data would help address outlier data, and whether these are true outliers or simply measurement errors. This study shows that it is feasible to undertake national-level assessments with different types of hospitals and its contextual factors. Further research should be done to investigate the hospital efficiency due to expanding primary health care.

6. Conclusions

The results of this empirical study indicate a wide variation in efficiency between hospitals. Internal (e.g. size, type of hospitals, etc) and external factors (e.g. geographical location, health insurance coverage, and education) were shown to be important in determining hospitals efficiency. High-performing hospitals were generally located in less concentrated health facilities and deprived areas. Hospitals in areas where there is high insurance coverage of the poor, located in Java and Bali Island performed better than in other geographical locations. Another notable finding is that efficiency of health facility cannot be explained by the health facility quality and ownership. Routine efficiency measurement is therefore important to be incorporated into regular health system monitoring.

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Table 1. Input and output variables

Variables	Definition	Measurement	Data source
Input variables			
doctor_no	Doctors	Total number of doctors	HFCS
nurse_total	Nurses and midwives	Total number of nurses and midwives	HFCS
other_prof	Non-medical staff	Total number of non-medical staff	HFCS
gp_FTE	Non-specialist doctor	Full time equivalent of non-specialist doctor	HFCS
spec_FTE	Specialist doctor	Full time equivalent of specialist doctor	HFCS
beds	Beds	Total number of beds	HFCS
Output variables			
outpatients	Outpatient visit	Total number of outpatient visits per year	HFCS
bed_days	Bed days	Total number of bed-days per year	HFCS
admisdeath	Adjusted admission	Total number of admission x (1-admission death rate) per year	HFCS
tot_surgery	Total surgery	Total number of surgery per year	HFCS
amb.bed	Outpatient and bed-days	Total number of outpatient + bed-days	HFCS
amb.admis	Outpatient and adjusted admission	Total number of outpatient + adjusted admission	HFCS
amb.admis.surg	Outpatient, adjusted admission and total surgery	Total number of outpatient + adjusted admission + total surgery	HFCS

HFCS: Health facility costing study

Table 2. PCA Variables

Description	PC1 loading	New variable	Test	Statistics			
			Bartlett test (p-value)	KMO	Mean	Min	Max
Water disruption in health facility in the past year	0.50	disruption_index	0.000	0.705	0.000	-2.793	2.274
Electricity disruption in health facility in the past year	0.43						
Medicine disruption in health facility in the past year	0.43						
Employee salary was late on schedule in the past year	0.40						
Employee incentive was late on schedule in the past year	0.47						
Regular meetings to discuss the performance of services (medical and management) once per week	-0.09	less_monitor _management_index	0.000	0.528	0.000	-0.887	5.684
Meetings to discuss the case of deaths in health facility, not limited to clinical staff but also the elements of management are being held, once per year or more	-0.37						
Regular Mentoring with clinical staffs	-0.66						
Regular Monitoring of working hours of the employee	-0.65						
Curative household expenditure for the last three months including expenditure on public or private hospitals, Puskesmas, Clinic, Medical practice (midwife/ nurse), traditional medicine, traditional delivery attendance	0.54	health_exp _index	0.000	0.655	0.000	-2.457	3.675

Description	PC1 loading	New variable	Test		Statistics		
			Bartlett test (p-value)	KMO	Mean	Min	Max
Preventive household expenditure for the last three months including expenditure on antenatal care, immunisation, medical check-up, family planning, other preventive expenditure	0.62						
Pharmacy household expenditure for the last three months including prescribed drugs, drugs without prescription, traditional drugs, glasses, protease, wheel chair.	0.57						
Proportion of family working in agriculture	-0.71	wealthy_economy_index	0.000	0.500	0.000	-5.421	1.628
Proportion of poor population in district	-0.71						
Ratio of hospital, including general hospital and maternal hospital over 1000 population	0.08	access_healthfac_index	0.000	0.528	0.000	-2.300	8.628
Ratio of primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post over 1000 population	0.45						
Proportion of very easy and easy to access hospital, including general hospital and maternal hospital	0.61						
Proportion of very easy and easy to access primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post	0.64						
Proportion of population with secondary school education in the district	0.56	higher_education_index	0.000	0.537	0.000	-2.772	3.049
Proportion of population with higher education in the district	0.56						

Description	PC1 loading	New variable	Test		Statistics		
			Bartlett test (p-value)	KMO	Mean	Min	Max
Proportion of population with primary school education in the district	-0.61						

TABLE 3. Explanatory variables

Variables	Definition	Measurement	Data source
Internal factors			
class2	Class A or B	Class of hospitals: 1 if class A or B, and 0 if class C or D.	HFCS
mou_ed_hospital	Teaching status	Whether hospital has an MoU or partnership with medical education university: 1 if yes, and 0 if not.	HFCS
publichospital	Public ownership	Ownership of hospitals: 1 if public, and 0 if private	HFCS
disruption_index	Index of disruption in health facilities	Principal component analysis score of water disruption, electricity disruption, missing medicine, delay of salary payment, delay of allowance payment	HFCS
less_monitor _management_index	Index of less management	Principal component analysis score of no regular meeting of service performance, no regular meeting to discuss cases, no mentoring clinical staffs, and no monitoring of working hours of employee	HFCS
ncd_disease	Non-communicable diseases	Proportion of non-communicable disease treated	HFCS
prop_r52f_1_4thn	Proportion of patients between 1 to 4 years old	Total number of patients between 1 to 4 years old divided by total number of all patients	HFCS
External factors			
health_exp_index	Index of health expenditure per household	Principal component analysis score of household curative expenditure, preventive expenditure, pharmacy expenditure	SUSENAS
wealthy_economy_index	Index of population economy	Principal component analysis score of less family proportion working in agriculture, and less proportion of poor population	PODES and SUSENAS
population2011per1000	Population	Number of population in sub-district in '000 in year 2011	PODES
access_healthfac_index	Index of health facilities availability	Principal component analysis score of less number of hospital per population, number of primary care facilities per population, proportion of villages that have easy access to hospitals, and proportion of villages that have easy access to primary care facilities.	PODES

Variables	**Definition**	**Measurement**	**Data source**
higher_education_index	Index of population education level	Principal component analysis score of district population proportion with primary school education, less secondary education, and less higher education	SUSENAS
JavaBali	Java and Bali island	Whether primary care facility is in Java or Bali island: 1 if yes, 0 if not	HFCS
jamsostekins	Employee insurance scheme	Proportion of household covered by Jamsostek insurance (scheme for employee)	SUSENAS
askesins	Civil servant insurance scheme	Proportion of household covered by Askes insurance (scheme for civil servant)	SUSENAS

HFCS: Health facility costing study; SUSENAS: National Socioeconomic Survey ; PODES: village potential statistics

Table 4. Model specifications

	DEA[a]												SFA[b]											
	I1	I2	I3	I4	I5	I6	O1	O2	O3	O4	O5	O6	CD1	CD2	CD3	C1	C2	C3	TD1	TD2	TD3	T1	T2	T3
Input																								
doctor_no		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X
nurse_total	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
other_prof	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
gp_FTE	X			X			X			X			X			X			X			X		
spec_FTE	X			X			X			X			X			X			X			X		
beds	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Output																								
ambulatory1	X	X	X				X	X	X				X	X	X				X	X	X			
bed_days			X						X						X						X			
admisdeath	X	X					X	X					X	X					X	X				
tot_surgery	X						X						X						X					
amb.bed						X						X						X						X
amb.admis					X						X						X						X	
amb.admis.surg				X						X						X						X		

[a] I1-I6 are input-oriented and O1-O6 are output-oriented of DEA models
[b] CD1-CD3 are multi output distance function, C1-C3 are Cobb-Douglas function, TD1-TD3 are Translog distance function, and T1-T3 are Translog function of SFA models
X indicates that the variable is included into the model

Table 5. The Spearman rank correlation coefficients across various model specifications

	I1	I2	I3	I4	I5	I6	O1	O2	O3	O4	O5	O6	CD1	CD2	CD3	C1	C2	C3	TD1	TD2	TD3	T1	T2	T3
I1	1.00																							
I2	0.86	1.00																						
I3	0.75	0.80	1.00																					
I4	0.67	0.72	0.58	1.00																				
I5	0.56	0.73	0.57	0.94	1.00																			
I6	0.59	0.76	0.60	0.94	0.99	1.00																		
O1	**0.80**	0.64	0.63	0.31	0.23	0.26	1.00																	
O2	0.68	**0.69**	0.68	0.27	0.25	0.29	0.83	1.00																
O3	0.55	0.54	**0.81**	0.22	0.21	0.24	0.68	0.78	1.00															
O4	0.46	0.36	0.44	**0.11**	0.05	0.08	0.73	0.65	0.61	1.00														
O5	0.32	0.31	0.41	-0.01	**-0.01**	0.03	0.61	0.68	0.66	0.90	1.00													
O6	0.33	0.31	0.47	-0.01	-0.02	**0.02**	0.62	0.70	0.74	0.88	0.98	1.00												
CD1	0.34	0.32	0.21	-0.06	-0.07	-0.05	**0.48**	0.55	0.38	0.28	0.29	0.28	1.00											
CD2	0.33	0.34	0.23	-0.03	-0.05	-0.02	0.44	**0.55**	0.39	0.28	0.29	0.29	0.98	1.00										
CD3	0.29	0.28	0.44	0.04	0.00	0.04	0.33	0.41	**0.59**	0.20	0.20	0.27	0.74	0.75	1.00									
C1	0.31	0.24	0.24	0.11	0.07	0.10	0.39	0.44	0.38	**0.58**	0.56	0.52	0.59	0.60	0.54	1.00								
C2	0.22	0.23	0.20	0.09	0.09	0.12	0.31	0.41	0.34	0.54	**0.56**	0.51	0.58	0.61	0.51	0.96	1.00							
C3	0.24	0.25	0.31	0.10	0.08	0.12	0.34	0.45	0.48	0.51	0.53	**0.52**	0.64	0.66	0.71	0.93	0.95	1.00						
TD1	0.40	0.35	0.25	-0.01	-0.02	0.00	**0.54**	0.54	0.40	0.36	0.34	0.33	**0.78**	0.77	0.54	0.52	0.51	0.52	1.00					
TD2	0.39	0.37	0.30	0.00	-0.04	-0.01	0.51	**0.62**	0.48	0.38	0.38	0.37	0.85	**0.86**	0.62	0.57	0.55	0.58	0.88	1.00				
TD3	0.25	0.19	0.41	-0.05	-0.10	-0.07	0.32	0.38	**0.63**	0.22	0.23	0.30	0.65	0.65	**0.87**	0.46	0.42	0.59	0.61	0.70	1.00			
T1	0.31	0.23	0.22	0.10	0.05	0.08	0.39	0.42	0.35	**0.58**	0.56	0.51	0.52	0.53	0.45	**0.92**	0.89	0.84	0.58	0.57	0.45	1.00		
T2	0.24	0.22	0.21	0.08	0.07	0.10	0.32	0.41	0.35	0.56	**0.58**	0.52	0.53	0.55	0.45	0.93	**0.97**	0.90	0.56	0.59	0.44	0.93	1.00	
T3	0.26	0.23	0.31	0.07	0.05	0.08	0.36	0.44	0.49	0.56	0.57	**0.55**	0.56	0.58	0.59	0.90	0.92	**0.92**	0.59	0.64	0.63	0.90	0.96	1.00

I1-I6 are input-oriented and O1-O6 are output-oriented of DEA models
CD1-CD3 are multi output distance function, C1-C3 are Cobb-Douglas function, TD1-TD3 are Translog distance function, and T1-T3 are Translog function of SFA models

TABLE 6. Hospital statistics

	Overall
n	200
doctor_no (median [IQR])	34.73 [21.98, 50.12]
gp_FTE (median [IQR])	13.01 [9.15, 18.84]
spec_FTE (median [IQR])	13.10 [6.23, 25.36]
nurse_total (median [IQR])	152.50 [95.24, 215.00]
other_prof (median [IQR])	110.50 [56.00, 194.00]
beds (median [IQR])	123.50 [89.00, 197.75]
outpatients (median [IQR])	34690.51 [14208.33, 78412.54]
bed_days (median [IQR])	27136.00 [15138.00, 43486.42]
admissions1 (median [IQR])	7625.00 [4306.00, 10996.33]
death_rate (median [IQR])	0.01 [0.01, 0.01]
tot_surgery (median [IQR])	1309.50 [537.50, 2710.75]
prop_r52f_1_4thn (median [IQR])	8.24 [6.24, 10.95]
disruption_index (median [IQR])	0.28 [-0.69, 1.29]
less_monitor_management_index (median [IQR])	-0.14 [-0.69, 0.06]
access_healthfac_index (median [IQR])	-0.17 [-0.69, 0.19]
ncd_disease (median [IQR])	38.17 [31.93, 43.76]
jamsostekins (median [IQR])	0.05 [0.01, 0.10]
askesins (median [IQR])	0.12 [0.08, 0.17]
poorins (median [IQR])	0.17 [0.12, 0.26]
higher_education_index (median [IQR])	-0.35 [-1.30, 1.54]
health_exp_index (median [IQR])	-0.31 [-1.16, 1.13]
population2011per1000 (median [IQR])	393.08 [209.20, 1003.59]
wealthy_economy_index (median [IQR])	0.00 [-0.88, 1.25]
class2 = Class A/B (%)	54 (27.0)
mou_ed_hospital = Teaching (%)	64 (32.0)
publichospital = Public (%)	122 (61.0)
JavaBali = Jawa and Bali (%)	79 (39.5)

TABLE 7. DEA and SFA efficiency score in hospitals

Statistic	N	Mean	St. Dev.	Min	Median	Max
DEA	200	0.61	0.23	0.11	0.58	1.00
SFA	200	0.67	0.18	0.14	0.70	0.93

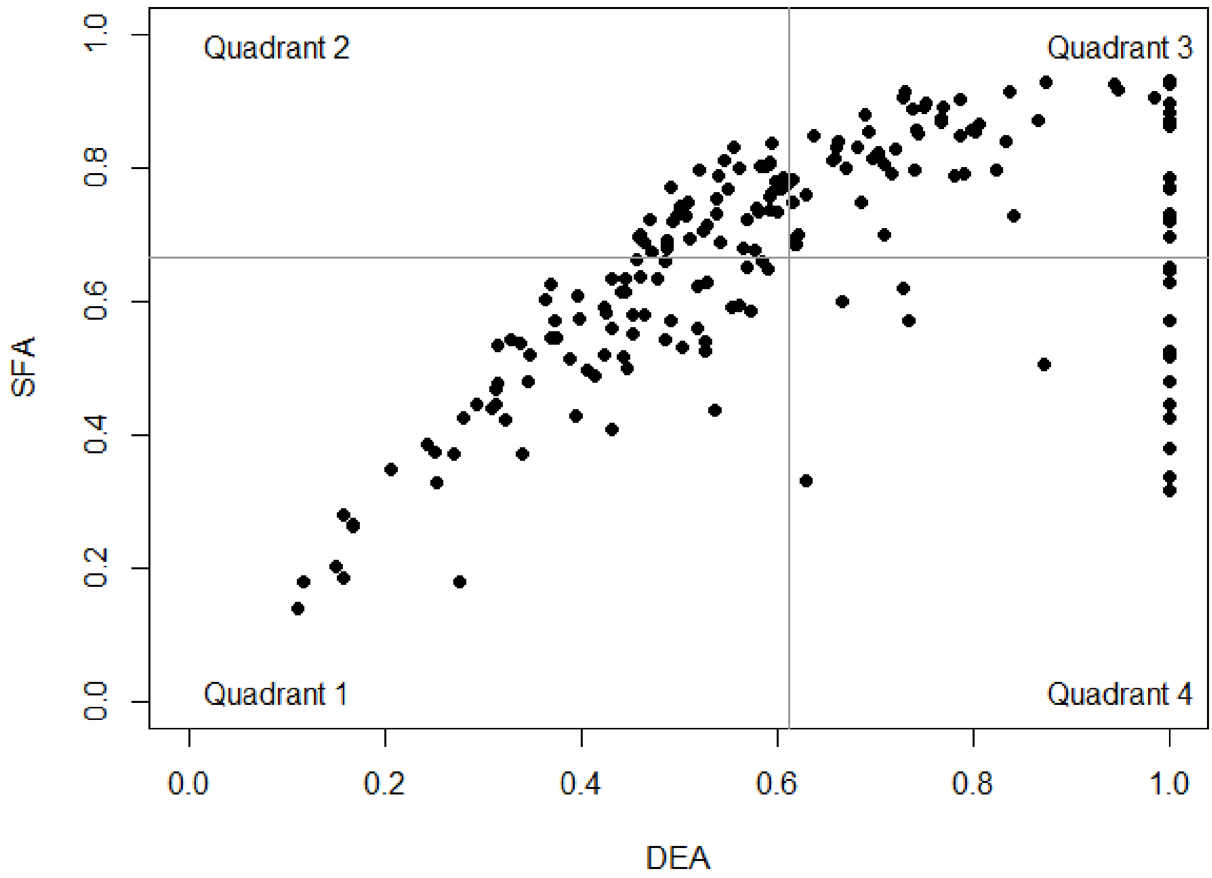

FIGURE 1. Quadrant scatter plot of DEA and SFA scores estimated in Hospitals

TABLE 8. Statistic by efficiency quadrant

	1	2	3	4	p	test
n	70	43	69	18		
DEA (mean (sd))	0.39 (0.12)	0.54 (0.05)	0.80 (0.14)	0.92 (0.13)	<0.001	
SFA (mean (sd))	0.50 (0.13)	0.74 (0.05)	0.83 (0.07)	0.51 (0.12)	<0.001	
doctor_no (mean (sd))	39.14 (24.92)	41.98 (16.40)	46.62 (57.85)	38.76 (47.88)	0.717	
nurse_total (mean (sd))	150.84 (85.31)	185.96 (97.87)	209.91 (191.57)	138.59 (132.16)	0.047	
other_prof (mean (sd))	126.89 (82.32)	162.79 (106.38)	166.38 (169.27)	122.50 (194.72)	0.245	
beds (mean (sd))	134.99 (76.57)	131.37 (63.27)	190.30 (151.52)	195.11 (205.73)	0.012	
outpatients (mean (sd))	38,534.57 (48,330.63)	53,759.87 (48,024.80)	111,886.43 (140,536.13)	81,850.34 (175,042.90)	<0.001	
bed_days (mean (sd))	20,490.95 (13,621.72)	31,138.76 (12,119.45)	53,597.59 (43,091.28)	34,470.87 (44,607.14)	<0.001	

TABLE 9. Regression on explanatory variables results in Hospitals

Variables	DEA (model 1)			DEA (model 2)			DEA (model 3)			SFA (Model 1)		SFA (Model 2)		SFA (Model 3)	
	Est.	SE		Est.	SE		Est.	SE		Est.[a]	SE	Est.[a]	SE	Est.[a]	SE
Internal factors															
Disruption index	0.00	0.02		0.00	0.02		0.00	0.02		-0.33	0.37	-0.28	0.24	-0.20	0.16
Less management index	-0.04	0.02	*	-0.04	0.02	**	-0.04	0.02	*	-0.20	0.23	-0.20	0.18	-0.14	0.14
% patient 1-4 years	0.00	0.00		0.00	0.00		0.00	0.00		0.02	0.05	0.03	0.05	0.02	0.03
% NCD patients	0.00	0.00	*	0.00	0.00	*	0.00	0.00	*	0.03	0.02	0.03	0.02	0.02	0.01
Class A/B	0.19	0.06	**	0.20	0.06	***	0.22	0.06	***	2.34	1.72	2.30	1.61	2.11	1.39
Public hospital	0.00	0.05		-0.03	0.05		-0.05	0.05		-0.18	1.00	-0.21	0.61	-0.11	0.42
Teaching hospital	-0.11	0.05	*	-0.11	0.05	*	-0.11	0.05	*	-0.27	0.73	-0.23	0.58	-0.08	0.32
External factors															
Insurance for civil servant	0.03	0.37								1.49	6.21				
Insurance for the poor	0.47	0.16	**							2.87	2.32				
access to health fac index	-0.03	0.01	*	-0.04	0.01	**	-0.04	0.01	**	-0.17	0.19	-0.17	0.15	-0.14	0.11
In Java Bali	0.12	0.05	*	0.09	0.05	.	0.08	0.05	.	3.51	4.02	2.42	2.22	1.37	1.12
Population (in 1000)	0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00
wealth index				-0.05	0.02	**						-0.39	0.27		
higher education index							-0.04	0.01	**					-0.32	0.21
Constant	0.40	0.11	***	0.53	0.09	***	0.54	0.09	***	0.25	2.11	0.61	1.92	0.17	1.16
R2	0.20			0.19			0.19			0.92		0.92		-0.91	
sigma	0.24	0.02		0.24	0.02		0.24	0.02							
sigmaSq										0.84	0.67	0.77	0.55	0.66	0.42
gamma										0.92	0.07	0.92	0.06	0.92	0.05
Log Likelihood	46.09			45.08			44.72			-68.33		-68.21		0.91	

Significance level: ***0.001, **0.01, *0.05; [a] The coefficients are multiplied with -1 to obtain the effects on efficiency ; Sigma (σ) is the estimated standard deviation of the assumed left-truncated distribution; SigmaSq (σ^2) is the estimate of total variance ; Gamma (γ) is the fraction of the total variance attributable to inefficiency; Est.= Estimate; SE=standard error