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Assessing primary care performance in Indonesia: An application of frontier analysis techniques

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Abstract

Despite increased national health expenditure in health facilities in Indonesia, health outcomes remain low. The aim of our study is to examine the factors determining the relative efficiency of public primary care facilities. Using linked national data sources from facility-, households, and village-based surveys, we measure the efficiency of 185 primary care facilities across fifteen provinces in Indonesia with output oriented data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Inputs include the number of doctors, midwife and nurses, and other staff while outputs are the number of outpatients and maternal child health patients. 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 primary care facilities are in affluent areas. Primary care facilities located in urban areas, in Java and Bali Island, with high coverage of insurance scheme for the poor perform better than other geographical location. We find an inconclusive impact of quality of care, patient mix, and availability of inpatient services on efficiency. This paper concludes by highlighting the characteristics of primary care facilities that have the potential to increase efficiency.

1 Introduction

Health care costs are rising rapidly in Indonesia placing and increasing strain on limited resources. Between 1995 and 2014, total healthcare expenditure per capita in Indonesia grew rapidly from US$ 20 to US$ 99, a higher increase than in lower middle-income countries over the same period (World Bank Data, 2016a). Even though there was a significant increase in nominal spending between 2005 and 2014, health care expenditure at 3% of Gross Domestic Product (GDP) remains low compared to other lower middle-income countries (average 4.5%) (World Bank Data, 2016b). The report on national health accounts shows that ambulatory care has relatively smaller funding allocations compared to hospitals. The general pattern shows that total spending on ambulatory care in Indonesia is just below 20%, which is 5% lower than in Asia-Pacific countries on average (Soewondo et al., 2011; Sari et al., 2015; Hopkins et al., 2010). The allocation for primary care only represents 15% of the overall budget under the current Indonesia national health insurance (Langenbrunner et al., 2014).

With limited funding for primary care facilities, there is an indication of sub-optimal healthcare utilisation. The average contact rate in public primary care (Puskesmas) was just above one visit per person per year compared to 3.5 in Malaysia, 2.3 in Vietnam and 2.1 in Thailand (Ensor and Indradjaya, 2012; OECD/World Health Organization, 2014; Cashin et al., 2002). Maternal mortality rate in Indonesia, with 133 per 100.000 live births, is generally higher than in other Asian Countries with similar or lower level of GDP per capita; 117 in the Philippines, 54 in Vietnam, 46 in Mongolia and 31 in Sri Lanka (World Bank, 2015). Making better use of the primary care resources by increasing the technical efficiency of healthcare delivery is an important policy issue and topic of research. Global evidence shows that primary care facilities play an important role to achieve universal health coverage and improve population health (Hsieh et al., 2013; Ikegami, 2016). Primary health care also contributes to improving equity for the poor to access care at reasonably low cost (Stigler et al., 2016; Kruk et al., 2010; Starfield et al., 2005). Most essential care and health interventions can be delivered at primary care level, and primary care facilities have a responsibility in public health care activities, including disease prevention and health promotion (Starfield, 1994).

However more than half of the worldwide studies on efficiency of health care facilities were conducted in hospitals while primary care facilities only represent between 10 to 20% (Hollingsworth, 2008; Hussey et al., 2009). Broadly, two main approaches have been used within the literature to measure efficiency: Data Envelopment Analysis (DEA) techniques, and

Stochastic Frontier Analysis (SFA). Most studies measured technical efficiency alone with one of the techniques, and without contextual variables (Hollingsworth, 2008; Hussey et al., 2009). The purpose of this paper is to examine the relative efficiency of health facilities using frontier analysis and identify factors determining the relative efficiency of primary care facilities. We applied both DEA and SFA to study the variation in productivity in Indonesian primary care facilities. We estimated the level of efficiency for each primary care facility along with the determining factors of the efficiency, including internal and external characteristics of primary care providers.

The rest of the paper is organised as follows. Section 2 provides a description of the public primary care facilities in Indonesia. Section 3 describes the methodological approach employed to analyse technical efficiency and the data. Section 4 presents the results and policy and practice implications are discussed in Section 5.

2 Primary care facilities in Indonesia

In Indonesia, primary care can be provided through public and private providers. Since we did not include private primary care in this study, the term “primary care facilities” used in this article refers to public primary care facilities. These facilities are the non-specialist health services, located at the sub-district level with a network in villages and accountable to District Health Office authorities. Three-quarters of primary care facilities are located in rural areas ensuring all Indonesians have access to care. In 2015, there were 3,396 primary care facilities with inpatient services, and 6,358 primary care facilities without inpatient services (Kemenkes, 2016). Primary health care facilities are responsible for both curative and preventive healthcare services. Primary health care facilities provide essential services such as a general clinic, maternal and child health (MCH), and disease control and prevention (Kemenkes, 2012).

Under the national health insurance, primary care facilities have an important role to play as gatekeepers. Health care seekers need to visit primary care facilities before accessing hospitals, except emergency cases. To expand primary care providers, national health insurances contracted private primary care providers. People are free to register in both public and private primary care facilities except people under the insurance scheme for the poor (Jamkesmas), who can only use public facilities. Competition between health facilities is expected to improve efficiency and quality (Le Grand, 2009; Propper, 2012). Hence a prospective payment mechanism employing a monthly capitation based on the number of registered population is employed to encourage efficiency in both public and private primary care facilities (Pantilat et al., 1999; Trisnantoro et al., 2014).

3 Materials and methods

3.1 Data

This study assesses the determinants of productivity in health facilities by analysing data from three different sources. The first source 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 the services, resources (infrastructure, equipment, staff, pharmaceuticals, and medical supplies), and expenditures (e.g. office supplies, maintenance, and transport expenses) for 234 public primary care facilities (3% of the public primary care facilities). 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 level 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 dataset and the MoH health facility survey data using districts identifiers for primary care facilities while the PODES dataset was merged with the MoH health facilities survey using sub-district identifier for primary care facilities.

1.1 Input and output variables

The efficiency analysis is based on a vector of inputs measuring labour and capital in primary care facilities. Five different inputs are considered: (1) the number of doctors, (2) the number of nurses (3) the number of midwives, (4) the number of other staff, and (5) the value of medical asset (Table 1). Three outputs are considered: (1) the number of bed-days, (2) the number of outpatients in general clinic, and (3) the number of outpatients in maternal and child health care (MCH). The choice of the inputs and outputs was guided by past efficiency measurement studies undertaken in primary care facilities (Alhassan et al., 2015; Cordero

Ferrera et al., 2014; Blaakman et al., 2014; Kirigia et al., 2011; Marschall and Flessa, 2009) and covered all primary care facilities production inputs and outputs with the different roles of health workers and types of services. The limited number of primary care facilities with inpatient services meant that our final analysis could not include the number of bed-days. The two specifications of DEA model with and without the number of bed-days were then compared using a Kruskal-Wallis test, which showed no difference between these two specification.

1.2 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, quality, and case-mix index); (2) external factors, outside the influence of a provider that can impact on facility efficiency (e.g. economic status, education level, and geography) (Besstremyannaya, 2013; Cordero Ferrera et al., 2014; Ding, 2014; Frohlof, 2008; Gok and Sezen, 2013; Heimeshoff et al., 2014; Nedelea and Fannin, 2013; Matranga and Sapienzab, 2015; Kirigia and Asbu, 2013; Mitropoulos et al., 2013; Mobley and Magnussen, 1998; Shreay et al., 2014; Varabyova and Schreyogg, 2013; Yang and Zeng, 2014).

Our large dataset with many explanatory variables that are potentially highly correlated can lead to problems for multivariate regression techniques (Everitt and Hothorn, 2011). To address the issue, principal components analysis (PCA) was used to create a smaller number of new variables, which were uncorrelated (Jolliffe and Cadima, 2016). The Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy were 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 and Hothorn, 2011). We thus transformed 21 variables into 6 new index variables: an index of less disruption in health facilities, an index of management, an index of population education level, an index of health expenditure per household, an index of health facility access and an index of primary education. PCA results are presented in Table 2, and all explanatory variables are available in Table 3.

In addition to PCA variables, the initial general model contained all the identified explanatory variables: availability of inpatient services, nurse vacancy, number of population in the sub-district, locations (urban area, Java and Bali islands), and health insurance coverage (employee insurance scheme, civil servant insurance, and poor insurance scheme). We ran several models, checked for multicollinearity and finalised a vector of explanatory variables. We developed two models, while in model 1 location was simply identified by a binary variable for Java or Bali island or not, in model 2 location was replaced by index of population education level, index of health expenditure per household, and population in model 2.

1.3 DEA

We applied DEA to estimate the efficiency scores for each of the providers in the sample. Variables returns to scale (VRS) were applied to run input and output-oriented models to estimate the individual primary care facility efficiency scores. VRS is more flexible than constant returns-to-scale (CRS) which assumes not all primary care facilities are operating at an optimal scale. However, this approach will also make fewer facilities appear as inefficient, particularly where there is much variation in the scale.

Input-oriented efficiency is the maximal proportional contraction of all resources that allows primary care facility to produce services. Under the assumption of output-oriented efficiency, each primary care facility is required to maximise health care services while maintaining the amount of health care resources used constant. In this study, output-orientation was chosen to identify factors determining efficiency because healthcare resources include workforce and capital investment in primary care facilities tends to be fixed and controlled by the government (Mahendradhata et al., 2017). The head of primary care facilities are mostly not able to control the level of inputs.

Input-oriented and output-oriented DEA are interpreted differently. While input-oriented technical efficiency and output-oriented technical efficiency scores both indicate that a primary care facility is operating on the best practice frontier when equal to 1, the inefficiency score in input-oriented DEA will be less than 1 and the output-oriented DEA inefficiency above 1. In order to allow direct comparison between the input-oriented DEA models, we used the reciprocals of DEA output-oriented efficiency scores. .

1.4 SFA

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

$$\ln y = \ln f(x) + v - u \qquad \text{(Eq. 1)}$$

with $v \sim N(0, \sigma_v^2)$ and $u \sim N_+(0, \sigma_u^2)$

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. In this study, we 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 estimated. The Cobb-Douglas function represents the unitary elasticity of substitution and is written as follows:

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + (v_{i-}u_i) \qquad \text{(Eq. 2)}$$

Where j represents the number of independent variables, i the primary care facility, y_i the output of the i-th primary care facility, x_i the input j of the i-th primary care 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 primary care facility i.

As the Cobb-Douglas form is restrictive because it assumes constant elasticity of substitution, 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

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{j,i} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + (v_{i-}u_i) \qquad \text{(Eq. 3)}$$

Where

$\log x_{ji}$ times $\mathrm{lo\,g} x_{hi}$ represents the interaction of the corresponding inputs j and h of the i-th primary care facility.

Both Cobb-Douglas and Translog forms in a standard SFA model were limited to only one output by aggregating general and MCH outpatients into one variable. The sum of the number of treated patients in (Eq. 3) might not be appropriate due to a different type of outputs.

Therefore, we estimated a multi-output distance function and a Translog distance function. The empirical model of distance function form is written

$$\log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \sum_{h=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \qquad \text{(Eq. 4)}$$

The multi-output Translog distance function to the purpose of the current study is

$$\log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2}\sum_{j=1}^{k}\sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + \sum_{h=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}} + \frac{1}{2}\sum_{j=1}^{k-1}\sum_{h=1}^{k-1} \beta_{jh} \log \frac{y_{hi}}{y_{ni}} \log \frac{y_{hi}}{y_{ni}} + \sum_{j=1}^{k}\sum_{h=1}^{k-1} \beta_{jh} \log x_{ji} \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \qquad \text{(Eq. 5)}$$

Where $\frac{y_{hi}}{y_{ni}} = \frac{patients\_mch_i}{patients\_gen_i}$

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

1.5 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, we first used a likelihood ratio test and investigated under the null-hypothesis whether there was 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). Second, Spearman rank correlation test was used to estimate the correlation between the SFA models (i.e. Cobb-Douglas, Translog, and multi-output 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 0.46 to 0.77, and between the SFA models from 0.90 to 0.99 (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 and 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 and SFA efficiencies ranged between 0.46 and 0.84. We found a tendency of negative correlation between internal and external validity correlation estimates suggesting that the disaggregation of health workers as well as services in output definition might considerably reduce the efficiency correlation. Finally, we included two models (models O6 and T3 in Table 5) with moderate internal validity estimate and very strong external validity estimate. The preferred specification of the model included the number doctors, the number of nurses and midwifes, and the number of other staffs among the inputs, and in the outputs the aggregated total number of outpatients and maternal and child health care patients.

1.6 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 primary care facilities 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.

1.7 Explanatory variable analysis

1.7.1 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 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 technical efficiency of health facilities. The appropriate regression for this second stage analysis is an on-going discussion; many studies used a Tobit regression because of the efficiency scores being bound between 0 and 1 (Hoff, 2007; Obure et al., 2016; Alhassan et al., 2015; Pavitra, 2013; Marschall and Flessa, 2011; Marschall and Flessa, 2009), another study argued that OLS is preferred over

Tobit regression because efficiency scores are generated from a fraction, instead censored (McDonald, 2009). A recent study showed that both OLS or Tobit regressions lead to biased and inconsistent estimates because DEA efficiency scores generated are truncated, not censored (Simar and Wilson, 2011). Since efficiency scores higher than 1 is impossible, we consider a 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.

1.7.2 Factors determining efficiency in SFA model

The two-step procedures in SFA model has also been found to be biased because of mis-specified or under-dispersed distribution (Battese and Coelli, 1995; Wang and 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.

1.8 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 and Otto, 2010), and SFA using frontier version 1.1-0 (Coelli and Henningsen, 2013). Truncated regression analysis was applied using the package truncreg version 0.2-4 (Henningsen and 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 outlier. Therefore, we did not drop outlier detected to prevent the loss of valuable information.

Since we applied a SFA multiplicative model, we excluded 49 observations from the sample of inputs and outputs, which were missing or equal to zero. 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 and Otto, 2010), i.e.

$K > 3(m+n)$ and $K > m.n$ where K is the number of health facilities, m the number of inputs and n the number of outputs.

We had 185 facilities, which exceeded the minimum sample of health facilities needed.

2 Results

2.1 Primary care statistics

Table 6 presents the characteristics and activities of primary care facilities. There was a wide variation in the number of outputs and inputs. On average, primary care facilities, including their satellites in villages, produced 18,600 general outpatient visits and 3,800 maternal and child health care visits. Primary care facilities produced these outputs using 4 doctors, 31 nurses and midwives, and 19 other staff on average.

2.2 Technical efficiency

Table 7 shows summary statistics of efficiency between two models; smaller average scores imply lower facility efficiency. The efficiency score in SFA was lower than DEA. The spread of DEA efficiencies was much larger than the spread in the SFA efficiency. There were eight primary care facilities with a DEA efficiency of 1 (i.e. fully efficient) while the maximum efficiency of SFA was 0.90.

The output orientation efficiency is the maximal number of services (output) given the number of health workers (inputs). The average scores of 0.4 in DEA and 0.6 in SFA suggested that we could expand the outputs by 150% and by 67% without spending additional resources. In absolute terms, primary care facilities could expand to 33,636 general outpatient visits and 14,949 maternal and child visits per year without increasing the number of health staff.

Figure 1 shows the scatter plot of primary care facilities; the vertical and horizontal lines represents the mean values of DEA (0.38) and SFA (0.59). It appears that 41% of primary care facilities are low-performing health facilities in the bottom-left (quadrant 1) while 36% are high performing in the upper-right (quadrant 3) with both techniques. A remaining 23% of health facilities are inconclusive (quadrant II and IV). Statistics of quadrant scores between DEA and SFA are presented in Table 8.

2.3 Contextual factors

The results of the two-stage DEA model, the one-step SFA, and the multilevel model are presented in Table 9. The signs of the coefficients between the SFA and DEA were consistent except for health insurance scheme of Askes and Jamsostek between models 1 and 2. The index of less disruption in health facilities, index of management, proportion of patients under 5 years old, and coverage of civil servant insurance scheme were inconclusive on all models.

The results of the truncated regression for DEA efficiency score indicated that availability of inpatient services, the geographic and demographic characteristics, and health insurance coverage were likely to influence inefficiency. For one unit increase in the proportion of population with poor insurance scheme coverage, there was a 0.42 (Model 1) and 0.34 (Model 2) increase in the predicted value of efficiency. For a one-unit increase in primary education index and healthcare expenditure index, there was a 0.07 (Model 1) and 0.05 (Model 2) decrease in the predicted efficiency. Beds availability when located in urban and Java or Bali islands showed a different interpretation. The predicted value of the efficiency score was 0.08 point lower for primary care facilities with beds than for primary care facilities without beds. The predicted value of the efficiency score in Model 1 was significantly higher for primary care facilities in Java or Bali Island, and in urban area.

The estimation of the SFA results cannot be directly interpreted as an efficiency score. For a one-unit increase in the proportion of the population with poor insurance scheme coverage, there were on average a 3.10 and a 2.99 increase in the predicted value of outpatient services, in respectively model 1 and model 2 (calculated as $\exp(estimate)$). Primary care facilities in urban areas produced 1.93 (Model 1) and 1.65 (Model 2) times as many outpatient services as rural areas with the same input quantities. In addition, the marginal effects of the contextual variables can be interpreted as the effect on the efficiency estimates. On average, primary care facilities in Java Bali Island, and urban areas were 4 and 10 percentage points (model 1 and model 2 respectively) more efficient than primary care facilities outside Java Bali Island, and rural areas. A one-unit increase in health insurance coverage scheme for the poor showed a 10 and 20 percentage points increase in the predicted value of efficiency. The predicted value of the efficiency score was significantly higher for primary care facilities in more educated population. However, the marginal effect of population coverage on efficiency was very small (0.1%).

3 Discussion

3.1 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, hence it is important to develop several specifications and employ both methods in tandem to act as a signal tool to find how results change (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 obtained may show inconsistency in individual efficiency level as best or worst performers (Mathiyazhagan, 2007; Chirikos and 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).

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

Health facilities as shown in Figure 1 can be grouped into three main groups. The first group consists of health facilities 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 on both techniques (quadrant I). Jacobs et al. (2006) suggested that conclusion should not be drawn from health facilities in the first group, as well as health facilities in the second group since they are considered as outliers. Meanwhile, more critical scrutiny, such as performance assessment and determinants of the inefficiency, should be directed to the third group to improve their efficiency.

3.2 Contextual variables affecting efficiency

We used both DEA and SFA to check the robustness of the association of contextual variables on the estimated efficiency (Nedelea and Fannin, 2012). We found mostly similar patterns in results in terms of factors determining efficiency. There was a significant effect of health insurance coverage, geographic location, and education level on efficiency while there was no significant effect of quality (as proxied by disruption index and monitor management index) nor of patient mix in health facilities. However, the relationship between health insurance coverage for employee scheme and efficiency was not consistent between SFA and DEA. This difference might be due to a different interpretation of inefficiency, where SFA considers a random component in measurement (Varabyova and Schreyogg, 2013).

In this study, high-performing primary care facilities were found in affluent areas particularly in urban areas and Java and Bali islands. As it has been shown elsewhere, the health facilities in rural areas were found to have lower performance than urban areas (Ramanathan et al., 2003; Pavitra, 2013). Rural areas with low-density population and inferior access are associated with a decreased use of services, and a reduced productivity of the health facilities (Ramanathan et al., 2003; Pavitra, 2013; Rattanachotphanit et al., 2008; Soucat et al., 1997). Regarding geographical location, Berman et al. (1989) supports our results that the higher performing primary care facilities are in Java provinces. Java is the most densely populated island in Indonesia with more developed infrastructure (Badan Pusat Statistik, 2015). Health facilities found to be efficient were in regions where there are better health care resources, such as the high ratio of population per health workers and facilities (Puenpatom and Rosenman, 2008). Noticably the population in Java and Bali islands and urban areas has higher education level and economic status. Education has proved to be a key input for population health and is positively correlated with the efficiency of health facilities (Spinks and Hollingsworth, 2009; Varabyova and Schreyogg, 2013).

Nevertheless, other evidence showed that primary care facilities located in rural areas had higher technical efficiency than those located in urban areas. This higher efficiency in rural area might be caused by higher utilisation of primary care by patients with low socioeconomic status who mostly live in this area (Dandona et al., 2005). Primary care facilities in urban areas however, have to compete with private sector health facilities, which are seen as providing better services than the public sector (Alhassan et al., 2015).

Our result demonstrated that better performing primary care facilities were associated with high health insurance coverage, especially the poor insurance scheme. Health insurance protects people from financial catastrophe and reduces financial barriers to access health care. The increasing health insurance coverage encourages health care demand and improves efficiency of health facilities and access to services, especially for the poor. However, we did not find a significant association between the insurance scheme for civil servants and efficiency of primary care facilities. The reason for this is not clear, but it may be due to the differences in regulation between insurance schemes since civil servants can register in private primary care facilities where presumably care quality is perceived to be higher (Mundiharno and Thabrany, 2012).

3.3 Policy implications

Investment in primary care for public health programmes and prevention activities would save lives, increase the quality of life, harvest economic benefits in terms of reduced health care costs, and increase productivity (Langenbrunner et al., 2014). To ensure resources are spent as intended, efficiency measurement is crucial in the 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.

We found waste of health resources at several levels, especially facilities located in rural area. However, downsizing or closure of health facilities would not be a practical intervention since this is likely to reduce overall demand as physical access becomes more difficult. Transport infrastructure to access health care is the main reason for reduced use of health facilities (Marschall and Flessa, 2009). A reallocation of health resources in excess to facilities with shortage might be a realistic intervention. However, commitment and motivation for health workers in deprived areas are crucial for sustainability (Alhassan et al., 2015). Health care services could be increased through outreach activities, which have been proved to be an efficient strategy (Alhassan et al., 2015; Soucat et al., 1997).

Our study confirms that quality had no significant association with technical efficiency. However continued quality care improvement remains important due to the fact that the availability of basic equipment at primary care facilities is often poor, especially in rural areas in Indonesia (Mahendradhata et al., 2017). Health facilities mentioned inadequate supplies and inadequate staffing as hurdles to low efficiency (Dandona et al., 2005). One previous empirical study demonstrated that choosing providers is associated with increased satisfaction and perception of quality (Hsu et al., 2003). This becomes very important since the new national health insurance scheme allows people to choose between public and private providers regardless of their economic status.

3.4 Limitations

This study focused on public primary care facilities in Indonesia and has therefore ignored private health facilities; this is not a problem in rural areas where there are few such facilities (3.5 private facilities per public facility) but it could be a bias in urban areas where private facilities are more common (11.8 private facilities per public facility) (Badan Pusat Statistik, 2011). The study used a stratified sample that represented different areas in Indonesia, however generalisation of the findings to other LMICs may be a challenge because the study was conducted in limited public primary care facilities nationwide. Finally, the study did not analyse the entire concept of efficiency, such as allocative efficiency, and cost function specification due to a limited availability of price data.

We did not capture all output activities in primary care facilities. Mostly, we measured curative care activity, while preventive care was limited to maternal and child health care including antenatal care, postnatal care, and immunisation. The number of bed days was omitted because only less than half of the sample were primary care facilities with inpatient services. However, we tested the inclusion of bed days in the models and found no significance difference between the models.

We used data from 2011, we suggest that the study should be replicated using longitudinal data in order to highlight changes in efficiency due to recent policy changes, especially the national health insurance reform that started in 2014.

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5 Tables and figures

Table 1 Input and output variables

Variables	Definition	Measurement	Data source
Input variables			

Variables	Definition	Measurement	Data source
doctorstotal	Doctors	Total number of doctors	Health facilities costing study
nurse	Nurses	Total numbers of nurses	Health facilities costing study
midwife	Midwives	Total number of midwives	Health facilities costing study
nurse_midwife	Nurses and midwives	Total number of nurses and midwives	Health facilities costing study
otherstaff	Non-medical staff	Total number of non-medical staff	Health facilities costing study
valueofasset_med	The annualised value of medical asset in US dollar	$A_i = \frac{rV_iN_i}{\left(1 - \frac{1}{(1+r)^{L_i}}\right)}$ A_i= the annualised value of medical asset i V_i= the replacement cost using a standardised price list N_i =number of medical asset i L_i = the useful life r = the discount rate (3%)	Health facilities costing study
Output variables			
patients_gen	Outpatient visits in general clinic	Total number of attendances in general clinic within a year	Health facilities costing study
patients_mch	Outpatient visits in maternal and child health care	Total number of attendances in maternal and child health care within a year	Health facilities costing study
all_patient	patients_gen + patients_mch	Total number of outpatient visits in general clinic and maternal and child health care	Health facilities costing study

Table 2 PCA Variables

No	Variable	Description	PC1 loading	New variable	Test: Bartlett test (p-value)	Test: KMO	Statistics: Mean	Statistics: Min	Statistics: Max
1	water2	Water disruption in health facility in the past year	-0.46	less_disruption_index	0.000	0.72	-0.04	-2.9	2
2	electricity2	Electricity disruption in health facility in the past year	-0.4						
3	medicines_missing2	Medicine disruption in health facility in the past year	-0.41						
4	salary_late2	Employee salary was late on schedule in the past year	-0.48						
5	incentive_late2	Employee incentive was late on schedule in the past year	-0.47						
6	performance_meet2	Regular meetings to discuss the performance of services (medical and management) once per week	0.16	monitor_management_index	0.000	0.57	-0.03	-2.9	1.9
7	death_meet2	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	0.4						
8	mentoring2	Regular Mentoring with clinical staffs	0.64						
9	workinghour_monitor2	Regular Monitoring of working hours of the employee	0.64						
10	curative_exp	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	0.51	0.1	-1.8	3
11	preventive_exp	Preventive household expenditure for the last three months including expenditure on antenatal care, immunisation, medical check-up, family planning, other preventive expenditure	0.66						
12	pharmacy_exp	Pharmacy household expenditure for the last three months including prescribed drugs, drugs without prescription, traditional drugs, glasses, protease, wheel chair.	0.52						
13	fam_agriculture	Proportion of family working in agriculture	0.71	poor_economy_index	0.000	0.50	-0.03	-2.1	2.2
14	poor	Proportion of poor population in district	0.71						
15	hospitalpop	Ratio of hospital, including general hospital and maternal hospital over 1000 population	-0.16	access_healthfac_index	0.000	0.54	-0.1	-2.3	5.2
16	primarypop	Ratio of primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post over 1000 population	0.41						

No	Variable	Description	PC1 loading	New variable	Test		Statistics		
					Bartlett test (p-value)	KMO	Mean	Min	Max
17	hospitaleasy	Proportion of very easy and easy to access hospital, including general hospital and maternal hospital	0.62						
18	primaryeasy	Proportion of very easy and easy to access primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post	0.65				-0.03	-4.5	2.3
19	secondaryschool	Proportion of population with secondary school education in the district	-0.57	primary_education_index	0.000	0.57	-0.03	-4.5	2.3
20	highereducation	Proportion of population with higher education in the district	-0.55						
21	primaryschool	Proportion of population with primary school education in the district	0.61						

Table 3 Explanatory variables

Variables	Definition	Measurement	Data source
Internal factors			
withbeds	Availability of inpatient services	Whether inpatient services is available: 1 if available, and 0 if not available.	Health facilities costing study
nurse_vac	Nurse vacancy	Whether primary care has difficulty to fill nurse vacancy: 1 if yes, and 0 if not.	Health facilities costing study
less_disruption_index	Index of less disruption in health facilities	Principal component analysis score of no water disruption, no electricity disruption, no missing medicine, no delay of salary payment, no delay of allowance payment	Health facilities costing study
monitor_management_index	Index of management	Principal component analysis score of regular meeting of service performance, regular meeting to discuss cases, mentoring clinical staffs, and monitoring of working hours of employee	Health facilities costing study
patients_0to4	Proportion of patients under 5 years old	Total number of patients under 5 years old divided by total number of all patients	Health facilities costing study
External factors			
health_exp_index	Index of health expenditure per household	Principal component analysis score of household curative expenditure, preventive expenditure, pharmacy expenditure	SUSENAS
poor_economy_index	Index of population economy	Principal component analysis score of family proportion working in agriculture, and 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
primary_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
urban	Urban area	Whether primary care facility is in urban area: 1if yes, 0 if not.	Health facilities costing study
JavaBali	Java and Bali island	Whether primary care facility is in Java or Bali island: 1 if yes, 0 if not	Health facilities costing study
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
poorins	Poor insurance scheme	Proportion of household covered by poor scheme insurance	SUSENAS

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	T1	T2	T3
Input variables																					
Asset	X			X			X			X			X			X			X		
Nurse	X	X		X	X		X	X		X	X		X	X		X	X		X	X	
Midwife	X	X		X	X		X	X		X	X		X	X		X	X		X	X	
Doctors	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Other staff	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Nurse + midwife			X			X			X			X			X			X			X
General outpatients	X	X	X				X	X	X				X	X	X						
MCH services	X	X	X				X	X	X				X	X	X						
General outpatients + MCH services				X	X	X				X	X	X				X	X	X	X	X	X

[a] I1-I6 are input-oriented and O1-O6 are output-oriented DEA models

[b] CD1-CD3 are Multi output distance function, C1-C3 are Cobb-Douglas function, and T1-T3 are Translog function

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	T1	T2	T3
I1	1.00																				
I2	0.95	1.00																			
I3	0.92	0.95	1.00																		
I4	0.95	0.90	0.87	1.00																	
I5	0.90	0.94	0.90	0.95	1.00																
I6	0.87	0.89	0.94	0.91	0.94	1.00															
O1	**0.68**	0.63	0.58	0.59	0.54	0.49	1.00														
O2	0.57	**0.62**	0.55	0.46	0.51	0.44	0.88	1.00													
O3	0.45	0.50	**0.53**	0.34	0.38	0.41	0.78	0.90	1.00												
O4	0.65	0.59	0.56	**0.61**	0.56	0.51	0.94	0.81	0.73	1.00											
O5	0.52	0.58	0.53	0.47	**0.53**	0.45	0.81	0.93	0.85	0.86	1.00										
O6	0.42	0.47	0.51	0.36	0.40	**0.42**	0.73	0.83	0.93	0.77	0.90	1.00									
CD1	0.10	0.14	0.17	0.01	0.05	0.07	**0.46**	0.56	0.71	0.47	0.61	0.76	1.00								
CD2	0.10	0.14	0.17	0.01	0.05	0.07	0.45	**0.56**	0.70	0.46	0.61	0.76	1.00	1.00							
CD3	0.10	0.14	0.17	0.01	0.06	0.07	0.46	0.57	**0.71**	0.48	0.63	0.77	0.99	0.99	1.00						
C1	0.10	0.14	0.17	0.02	0.05	0.07	0.45	0.56	0.71	**0.46**	0.62	0.77	**0.99**	0.99	0.99	1.00					
C2	0.10	0.14	0.17	0.02	0.05	0.07	0.45	0.56	0.71	0.47	**0.62**	0.77	0.99	**0.99**	0.99	1.00	1.00				
C3	0.10	0.14	0.17	0.02	0.06	0.07	0.45	0.57	0.71	0.47	0.63	**0.77**	0.98	0.98	**0.99**	1.00	1.00	1.00			
T1	0.13	0.18	0.20	0.06	0.10	0.11	0.48	0.62	0.74	**0.49**	0.67	0.79	0.89	0.89	0.89	**0.90**	0.90	0.90	1.00		
T2	0.15	0.19	0.21	0.07	0.12	0.12	0.54	0.67	0.77	0.56	**0.72**	0.82	0.92	0.92	0.93	0.93	**0.93**	0.93	0.95	1.00	
T3	0.13	0.16	0.21	0.05	0.08	0.12	0.53	0.64	0.80	0.54	0.69	**0.84**	0.93	0.93	0.94	0.94	0.94	**0.94**	0.93	0.98	1.00

Table 6 Primary care statistics

Variable	N	Mean	St. Dev.	Min	Median	Max
Inputs						
doctorstotal (number of doctors)	185	3.5	4.6	1	2	48
nurse (number of nurses)	185	16.4	21.5	2	11	157
midwife (number of midwives)	185	14.4	22.1	2	10	229
nurse_midwife (number of nurses and midwives)	185	30.8	40.8	5	21	337
otherstaff (number of non-medical staff)	185	18.6	21.3	2	14	191
Outputs						
patients_gen (number of visits per year)	185	18598	13091	1818	14668	79556
patients_mch (number of visits per year)	185	3826	3793	51	2544	19706
all_patient (number of visits per year)	185	22424	15032	2114	18734	90442
Explanatory variables						
Continues variables						
less_disruption_index	185	-0.04	1.4	-2.9	-0.01	2
monitor_management_index	185	-0.03	1.4	-2.9	0.3	1.9
patients_0to4	185	0.10	0.10	0	0.10	0.30
primary_education_index	185	-0.03	1.6	-4.5	0.4	2.3
health_exp_index	185	0.10	1.40	-1.80	-0.10	3.00
population2011per1000	185	43.60	40.80	4.70	31.40	231.60
Health insurance coverage by scheme						
jamsostekins (proportion)	185	0.04	0.05	0.00	0.02	0.20
askesins (proportion)	185	0.10	0.10	0.04	0.10	0.30
poorins (proportion)	185	0.20	0.10	0.01	0.20	0.60
Categorical variables	**Number**	**Percentage**				
Without bed	107	58				
With bed	78	42				
Rural	130	70				
Urban	55	30				
Outside-Java Bali	105	57				
Java and Bali	80	43				

Table 7 DEA and SFA efficiency score in primary care

Statistic	N	Mean	St. Dev.	Min	Median	Max
DEA	185	0.40	0.20	0.02	0.30	1.00
SFA	185	0.60	0.20	0.10	0.60	0.90

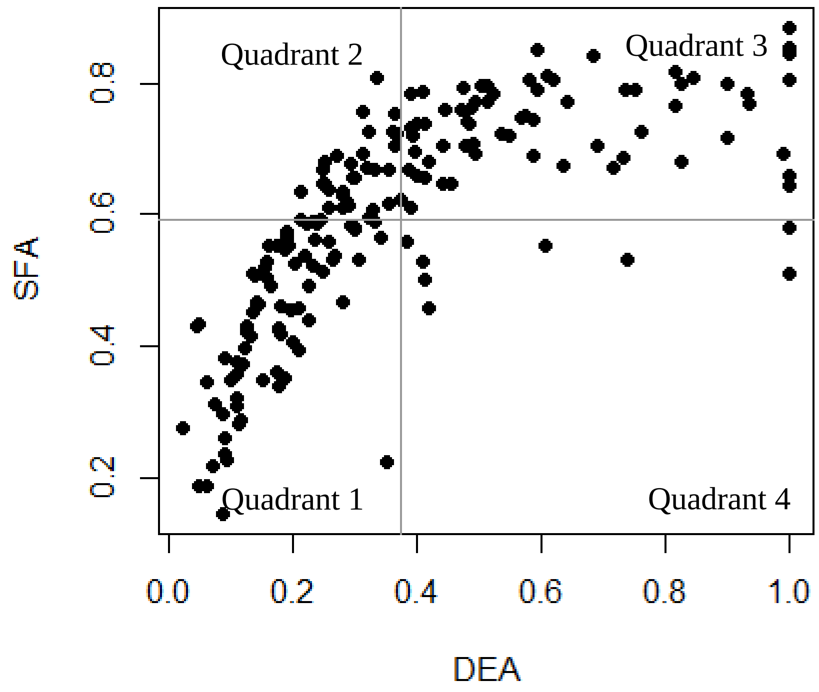

Figure 1 Quadrant scatter plot of DEA and SFA score estimated

Table 8 Statistic of efficiency quadrant

Statistic		Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
N		76	34	67	8
Mean	DEA	0.17	0.30	0.62	0.62
	SFA	0.43	0.66	0.74	0.53
Min	DEA	0.02	0.21	0.38	0.38
	SFA	0.14	0.59	0.61	0.46
Max	DEA	0.35	0.37	1.00	1.00
	SFA	0.59	0.81	0.88	0.58

Table 9 Regression on explanatory variables results

Variables	DEA (model 1)		DEA (model 2)		SFA (Model 1)			SFA (Model 2)		
	ME	SE	ME	SE	Estimate	SE	ME	Estimate	SE	ME
Internal factors										
less_disruption_index	-0.01	0.01	-0.02	0.01	-0.06	0.04	-0.01	-0.03	0.04	-0.00
monitor_management_index	-0.01	0.01	-0.02	0.01	-0.05	0.04	-0.00	-0.05	0.04	-0.01
patients_0to4	-0.14	0.32	-0.32	0.32	-0.36	0.94	-0.03	-0.36	0.95	-0.05
withbeds	-0.06	0.04	-0.08	0.04 *	-0.05	0.10	-0.00	-0.08	0.11	-0.01
External factors										
jamsostekins	1.08	0.40 **	0.73	0.60	3.71	1.26 **	0.30	-2.22	2.10	-0.30
askesins	0.38	0.36	-0.50	0.57	1.67	1.19	0.10	-1.55	2.19	-0.20
poorins	0.42	0.13 **	0.34	0.13 *	1.13	0.39 **	0.10	1.10	0.44 *	0.20
urban	0.09	0.04 *	0.07	0.04	0.66	0.15 ***	0.10	0.50	0.18 **	0.10
JavaBali	0.13	0.04 **			0.52	0.12 ***	0.04			
primary_education_index			-0.07	0.02 **				-0.34	0.09 ***	-0.05
health_exp_index			-0.05	0.02 *				-0.05	0.06	-0.01
population2011per1000			0.00	0.00				0.01	0.00 *	0.00
Constant	0.15	0.08 *	0.36	0.10 ***	-7.82	-0.80 ***		-1.11	0.38 **	
R2	0.23		0.23		0.17			0.15		
sigma	0.22	0.01 ***	0.22	0.01 ***	0.54	0.04 ***		0.54	0.04 ***	
sigmaSq					0.29	0.04 ***		0.29	0.04 ***	
gamma					0.77	0.13 ***		0.77	0.13 ***	
Log Likelihood	19.64		19.79		-131.18			-122.72		

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