Assessing the Efficiency of Health Facilities in Indonesia

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contributions of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given where reference has been made to the work of others.

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Abstract

Despite increased expenditures in Indonesian health facilities since 1999, health outcomes remain relatively poor. Inefficiency in health facilities contributes to the rising cost of healthcare. This thesis uses an innovative combination of ratio and frontier analyses to ascertain the factors determining relative efficiency in Indonesian health facilities.

Chapter 1 presents the aim of the thesis. Chapter 2 offers a description of Indonesia and its healthcare system, and Chapter 3 discusses the methods used and the theoretical background of the study.

In Chapter 4, we review measurements of efficiency in empirical analyses conducted in low- and middle-income countries. We demonstrate that there is no consensus regarding the most appropriate technique to measure efficiency, though most existing studies have relied on ratio analysis and data envelopment analysis.

The empirical findings in this thesis provide comprehensive analyses of the efficiency of both primary care facilities and hospitals; this study makes a distinct contribution as the first to use multiple national datasets.

In Chapter 5, we combine Pabón-Lasso models and costing analysis to explore the characteristics of high-performing health facilities. In so doing, we demonstrate that it is feasible to measure efficiency using easily reproducible, readily understandable methods.

In Chapter 6, we analyse efficiency in primary care facilities using frontier analysis, including both data envelopment analysis and stochastic frontier analysis. Chapter 7 uses frontier analysis to investigate efficiency in hospitals by considering the complexity (case mix index) and quality (mortality ratio) of healthcare services. The use of a multiple approach offers a way of cross-checking the consistency of the results. This empirical analysis enable us to conclude unambiguously and robustly that there exist significant associations between health facilities' contextual factors and their estimated efficiency scores.

Finally, Chapter 8 draws together the findings, assesses the policy implications, and comments on appropriate further research.

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List of Abbreviations

ALOS	Average Length of Stay
Askes	*Asuransi kesehatan* (Social health insurance scheme for civil servants)
BEmONC	Basic Emergency Obstetric and Newborn Care
BOR	Bed Occupancy Rate
BPJS	*Badan Pelaksana Jaminan Sosial* (Social Security Agency)
BPJS-K	*Badan Pelaksana Jaminan Sosial Kesehatan* (Social Security Agency for Health)
BPS	*Badan Pusat Statistik* (Central Bureau of Statistics)
CMI	Case Mix Index
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMU	Decision Making-Unit
DRG	Diagnosis Related Group
EE	Econometric Estimation
FTE	Full-Time Equivalent
GDP	Gross Domestic Product
HFCS	Health Facility Costing Study
HIC	High Income Countries
HIV	Human Immunodeficiency Virus
ICD	International Classification of Diseases
IDR	Indonesian Rupiah
INA-CBGs	Indonesian-Case Base Groups
Jamkesmas	*Jaminan kesehatan masyarakat* (National Health Insurance for the Poor and Near Poor)
Jamsostek	*Jaminan sosial tenaga kerja* (Workforce and Social Insurance)
KMO	Kaiser-Meyer-Olkin
LMICs	Low- and Middle-Income Countries
LOS	Length of Stay
MCH	Maternal and Child Health
MDG	Millennium Development Goals
MIMS	Monthly Index of Medical Specialities

MoH	Ministry of Health
NCD	Non-Communicable Disease
OLS	Ordinary Least Squares
PCA	Principal Components Analysis
PhD	Doctor of Philosophy
PODES	*Potensi desa* (The Village Potential Statistics)
Polindes	*Pondok bersalin desa* (Village delivery centres)
Poskesdes	*Pos kesehatan desa* (Village health centres)
Puskesmas	*Pusat kesehatan masyarakat* (primary health care centre)
RA	Ratio Analysis
ROC	Receiver Operating Characteristic
SEAR	South-East Asia Region
SFA	Stochastic Frontier Analysis
SUSENAS	*Survei Sosial Ekonomi Nasional* (National Socioeconomic Survey)
USD	United States Dollar
USA	United States of America
VRS	Variable Returns to Scale
WHO	World Health Organization

Chapter 1

Introduction

"At a time when money is tight, my advice to countries is this: before looking for places to cut spending on health care, look first for opportunities to improve efficiency." Message from former World Health Organization Director-General, Dr Margaret Chan (2010).

The subject of this thesis is the efficiency of health facilities in Indonesia. The thesis compares and contrasts different efficiency measurement techniques and applies them in primary care facilities and hospitals. The thesis aims to provide evidence on the improvements that can be made in both primary care facilities and hospitals. It provides empirical insights regarding relative efficiency and explores factors determining efficiency within health facilities. It makes use of previous studies in healthcare and other sectors to provide recommendations on policy-making decisions before presenting an agenda for future research.

1.1 Background

Investigating efficiency is a continuing concern within healthcare services. A strong and efficient healthcare system is essential given the ballooning of healthcare spending. Between 2002 and 2014, total healthcare expenditure per capita in Indonesia grew from USD 20 to USD 99, which is equivalent to a 12% annual growth. The increase was higher than in lower middle-income countries, which showed an average of 8% annual growth over the same period (The World Bank, 2018). Apart from inflation, new medical technologies and demographic change, it is also believed that inefficiency in health facilities has contributed to the rising healthcare costs (Jacobs *et al.*, 2006; Hajialiafzali *et al.*, 2007).

Health facilities represent the largest share of healthcare expenditures. Internationally, hospitals consume the largest proportion of healthcare expenditures representing between 30% and 50% of the total healthcare expenditures (Barnum & Kutzin, 1993; Soewondo *et al.*, 2011). In the Asia-Pacific region, including Indonesia, both hospitals and providers of ambulatory care consume from 50% to 80% of total healthcare expenditures (Hopkins *et al.*, 2010; Soewondo *et al.*, 2011; Kemenkes, 2014d).

However, healthcare utilisation in Indonesia is considered low in both hospitals and primary healthcare facilities. The hospital bed occupancy rate (total number of inpatient days in a year over the number of beds available in that year) is just above 60% on average, lower than the recommended occupancy levels (85-90%) (Kemenkes, 2006; Chisholm & Evans, 2010; Kemenkes, 2011b; TNP2K, 2015; Mahendradhata *et al.*, 2017). The average contact rate in primary healthcare facilities was just above one visit per person per year, which was low compared to other countries in Asia, including Malaysia (3.5), Vietnam (2.3), and Thailand (2.1) (Cashin *et al.*, 2002; Ensor & Indradjaya, 2012; OECD/WHO, 2014). The low level of utilisation suggests inefficiency in Indonesian health services (Giokas, 2001; Rokx, 2009). Studies show that excessive and inappropriate staff mix, over-capacity in health facilities, and barriers to accessing health services affect efficiency in health facilities (Weaver & Deolalikar, 2004; The World Bank, 2008; Chisholm & Evans, 2010; Chalidyanto, 2013).

Given the scarcity of healthcare resources worldwide, evaluating efficiency is important for health policy. However, there is a lack of efficiency studies in developing countries. Research on this topic is therefore particularly relevant; identifying the determinants of efficiency will allow policy-makers to work toward better healthcare resource allocation and a more efficient organisation of the healthcare system.

1.2 Aim and Objectives

1.2.1 Aim

The aim of this PhD project is to measure efficiency as well as determine the factors affecting efficiency in health facilities in Indonesia.

1.2.2 Objectives

To address the aim, the following objectives in Table 1.1 are deemed necessary.

Table 1.1: Objectives

No.	Objective	Question	Method
1	To understand the factors influencing efficiency in health facilities in LMICs.	What can we learn from previous studies in LMICs on efficiency in health facilities and its determining factors?	Literature review
2	To examine the relative efficiency of health facility operations from a sample of healthcare facilities across Indonesia	What is the variation in utilisation and average cost of delivering health services among health facilities with similar roles?	Ratio analysis: Pabón Lasso, and unit cost analysis approach
		What is the variation in efficiency scores in health facilities?	Analysis using data envelopment analysis (DEA) and stochastic frontier analysis (SFA)
3	To identify factors determining differences in efficiency of health facilities in Indonesia	What are the internal and external contextual factors underlying the relative efficiency?	Empirical analysis using multivariate regressions

1.3 Contribution of thesis

This thesis contributes to the literature in several ways. First, it undertakes a review of efficiency measurement in low- and middle-income countries (LMICs). Second, this study adds significantly to the current body of knowledge on efficiency in hospitals and primary care facilities using ratio analyses and frontier approaches and by employing four national datasets. Third, the empirical findings will provide evidence to policy-makers to aid decision-making processes in healthcare resource allocation. Fourth, although the current study focuses on Indonesia, similar approaches to efficiency measurement may be applied in other LMICs which have similar contexts.

1.4 Structure of this thesis

The remainder of this thesis is set out as follows: Chapter 2 provides information on the background and context of Indonesia. It provides an overview of general geography, demography, and health status indicators with a specific focus on health facilities. It also summarises the health policy and planning framework in place in Indonesia and describes the recent health sector reform programme in which national health insurance was implemented to achieve universal health coverage.

Chapter 3 provides an overview of the data used and the methodological approach to efficiency measurement. This chapter also provides definitions of various methods and compares and contrasts the strengths and weaknesses of the approaches.

The literature review presented in Chapter 4 synthesises the empirical studies on the efficiency of health facilities in LMICs. It identifies the range of methods used, model specifications, results and recommendations. The literature review identifies a number of key gaps and unanswered questions concerning the measurement of efficiency in low-and middle-income settings.

Chapter 5 estimates the performance of health facilities using ratio analyses and the determining characteristics of the high-performing facilities. Four national Indonesian datasets from 2011 were used, and 200 hospitals and 95 health centres were analysed. We first applied the Pabón-Lasso model to assess the relative performance of health facilities in terms of bed occupancy rate and the number of admissions per bed. A step-down costing method was used to estimate the cost per outpatient visit, inpatient admission, and bed day in hospitals and health centres. Ratio analysis and applied logistic regression were then combined to identify the predictors of the high-performing health facilities. This demonstrates that it is feasible to identify the high-performing health facilities and to provide information about how to improve efficiency using simple methods.

Chapters 6 and 7 examine the efficiency of 185 primary care facilities and 200 hospitals using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The results using the two techniques are compared in order to assess the stability of the findings. In addition, the multivariate analyses that we performed identify the contextual factors explaining some of the variation in efficiency observed in the sample data. These chapters also discuss some of the policy implications of the findings, focusing on contextual factors as targets for efficiency improvement.

Finally, Chapter 8 concludes by bringing together the three empirical studies. We discuss the main findings of the thesis, compare the results and then turn to policy implications. The closing chapter also offers recommendations as to how policy-makers in Indonesia and elsewhere in similar settings can best approach the issue of inefficiency within the health sector. Methodological issues are then discussed, particularly the limitations of the data and analyses. Lastly, conclusions are drawn and suggestions made in terms of useful areas for future work.

We now move to Chapter 2 to discuss the context of the Indonesian health system and its healthcare facilities.

Chapter 2

Context of Indonesia

This chapter provides a description of Indonesia and its health system. The aim of this chapter is to place in context the case studies of efficiency in Indonesian health facilities, both the hospitals and primary care facilities, which will be examined in Chapters 5 to 7. A summary of the Indonesian and English-language literature on Indonesia's healthcare delivery system is provided, along with a brief treatment of the country's characteristics including geography, demography, and health statistics. Finally, the country's profile of efficiency in the health sector and its implications are discussed.

2.1 Geography

Indonesia is a Southeast Asian republic bordering Malaysia, Papua New Guinea, and East Timor. The archipelago lies scattered over the equator. The country is diverse and consists of 17,504 islands with 34 provinces and 514 districts or municipalities (Kemendagri, 2015; BPS, 2015). The largest islands are Java, Sumatra, Papua, Kalimantan, and Sulawesi. Indonesia has a tropical climate with two different monsoon seasons, which are a wet season, and a dry season (BPS, 2015).

2.2 Demography

Indonesia is a very diverse country both ethnically and linguistically. Native Indonesians make up 95% of the population, with the Javanese as the largest ethnic group, but it is estimated that there are more than 300 other ethnic groups. The constitution of Indonesia states that every citizen has the right to choose and practise the religion of their choice. There are five religions officially acknowledged by law, namely Islam, Christianity, Buddhism, Hinduism and Confucianism (Hosen, 2005). Almost 90% of the population identify themselves as Muslim, making Indonesia the most populous Muslim-majority country in the world (Miller, 2009).

The estimated population in 2016 was 259 million, making Indonesia the world's fourth most populous country after the Republic of China, India, and the United States of America. The annual population growth rate between 2010 and 2015 was 1.38% higher than the average for developing countries in East Asia and the Pacific (0.72%) (BPS, 2015; The World Bank, 2015c). The population is projected to increase to approximately 305 million by the year 2035 (BPS, 2014d). According to BPS-Statistics Indonesia, the urban population in Indonesia is currently at 53.3% and has increased by 3.5 percentage points during the last five years (BPS, 2014c). The island of Java has the largest proportion of Indonesia's population with 56.7%. Meanwhile, the regions with the fewest inhabitants are Maluku (1.12%) and Papua (1.59%), both of which are located in eastern Indonesia (Kemenkes, 2017d). The population density ranged from 9 people per square kilometre in West Papua to 15,328 people per square kilometre in Jakarta (BPS, 2014d). The uneven spread of population may be reflected in differences in access to healthcare.

2.3 Health statistics

Indonesia's health indicators are generally better than the averages reported for the World Health Organization (WHO) South-East Asia Region (SEAR). For example, life expectancy at birth is 71 years, which is four years longer than the WHO SEAR average (WHO, 2015c). This figure has increased remarkably since 1990 when Indonesia's life expectancy was 63.2 years. The under-five mortality rate and infant mortality rate for Indonesia are also better than average in the WHO SEAR, with 40 per 1,000 live births vs 55 per 1,000 live births, and 32 per 1,000 live births vs 42 per 1,000 live births respectively (WHO, 2015a).

However, in terms of health indicators such as the maternal mortality ratio, Indonesia compares poorly to other countries with similar gross domestic product (GDP). Indonesia's GDP per capita is USD 1,811, which is higher than that reported for lower-middle-income countries on average (USD 1,269) (The World Bank, 2015b). However, the maternal mortality ratio, at 133 per 100,000 live births, is still behind that of other Asian countries with similar or lower GDP per capita such as the Philippines (117 per 100,000 live births), Pacific island small states (78 per 100,000 live births), Vietnam (54 per 100,000 live births), Mongolia (46 per 100,000 live births), and Sri Lanka (31 per 100,000 live births) (Figure 2.1). There are stark differences across the Indonesian archipelago; the maternal mortality ratio in the eastern region of Indonesia is higher than in the western region. Delays in decisions to seek care, as well as delays in reaching health facilities due to lack of telecommunication, long distances, and lack of availability of transportation, are the main reasons for maternal mortality (Scott *et al.*, 2013; Belton *et al.*, 2014). Socio-economic household characteristics such as residing in a rural area are also associated with delays in receiving health care (Taguchi *et al.*, 2003).

Availability of assistance with antenatal care and delivery care is substantially better in urban areas (Ansariadi & Manderson, 2015). Women in rural areas receive fewer than four antenatal care visits, and prefer to deliver at home assisted by a traditional birth attendant (Shono *et al.*, 2014). The percentage of facility-based deliveries is still considered low (73.6%), especially in the eastern region of Indonesia. This is partly due to physical and financial barriers to accessing health services, despite the existence of universal maternal health coverage (Kosen *et al.*, 2014b). In addition, families' cultural beliefs and educational levels have an enormous influence on the healthiness of women's lifestyles and on women's participation in antenatal care programmes (Titaley *et al.*, 2010a,b; Erlyana *et al.*, 2011; Agus *et al.*, 2012; Osaki *et al.*, 2015).

There is also a wide discrepancy of health outcomes across Indonesia, which reflects the country's double burden of emerging epidemics and persistent diseases. Communicable diseases such as tuberculosis, diarrhoea, and lower respiratory tract infections remain as significant health issues in Indonesia, especially in remote areas (e.g. Papua) (IHME, 2016). At the same time, non-communicable diseases (NCDs) are becoming a major public health problem, especially in urban areas (e.g. Java). While ischemic heart disease and cerebrovascular disease remained as the first and second leading causes of deaths in 2016 as in 2005, diabetes and chronic obstructive pulmonary diseases (COPD) have risen to fourth and fifth from sixth and

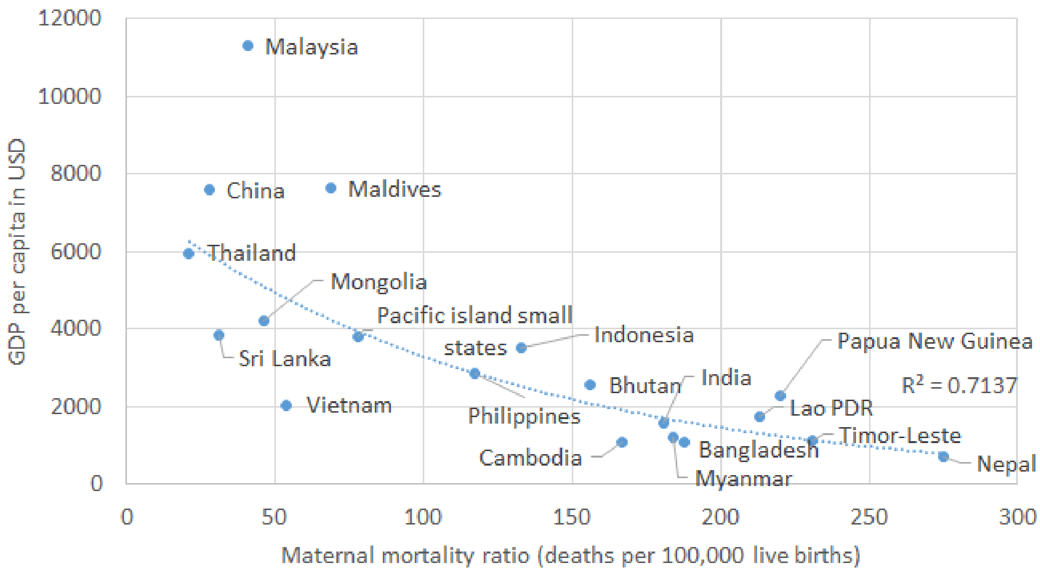


Figure 2.1: GDP per capita and maternal mortality ratio (deaths per 100,000 live births) in East and Asia Pacific. Source: The World Bank (2016)

eighth places respectively (IHME, 2016). The rise in NCDs among the Indonesian population is a result of ageing, high blood pressure, smoking, and obesity (Kosen *et al.*, 2014a). The number of deaths caused by diabetes rose by 62.9% from 2005 to 2016, followed in severity of increase by Alzheimer disease (46.0%) and cerebrovascular disease (35.5%). Meanwhile, the number of deaths caused by communicable diseases has declined. The mortality of tuberculosis, while still the third leading cause of death in 2016, has been reduced by 28.3% since 2005. The mortality rates of diarrhoea and lower respiratory tract infections have declined even further by 30.1% and 34.7% respectively (IHME, 2016).

2.4 Health workforce

In 2016, 55% of medical personnel were located on Java Island, with the largest number in West Java (15,139 people), East Java (12,061 people), and Central Java (11,247 people). The provinces with the fewest medical personnel were North Kalimantan (301 people), West Sulawesi (316 people), and West Papua (340 people) (Kemenkes, 2017d).

Indonesia's diversity poses challenges for the equitable distribution of health workers around the country. Indonesia produces approximately 6,000 new physicians annually, but compared to SEAR averages, Indonesia employs fewer health workers per 10,000 people in terms of physicians (2.0 vs. 5.9), nursing and midwifery personnel (13.8 vs. 15.3), and pharmaceutical personnel (1.0 vs. 3.8) (WHO, 2014).

By 2016, the ratios of doctors and dentists in Indonesia were still far below the government's target in all provinces (Menkokesra, 2013). Nationally, the ratio of general practitioners in Indonesia was 1.6 per 10,000 population, far below the target of 4.5 general practitioners per 10,000 population to be achieved in 2019. The province with the highest ratio of doctors was the DKI (Special Capital City of) Jakarta (3.8 per 10,000 population), while the province with the lowest ratio was Lampung (1.0 per 10,000 population). The dentist ratio was 0.45 per 10,000 population, below the target of 1.3 dentists per 10,000 population, with Jakarta's ratio the highest at 1.0 dentists per 10,000 population and Maluku's the lowest at 0.2 dentists per 10,000 population. The ratio of nurses also remained below the target of 18 nurses per 10,000 population with 11.4 nurses per 10,000 population. The province with the lowest nurse ratio was Lampung with 4.94 nurses per 100,000 population (Kemenkes, 2017d). The nurse ratios of only eight provinces met the targets (DKI Jakarta, East Kalimantan, Bangka Belitung Islands, Aceh, Maluku, North Sulawesi, Bengkulu and Jambi).

Results retrieved from the PODES report showed similar results in general. Using the availability of at least one doctor in *Puskesmas* (community healthcare centres) and at least one midwife in each village as the indicators, it was found that on average 85.8% of *Puskesmas* have at least one doctor and 84.8% of villages have at least one midwife (Sparrow & Vothknecht, 2011). However, these indicators conceal an unequal pattern of distribution; the eastern part of Indonesia has fewer health workers than the region of Java. Approximately one fourth of sub-districts located outside of Java Island did not have a general practitioner in their *Puskesmas*. This figure soared to 40% in Maluku and 69% in Papua and West Papua (Sparrow & Vothknecht, 2011). Ninety-six percent of villages in urban areas had at least one midwife, while only 78% of villages in rural areas had one. Rural areas with the poorest access to midwives were North Maluku (50%), Papua (30%) and West Papua (27%) (Sparrow & Vothknecht, 2011).

The disparity in the distribution of Indonesia's medical workforce might be caused by the poor housing facilities available to personnel in rural areas. The

PODES survey also found that approximately 12,000 housing units for doctors and nurses were damaged and in need of repair (Sparrow & Vothknecht, 2011).

To address the issue of the health worker shortage, the Ministry of Health and Ministry of Education developed a health worker education system. The capacity of health education institutions was increased by 17% annually from 2004 to 2008. The predominant programme is midwifery as part of the government policy to deploy a midwife in every village across the country. However, more than two-thirds of health education institutions lack accreditation, which impacts the quality and competence of the health workers receiving training (Kemenkes, 2011c).

In addition, the government has established a policy encouraging new graduates to work in rural and remote areas. This policy is focused on primary care. It has been considered the major policy lever to improve health worker distribution as it offers significant financial benefits with a relatively short-term contract. However, the policy has not achieved the expected outcomes; health workers have remained heavily concentrated in urban areas, and this unequal distribution is partly influenced by dual practice in both public and private sectors (Anderson, 2014).

According to the World Bank, the number of physicians working in the private sector increased by almost 48% between 1996 and 2006 (Rokx, 2010). The increasing number of private practice has been significantly greater in urban than rural areas, where opportunities for attracting paying patients is higher than in more sparsely populated and poorer rural areas (Rokx, 2010). However, private practice also rose 21% in rural areas, with ratio of one physicians providing services for every 25,000 people (Rokx, 2010). A recent study demonstrated that up to 80% of medical specialists earn from private practice because regulations and public sector compensation have not been effective in addressing the unequal distribution of specialist physicians (Meliala *et al.*, 2013).

2.5 Primary care facilities

Public primary healthcare is mainly provided by community health centres or *Puskesmas* (*Pusat Kesehatan Masyarakat*). *Puskesmas* are the first tier of health service, ensuring that all Indonesians have access to care. *Puskesmas* have two main roles: curative care and public healthcare services. Nearly 50% of *Puskesmas* provide eight essential services. These are general clinic; maternal and child health (MCH), including family planning (FP); dental services; pharmacy; laboratory; disease control and prevention; consultation clinic; and emergency room. In addition to essential health services, 32% of *Puskesmas* offer nutrition consultation, and only 18.6% have basic obstetric and basic neonatal emergency services (Kemenkes, 2012a).

Most *Puskesmas* are located at the sub-district level with a network in villages and are accountable to District Health Office authorities. *Puskesmas* can be categorised based on location (urban, rural, and remote areas) and on the availability of inpatient services (Kemenkes, 2014c). Three-quarters of *Puskesmas* are located in rural areas, with 9.5% and 17% classified in remote and very remote areas respectively.

On average, 92.6% of the Indonesian population have access to primary care, a figure which increases to 95.5% when including access to satellite primary health care at village health centres (*Poskesdes*), village delivery centres (*Polindes*), and midwifery practices in the village (Sparrow & Vothknecht, 2011). A community's access to primary care is influenced by various factors such as geographical condition, area characteristics, availability of basic facilities and infrastructure, and regional development. The number of *Puskesmas* per sub-district illustrates the degree of community accessibility to primary health care. The province with the highest ratio of *Puskesmas* to sub-districts in 2016 was Jakarta at 7.7, while West Papua had the lowest ratio of 0.7 (Kemenkes, 2017d).

In 2016, there were 9,767 *Puskesmas*, of which 3,411 *Puskesmas* had inpatient services and 6,356 did not (Kemenkes, 2017d). Primary care facilities with inpatient services are intended as intermediate referral centres from the primary care facilities without inpatient services. Health workers stationed at *Puskesmas* in rural, remote and very remote areas where there are geographical barriers to hospital access may be given additional authority and trained in supplementary clinical skills such as the performance of C-sections, administration of anaesthetics, and delivery of paediatric services (Kemenkes, 2014c).

In delivering health services, *Puskesmas* are generally assisted by satellite *Puskesmas*. Eighty-six percent of *Puskesmas* have satellite-*Puskesmas*, with the majority located in rural areas. *Puskesmas* also extend their maternal and child health services through village maternity centres or village health centres assisted by village midwives. About 84% of *Puskesmas* have village midwives who are responsible to one village (Kemenkes, 2012a).

There are differences in the minimum number of health workers in *Puskesmas* with inpatient and without-inpatient services. In *Puskesmas* without inpatient services, there should be at least one medical doctor, one dentist, five nurses, and four midwives. In *Puskesmas* with inpatient services, there should be at least two medical doctors, one dentist, eight nurses, and seven midwives (Kemenkes, 2014c). In 2016, the number of health workers in *Puskesmas* in Indonesia was 341,536, consisting of 289,465 medical personnel (84.75%) and 52,071 support staff (15.25%). Midwives are the largest group of medical personnel (35.2%), while clinical laboratory analysts are the smallest (1.9%). Nationally, 35.5% of *Puskesmas* exceeded the standard number of doctors, 33.6% had the exact required number, and 26.4% had fewer physicians than required. By region, the largest proportions of *Puskesmas* that met or exceeded the requirement were found in the Java-Bali (82.2%) and Sumatra (73.7%) regions, whereas the largest proportion of *Puskesmas* with fewer than the required number was in the Nusa Tenggara-Maluku-Papua region (50.86%) (Kemenkes, 2017d).

The availability of health workers affects *Puskesmas*' quality of services (Barber *et al.*, 2007). Health workers in *Puskesmas* consist mostly of midwives and nurses. Midwives in particular provide many of the services in *Puskesmas*, including maternal and child health care services such as anaemia prevention during pregnancy, patient referral, and child growth monitoring (Frankenberg *et al.*, 2005; Makowiecka *et al.*, 2008; D'Ambruoso *et al.*, 2009; Widyawati *et al.*, 2015). Meanwhile, a critical shortage of pharmacists in *Puskesmas* has been observed despite the WHO minimum recommendation of one pharmacist per 2,300 people. There was only one pharmacist for 21,930 people reported in 2006 in Indonesia. Consequently, pharmaceutical services have been commonly provided by nurses and pharmacists' assistants with senior level diploma equivalents (Kemenkes, 2012c).

In terms of service delivery, although midwives play pivotal roles in *Puskesmas*, midwifery services are not always available because of insufficient facilities, high workload, lack of skills, and limited support staff (Widyawati *et al.*, 2015). To help overcome this problem, the concept of the 'alert village' was developed to ensure that communities, especially husbands, are aware of their wives' needs, including funding, transportation, and blood donors, to ensure prompt access to healthcare (Hill *et al.*, 2014).

The government of Indonesia applies national and international accreditation to improve the quality of health services and clinical performance (Gunawan, 2007). A national survey of health facilities found that more than 90% of *Puskesmas* have at least one each of essential instruments such as stethoscopes, sphygmomanometers, weight scales, thermometers and examination beds. However, more than 50% of *Puskesmas* lack complete immunisation toolkits and experience shortages of laboratory supplies. Seventy percent of urban *Puskesmas* could conduct a blood glucose test, but this figure drops to just above 50% nationwide in rural *Puskesmas*. Basic pharmaceutical treatment for diabetes mellitus, such as metformin, is more widely available (Kosen *et al.*, 2014a). Almost 30% of *Puskesmas* lack access to clean water and medical and non-medical waste management, such as an incinerator. Seventeen percent of *Puskesmas* lack access to 24-hour electricity. Almost 50% of *Puskesmas* lack at least one of the three communication tools (i.e. phone or mobile phone or ham radio) and only a very small proportion of them have an internet connection (Kemenkes, 2012a). Moreover, there is limited availability of urine tests for diagnosing hypertensive disorder during pregnancy, as well as key drugs (such as magnesium sulphate) and antibiotic injections. These deficiencies may also reflect limitations in demand for these treatments (Kosen *et al.*, 2014b).

2.6 Hospitals

Hospitals focus mainly on curative and rehabilitative services, including inpatient, outpatient, and emergency services. Hospitals are categorised according to the capacity of services (Class A to D), and ownership (public or private) (Kemenkes, 2014a). Hospitals in Class A are the largest hospitals, mainly for national referral (2.42%), followed by Class B (14.11%), Class C (41.25%), and Class D (21.07%) (Kemenkes, 2017d). The remaining 21% of Indonesian hospitals have not been assessed for the purpose of assignation to a class. Public hospitals are managed by the government including army and police, and non-profit organisations. Private hospitals are managed by for-profit organisations, including enterprises, and state-owned companies. In

2016, there were 2,601 hospitals in Indonesia, 35% of them in the public sector (Kemenkes, 2017d).

When compared to primary care facilities, hospitals are far less accessible. A PODES report showed that only 67.3% of the population have access to a hospital for secondary care (Sparrow & Vothknecht, 2011). The number of hospitals increased by 16.74% between 2013 and 2016. Nationally, the hospital bed ratio was 1.12 per 1,000 people, which exceeds the WHO standard of 1 bed per 1,000 people (Kemenkes, 2017d). While bed ratio has achieved the target, there are still seven provinces with fewer 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 hospital bed ratios are in Jakarta (2.23), North Sulawesi (2.05), and Yogyakarta (1.80) (Kemenkes, 2017d).

In 2015, there were 322,607 health workers in hospitals, including 147,264 nurses, 30,561 midwives, and 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, 2014d).

Hospitals provide four basic medical specialist services: internal medicine, paediatrics, surgery, and obstetrics and gynaecology supported by other specialties (e.g. anaesthesiology, radiology, clinical pathology, anatomical pathology, rehabilitative medicine, and psychiatry). The total number of specialists working in hospitals in Indonesia in 2016 was 49,742. 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%). While the greatest numbers of medical specialists reside in West Java and Jakarta, North Kalimantan and West Sulawesi have the smallest numbers of medical specialists (Kemenkes, 2017d).

The Ministry of Health regulates the scope of services that must be provided by hospitals to ensure the quality of services. To improve the availability and quality of human resources in accordance with the standard of health services, the Ministry of Health Strategic Plan indicator for 2015-2019 stated that at least 35% of Class C hospitals should meet the minimum requirements of four basic medical specialists and three supporting specialists in radiology, anaesthesiology, and clinical pathology. By 2016, 45.22% of Class C public hospitals in Indonesia reported that they had met the required number of specialists. Provinces with the highest percentage of public Class C hospitals meeting the requirements were Bali, Bangka Belitung Islands, North Kalimantan and Gorontalo at 100%. Meanwhile, the provinces with no public Class C hospitals that met the requirements were Bengkulu, East Nusa Tenggara, North Sulawesi, Maluku and North Maluku (Kemenkes, 2017d). However, in total, 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). Public hospitals are expected to have the capacity to treat obstetric and new-born emergencies. However, only 16% of hospitals meet the minimum requirement of comprehensive emergency obstetric and neonatal care (Kemenkes, 2012a).

To improve the quality of services, the Ministry of Health formed an independent body, the hospital accreditation commission, and started a hospital accreditation programme in 1996. This programme aimed to increase the quality of services and patient safety as well as to protect the rights of patients, the community, hospital human resources and the hospital as an institution. Hospitals must be accredited every three years, with the purpose of increasing the quality of services through application of the standard services offered. In addition to national accreditation, the government also encourages hospitals to seek international accreditation by an independent body accredited by the International Society for Quality in Health Care (Kemenkes, 2012d). The Ministry of Health aimed to have at least one accredited hospital in each district. However, in 2016, only 33.12% of Indonesia's 2,500 hospitals had been accredited. The provinces with the highest percentages of accredited hospitals were Bali, Jakarta and Lampung with 69.09%, 53.30% and 52.94% respectively. None of the seven hospitals in North Kalimantan had, yet been accredited (Kemenkes, 2017d). Challenges in hospital accreditation implementation include the fact that the accreditation bodies are not yet integrated, a lack of clarity on the role of provincial and district health offices, a lack of accreditation guidelines, a lack of engagement and support from clinical staff, and political pressure to provide licences to hospitals that do not satisfy the minimum licensing requirements (Hort *et al.*, 2013).

Almost all public hospitals in Indonesia have access to clean water and electricity. Ninety-six percent of public hospitals are equipped with a water reservoir and 60% have an uninterrupted power supply. Ninety-nine percent of public hospitals have at least one ambulance. With regard to telecommunication, most public hospitals have telephones (94%), internet connections (82%), and facsimile (90%); fewer have, radio communication (40%) and mobile phones (27%) (Kemenkes, 2012a).

2.7 Health financing and performance

Between 1995 and 2014, total healthcare expenditure per capita in Indonesia grew rapidly from USD 20 to USD 99, which is equivalent to 12% annual growth. The increase was slightly higher than the average in low- and middle-income countries (LMICs), which rose 8% during the same period (Figure 2.2) (The World Bank, 2018). Despite its higher total health expenditure per capita, Indonesia performs less well than other LMICs in terms of health statistics such as mortality and vaccination coverage (Rokx, 2009; WHO, 2015b; The World Bank, 2018).

Figure 2.2: Total healthcare expenditure per capita in USD between 1995 and 2014. Source: The World Bank (2018)

The monetary crisis in 1998 affected the price of medical services, especially drugs and medical supplies. Apart from inflation, demographic changes and inefficiency in health facilities have contributed to the rising health care costs (Jacobs *et al.*, 2006; Hajialiafzali *et al.*, 2007). The Indonesian population structure is dominated by those aged 25 to 34 years (Kemenkes, 2015). Essential health services are particularly necessary in areas where under-five and eligible couple population (ages 15 to 49) predominate (Ensor *et al.*, 2012). The improvement of welfare and health status has also had an impact on the increased life expectancy from 66.2 in 2002 to 70.8 in 2015, which in turn augments the elderly population (Kemenkes, 2006, 2016b). West Sulawesi province has the lowest life expectancy (age 64) while Yogyakarta has the highest (age 74.5) (Kemenkes, 2016b).

The availability of medical technologies, such as magnetic resonance imaging (MRI) and computerised tomography (CT) scans in health facilities in Indonesia is lower than in other Asian countries (Hutubessy & Edejer, 2002). Moreover, investment in state-of-the-art medical technology is rather low, particularly in for-profit private hospitals. As a consequence, medical errors occur, leading to inefficiency (Hutubessy & Edejer, 2002).

Medicines account for more than 30% of health spending and inappropriate drug prescriptions are a considerable concern in terms of inefficiency (WHO, 2010). Inadequate use of standard treatment guidelines, irrational prescribing of antibiotics, and wasted drugs due to poor storage all cause inefficiency (Kemenkes, 2012a,b; Sidik *et al.*, 2013). Although most respiratory tract infections are of viral origin, doctors prescribe inappropriate and ineffective antibiotics, especially when patients are covered by health insurance (Hadi *et al.*, 2008). In many settings, antibiotics can be purchased without a prescription in drug stores without assessment or instructions for use (Puspitasari *et al.*, 2011). A qualitative study in Yogyakarta showed that people using non-prescribed antibiotics were attempting to save the time and cost of a doctor's visit (Widayati *et al.*, 2015). Limited coordination between and support from central and local government, poor dissemination of information, and the absence of sanctions are the main challenges in terms of the rational prescription of drugs (Kemenkes, 2016a).

Health facilities, especially hospitals, represent the largest share of healthcare spending; hospitals account for 38% of total public health expenditures (Rokx, 2009). Between 2005 and 2014, the share of hospitals' expenditures increased by 23 percentage points, but performance did not improve (Figure 2.3).

A report on the national health accounts shows that funding allocations for ambulatory care are lower than for hospitals. Total spending on ambulatory care in Indonesia is just below 20%, which is 5% lower than in Asia-Pacific countries on average (Hopkins *et al.*, 2010; Soewondo *et al.*, 2011; Sari *et al.*, 2015). The allocation for primary care represents a mere 15% of the overall budget under the current Indonesian national health insurance system (Langenbrunner *et al.*, 2014).

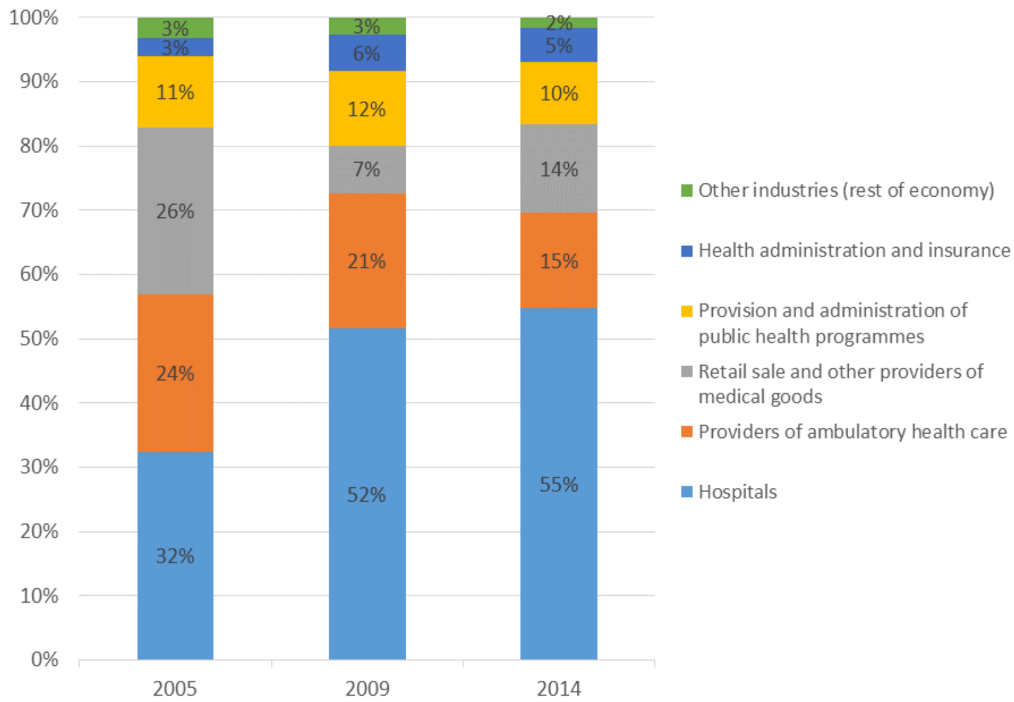


Figure 2.3: Health expenditure by provider in Indonesia. Source: Soewondo *et al.* (2011); CHEPS *et al.* (2016)

Indonesia's total health expenditure is mainly derived from private expenditures, including out-of-pocket expenditures (62.1%). This figure is slightly lower than the WHO SEAR average (63.3%), but it is considerably higher than the global average (41.1%) (WHO, 2014). The government is concerned with reducing financial barriers and avoiding cost escalations due to inefficiencies.

Indonesia started developing health insurance in 1946; insurance was extended to civil servants in 1968 and to employees in 1971 (Thabrany, 2011). After the 1998 economic crisis, the Indonesian government introduced national health insurance for the poor to reduce financial barriers to health care access. Between 2011 and 2014, there were three major insurance schemes: 1) *Jamkesmas* (*Jaminan kesehatan masyarakat*), which offered health insurance for the poor and near-poor; 2) *Jamsostek* (*Jaminan sosial tenaga kerja*), which offered health insurance for formal sector workers; and 3) *Askes* (*Asuransi kesehatan*), which offered social health insurance for civil servants (Marzoeki *et al.*, 2014). Sixty-five percent of Indonesians were covered by insurance, most of these under *Jamkesmas* (32%), *Askes* (7%) and *Jamsostek* (2%); other insurance schemes covered the remaining 24 percent of the population with insurance (Kemenkes, 2012e). Healthcare cost containment is important to ensure the sustainability of the national health insurance programme. *Jamkesmas*, *Askes*, and *Jamsostek* used the gate-keeping system; people could thus only access hospitals after first visiting a primary health institution, which served as gatekeeper. The three schemes all used capitation for primary healthcare, but each had its own payment system in hospitals. *Jamkesmas* used an Indonesian-case base group system (INA-CBGs), *Askes* used a fee schedule, and *Jamsostek* used a fee-for-services system without a fee schedule (Marzoeki *et al.*, 2014). In 2014, the Indonesian government introduced a new national health insurance scheme. This scheme is run by BPJS-K (*Badan Penyelenggara Jaminan Sosial-Kesehatan*), which is a public institution under the government, and it combines the three major insurance schemes: *Jamkesmas*, *Jamsostek*, and *Askes*. BPJS-K aims to cover the entire population by 2019 (Mundiharno & Thabrany, 2012). Since all three schemes are combined under BPJS-K, the INA-CBGs payment is applied to hospitals, and capitation is in place at the primary healthcare facilities (Kemenkes, 2014b). Because prospective payment mechanisms such as the INA-CBGs shift the financial risk to health providers, profit maximisation can only be yielded if health providers perform in an efficient manner.

Prospective payment mechanisms force health facilities to practice cost containment. Each hospital has its own strategies, including developing clinical pathways, controlling the cost of medical equipment and medical supplies, providing an equal reimbursement rate for medical services for different inpatient classes, requiring the use of generic drugs, and controlling laboratory and radiology examinations (Wibowo, 2014). Research has showed that clinical pathways may increase efficiency in providing surgical care; they can also estimate healthcare costs, enabling providers to better allocate their resources (Supraba, 2014). Hospitals can also improve their value-added activities by reducing outpatient waiting time (Tjahjanto, 2016). However, a study at Bandung District Hospital showed no significant differences in cost or quality of services between prospective payment mechanisms and fee-for-services approaches (Muharromah, 2011).

Despite health facilities' strategies for improving efficiency in the Indonesian healthcare system, little progress has been made toward understanding the contextual factors determining efficiency in health facilities. This thesis will report estimates of relative efficiency of health facilities using efficiency measurements and will identify the specific determinants of efficiency in order to inform policies and practices that may improve efficiency.

Before presenting the empirical studies, it is important to define and set out the methodological approaches. Chapter 3 provides an explanation of the efficiency measurement methods, followed by a literature review on efficiency measurement in LMICs in Chapter 4.

Chapter 3

Methods for Measuring Efficiency

To satisfy the objectives of the thesis, an understanding of the methodological approaches is necessary. The previous chapter discussed the Indonesian setting, including the health system as well as health facilities and their efficiency. In the chapter, efficiency measurement methods are discussed further to construct the basis of the methodology used both in the literature review and in the empirical studies in the next chapters.

Chapter 3 is organised as follows. In the first section, theoretical background on the theory of production and the concept of efficiency is provided. In the second section, the methodological approaches used as the basis of the empirical studies are presented. This second section consists of three parts. First, the literature review of the methodology used to synthesise the current evidence on efficiency based on a summary of published evidence to date is provided. Second, efficiency measurement and its components are further discussed. The third part consists of a presentation of the analysis used to identify the contextual factors determining efficiency. The last section of this chapter offers an explanation of the dataset used in the empirical studies, concluding with ethical issues.

3.1 Theoretical background

3.1.1 Production

Production involves the methods and process of combining and converting various tangible and intangible inputs (information, knowledge) into products for consumption, including goods or services (output) which have exchange value for others (Morris *et al.*, 2007; Goolsbee *et al.*, 2013). Conceptually, there are three categories of inputs: 1) capital, which includes durable inputs such as land, buildings, and equipment; 2) labour, which consists of human services provided by managers, skilled workers (e.g. medical doctors, economists, and engineers) and less-skilled workers (e.g. custodians, cleaners, maintenance workers); and 3) material, including raw goods such as drugs, medical supplies, and water (Perloff, 2014). Firms, which in the health sector include hospitals and health centres, use labour (doctors, nurses, administrative staff), material (drugs, medical supplies), and capital (beds, building) inputs to provide healthcare services (output).

In the context of healthcare services, output may refer to intermediate outputs (number of outpatients, inpatient-days, surgery, etc.) or final health outcomes (mortality rates, life expectancy) (Palmer & Torgerson, 1999). However, final health outcomes such as improvements in health status may be difficult to measure due to issues with the availability of data as well as the time it takes to affect change and the difficulty of attributing change (Masiye, 2007). In addition, since patient care is the main objective of health facilities, intermediate outputs are used with the aim of improving patient health status, preventing deterioration in patient health status or preventing people from falling ill (Morris *et al.*, 2007; Blank & Valdmanis, 2010). The relationships between the different combinations of inputs used to produce outputs with the existing knowledge of technology and organisation are described in a production function (Morris *et al.*, 2007; Nicholson & Snyder, 2007; Pindyck & Rubinfeld, 2008; Varian, 2010; Goolsbee *et al.*, 2013; Perloff, 2014) that can be written as follows

$$q = f(L, K) \tag{3.1}$$

where q represents units of output that are produced using L units of labour and K units of capital as the inputs. Variations in inputs cause variations in outputs, but variations in outputs do not cause variations in inputs (Archibald & Lipsey, 1982; Perloff, 2014).

The time horizon affects the extent to which a health facility can vary factors of production. Health facilities can change both fixed (e.g. beds, building, etc.) and variable (e.g. health workers, medical supplies, etc.) inputs to increase production more easily in the long run than in the short run (Perloff, 2014). In practice, payment systems change the way in which health facilities react to decisions about factors of production. For example, after the prospective payment system was introduced in the United States, hospitals used CT scans more than physical examinations as part of a screening process to decide whether patients with head injuries needed to be admitted on an inpatient or outpatient basis (Acemoglu & Finkelstein, 2008).

At this stage, we consider a health facility to produce one service with only two inputs in which capital (including land) is a fixed input, and labour (including material) is a variable input. The combination of inputs at the certain level of output (quantity) can be shown as an isoquant (iso=equal / quant=quantity). An isoquant shows the technically efficient combinations of inputs that can be used to produce a specific quantity of outputs. The technically efficient level is achieved when providers cannot produce more of a service without using additional input. Consider an isoquant producing the output $X_2 = 40$ (see Figure 3.1) and three alternative combinations of labour and capital labelled a, b, and c. If labour is reduced from $L1$ to $L3$, the same level of output X_2 could be achieved in c if labour is substituted by additional capital from $K1$ to $K3$. Isoquants are assumed to have three properties. First, the further away from the origin an isoquant is, the greater the level of output; second, isoquants do not cross; and third, isoquants slope downward.

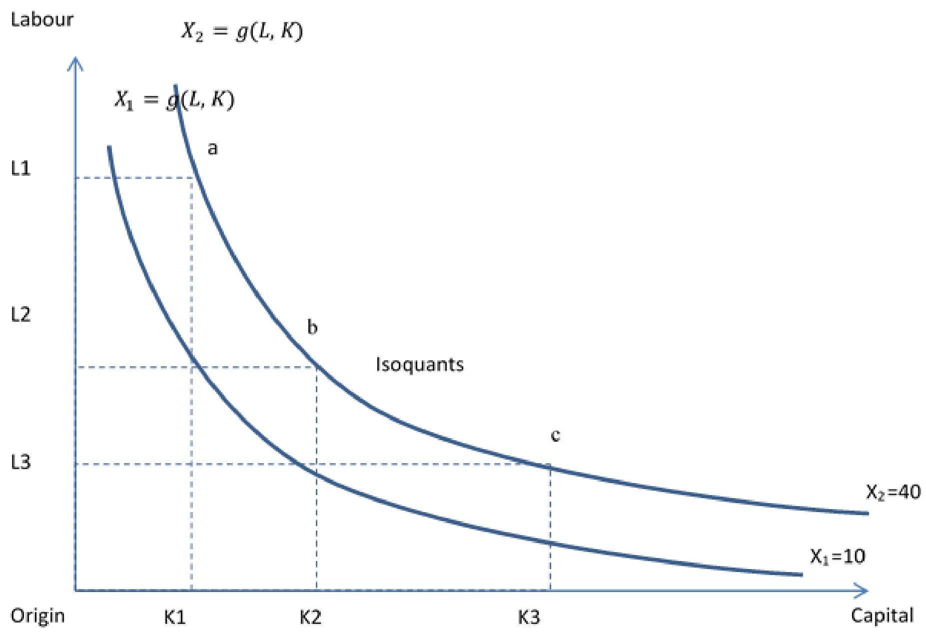


Figure 3.1: Isoquants map

Consider C the total cost of a hypothetical health facility

$$C = wL + rK \tag{3.2}$$

C is derived from multiplying the quantity of each input with its price: namely, w is labour wages per hour and r is capital cost. Using a specific budget, all possible combinations of amounts of labour (L) and capital (K) can be shown as an isocost curve (Figure 3.2). Isocost curves have three properties: first, if an isocost touches one of the axes, it means that the providers can use either only capital or only labour. Second, an isocost line further from the origin (for example, C_3) indicates that the total cost is higher compared to an isocost line nearer to the origin (for example, C_1). Third, isocost lines have the same slope determined by the factor price ratio (Perloff, 2014).

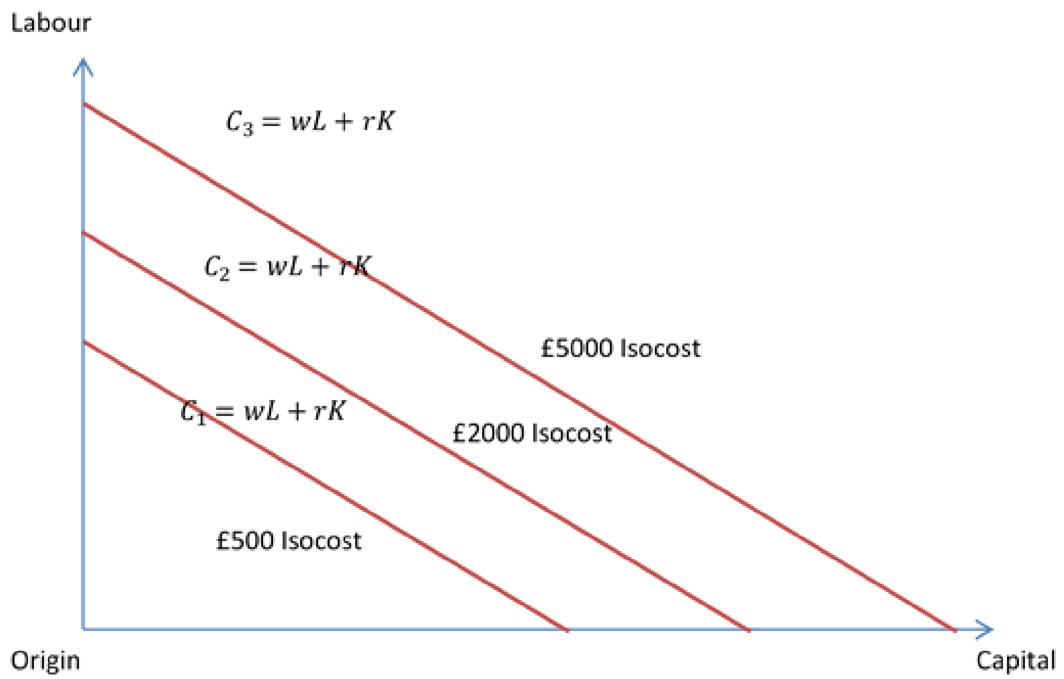


Figure 3.2: Isocost line: combination of labour and capital

If it is assumed that the objective of the providers is to maximise profit, in the healthcare context, health facilities maximise the health outcomes from the resources allocated. By combining information on costs in the isocost lines with the efficient production illustrated in isoquants, the optimum combination of labour and capital producing a certain quantity of services can be determined. Consider two isoquants producing X_1=10 and X_2=40 units of output respectively, and one isocost line (C_2) (see Figure 3.3). Point d is on the isoquant producing X_1 and so is considered as technically efficient, where maximum possible output is obtained from number of labour and capital given; however, with the isocost C_2, a higher level of output could be produced at point b that lies on the isocost producing 40 units by varying the combination of capital and labour. The maximisation of output for a given cost refers to productive efficiency.

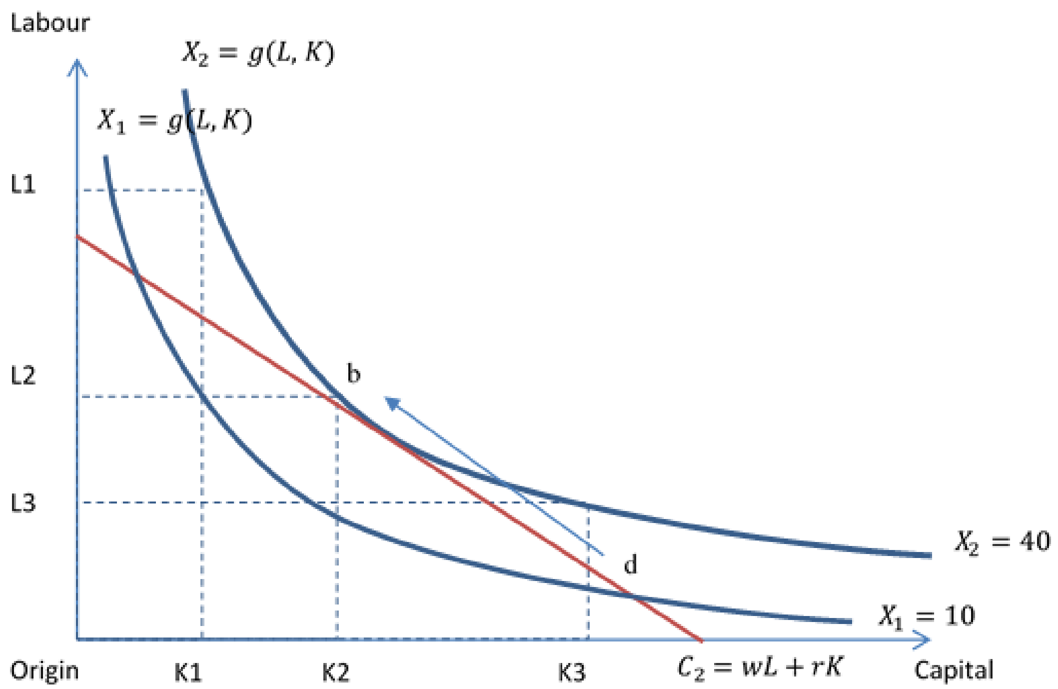


Figure 3.3: Maximising output

3.1.2 Concept of efficiency

Assessing efficiency is a key concern in evaluating performance as health budgets are consistently under pressure due to growing demand (Jacobs *et al.*, 2006). Efficiency is the amount of output that can be produced using inputs with minimum wasted effort or expense (Mas-Colell *et al.*, 1995; Jacobs *et al.*, 2006). There are three main concepts of efficiency: technical efficiency, productive efficiency and allocative efficiency (Palmer & Torgerson, 1999).

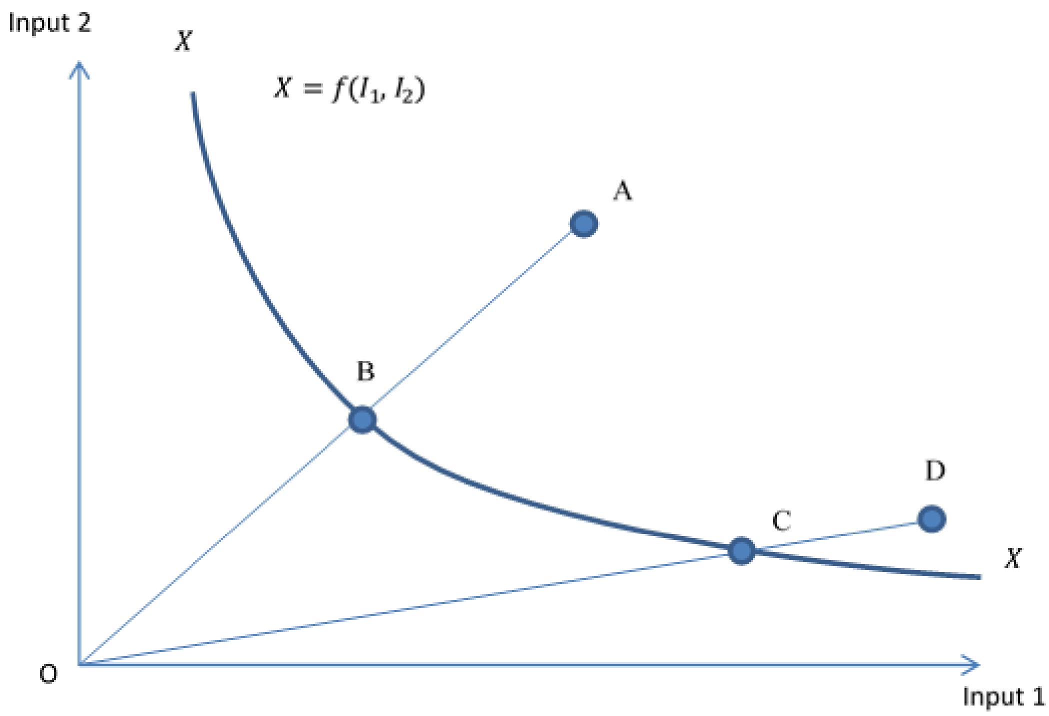


Figure 3.4: Technical efficiency under input orientation

Technical efficiency is the ability of a provider to use a minimum amount of input to produce a given level of output, and alternatively to obtain a maximum amount of output from the available resource input (Palmer & Torgerson, 1999; Coelli *et al.*, 2005). Consider a frontier line which illustrates concepts of a feasible production of output with four firms (see Figure 3.4). Firms that are operating on the frontier line XX are considered as efficient (B and C). In contrast, firms above the frontier are firms that are not technically efficient (A and D) (Coelli *et al.*, 2005; Jacobs *et al.*, 2006).

Productive efficiency refers to maximising output for given total cost, or minimising cost for given outputs. If output maximisation are the only objective, combination of inputs' price is considered to find the smaller total cost (Glied & Smith, 2011). Allocative efficiency is the ability of a provider to not only take productive efficiency into account, but also to allocate the optimum proportional combination of inputs or outputs to maximise social welfare (Palmer & Torgerson, 1999; Glied & Smith, 2011). Allocative efficiency can be regarded as not only choosing different combinations of resources to achieve maximum benefit for a given cost, but also ensuring that these outcomes are

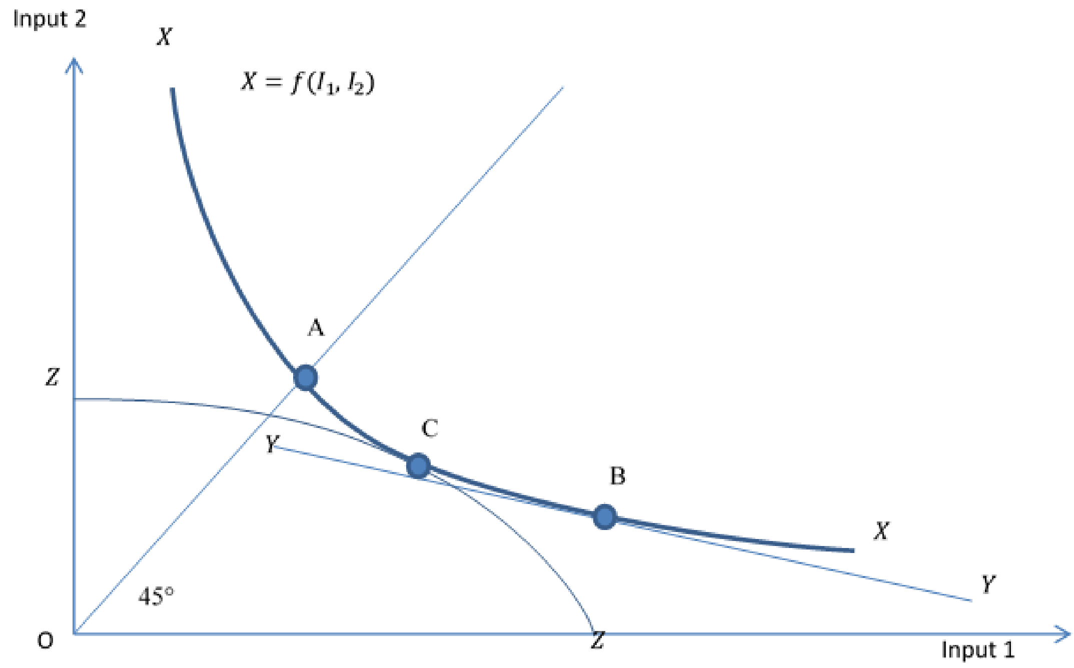


Figure 3.5: Allocative efficiency under input orientation

distributed in line with society's equity objectives (Palmer & Torgerson, 1999; Coelli *et al.*, 2005; Morris *et al.*, 2007).

Consider a context where two inputs are used to produce an output. In Figure 3.5, XX is the production function; it represents the combination of inputs used by a set of technical efficient providers as a frontier line. YY is the isocost line, which can be viewed as a budget constraint, while ZZ reflects the welfare function. A is the point at which inputs are allocated to the most equal distribution (45-degree line from the origin), whereas B (tangency between isocost line and production function) is the point at which productive efficiency is achieved by producing output at the lowest possible cost given the prices of inputs. Allocative efficiency is achieved when optimal proportions of inputs are allocated between two objectives on the frontier to maximise social welfare for the community, Point C. The tangent of interest is between the production function and the welfare function (Glied & Smith, 2011).

A facility is classified as technically efficient if it they are on the frontier line, those located outside are classified as inefficient. Details of frontier analysis will be discussed in DEA and SFA sections. In this thesis we focus on technical and productivity efficiency, while allocative efficiency is not investigated because of the wide variation in cost across the country, complexity of cases and lack of information on health service outcomes. In order to better understand the application of efficiency theories of health facilities, it is important to translate the theory into the empirical evidence. Therefore, proper step-by-step methodological approaches are necessary.

The next section describes the stages of the methodological approaches used in this PhD thesis.

3.2 Methodological approaches

3.2.1 Stage 1: Synthesising evidence on efficiency

Before proceeding with empirical studies, it is important to conduct a literature review to synthesise the evidence of the determinant factors of efficiency in health facilities in low- and middle-income countries (LMICs). A search strategy was developed to identify the relevant literature and was applied to a number of literature databases. Titles and abstracts were screened for eligibility as defined by the pre-specified inclusion/exclusion criteria. Full-text copies of articles were obtained and examined against the inclusion/exclusion criteria. The literature review method is detailed further in Chapter 4.

3.2.2 Stage 2: Measuring efficiency

A three-step procedure is commonly used in efficiency studies: 1) choosing efficiency measurement technique; 2) selecting inputs and outputs; 3) examining factors determining efficiency (Worthington, 2004). After exploring efficiency measurement in the literature, the first two steps were conducted by identifying the suitable measurements (i.e. ratio analysis and frontier analysis) and potential components using available datasets. Step 3 as explained below in Stage 3, identifies contextual factors and appropriate methods of measuring efficiency.

Ratio Analysis

We use ratio analysis (RA) to measure efficiency by comparing the ratios of inputs and outputs among health facilities. There are two types of ratios: input to output ratios (RA of technical efficiency) and cost of input to output ratios

(RA of economic efficiency) (Bitran, 1992). RA is typically limited to one type of input and one type of output. For example, number of beds and bed days are the input and output used to estimate bed occupancy rate. However, it is also possible to perform ratio analysis across a range of inputs simultaneously using the Pabón-Lasso model (Lasso, 1986).

Lasso (1986) developed a graphical technique, plotting the health facilities in four sectors using a combination of efficiency indicators. There are three main indicators: 1) Average bed occupancy rate, which is represented on the horizontal axis and measures the percentage of time an average bed was occupied during the year, 2) Average bed turnover rate, which is represented on the vertical axis and measures the average annual number of discharges per bed in the year, and 3) Average length of stay, which is represented by the gradient of a straight line from the origin to the observation and measures the average duration of inpatient stays.

Regarding economic efficiency, the performance of health facilities can be evaluated using the average cost per service. It is useful to compare the average cost among health providers with similar roles to assess their performance (Barnum & Kutzin, 1993). Decreasing the average cost per service by maintaining high utilisation is possible because of the large proportion of fixed costs of institutions (Milsum *et al.*, 1973). Nonetheless, the variation in the average cost of services among providers must be interpreted carefully because of differences in input prices (Morris *et al.*, 2007).

Frontier Analysis

Frontier analysis comprises two approaches: a non-parametric approach, data envelopment analysis (DEA); and a parametric approach, stochastic frontier analysis (SFA). Both approaches estimate the production frontier from cross-sectional sample data (Coelli *et al.*, 2005; Jacobs *et al.*, 2006) and have been increasingly employed in research to measure relative efficiency of healthcare services (Hollingsworth *et al.*, 1999; Hollingsworth, 2003, 2008).

DEA developed by Charnes *et al.* (1978), involves using mathematical programming to construct a frontier line such that no observed point should lie outside it. This technique identifies providers' performance by benchmarking with the fully efficient providers lying at the frontier (Coelli *et al.*, 2005; Jacobs *et al.*, 2006). DEA can be measured using input-oriented and output-oriented approaches. Input-oriented efficiency is the maximal proportional contraction of all inputs that allows health facilities to produce the same level of services. 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.

$$\begin{aligned}
&\max \phi, \\
&\text{subject to} \\
\sum_{i=1}^{n} \lambda_i x_{ji} \leq x_{jo} \qquad & j = 1, 2, .., m; \\
\sum_{i=1}^{n} \lambda_i y_{ri} \geq \phi y_{ro} \qquad & r = 1, 2, ..., s; \\
\sum_{i=1}^{n} \lambda_i = 1 \qquad \lambda_i \geq 0 \qquad & i = 1, 2, ..., n
\end{aligned} \tag{3.3}$$

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 under evaluation; the left-hand side represents the convex combinations of observed values on the inputs and outputs.

Both input- and output-oriented approaches use the number one to indicate fully efficient facilities. Inefficiency in input-oriented models is assigned a value less than one, while inefficiency in output-oriented models is represented by a value greater than one. Thus, to allow direct comparison to the input-oriented DEA models, the reciprocals of DEA output-oriented efficiency scores are used in the empirical studies.

DEA frontier lines differ depending on the scale assumptions applied. Generally there are two scale assumptions applied: constant returns to scale (CRS) and variable returns to scale (VRS). CRS are applied when the providers can be operating at an optimal scale where output changes proportionately to input; in such a case, the surface is linear and there is only one DMU at the frontier. Meanwhile, VRS are built to accommodate a more flexible return to scale, which is often the case since providers are frequently subject to financial and regulatory constraints, as well as other restrictions, and are thus operating on a sub-optimal scale. VRS frontiers exhibit increasing returns to scale where output increases proportionately more than inputs and decreasing returns to scale where output changes proportionately less than inputs (Jacobs *et al.*, 2006). Therefore, VRS are more flexible than CRS, which assume that not all facilities are operating at an optimal scale. However, the VRS approach also causes fewer facilities to appear as inefficient, particularly where there is considerable variation in the size of facilities.

DEA has been identified as the dominant method utilised in the measurement of efficiency studies because of its ability to accommodate multiple inputs and outputs typical of the healthcare setting (Hollingsworth *et al.*, 1999; Hollingsworth, 2003; Worthington, 2004; Hollingsworth, 2008; Hussey *et al.*, 2009). Despite its ability to employ multiple inputs and outputs, DEA does not accommodate error, outliers or noise measurement; thus, inclusion of a facility whose inputs and outputs lie in the outlier region could affect the efficiency measurement (Coelli *et al.*, 2005; Jacobs *et al.*, 2006).

SFA differs from DEA in that it estimates a best-practice frontier using the least squares method to define the functional relationships between one dependent variable and a multiple number of independent variables (Aigner *et al.*, 1977). It decomposes the error into two components: random noise (unobserved heterogeneity) and true inefficiency. Thus, SFA is often preferred because it can handle noise present in the data such as measurement errors, epidemics, or other factors, whereas such noise would influence the placement of the frontier line in DEA (Giuffrida & Gravelle, 2001). Approximately 18% of studies have utilised SFA and the trend is increasing (Hollingsworth, 2008). However, SFA has a number of drawbacks: it requires assumptions about functional form and error distribution, and it is vulnerable to small sample sizes (Giuffrida & Gravelle, 2001; Coelli *et al.*, 2005).

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

$$\begin{gathered} \ln y = \ln f(x) + v - u \\ \text{with } v \sim N(0, \sigma_v^2) \text{ and } u \sim N_+(0, \sigma_u^2) \end{gathered} \tag{3.4}$$

v represents the stochastic nature of the production process and possible measurement errors of the inputs x and output y, and the term u is the potential level of inefficiency of the provider. We assume 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.

Four different SFA models are used in the empirical studies: a Cobb-Douglas production function, a Translog function, a distance function, and a Translog distance function. The Cobb-Douglas function represents the unitary elasticity of substitution and is written as follows:

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + (v_{i-} u_i) \tag{3.5}$$

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 the technical inefficiency of health facility i.

However, Cobb-Douglas functions have one weakness; all first-order derivatives of linear function are constants, and all second-order derivatives are zero (Bogetoft & Otto, 2010). The Translog function offers a functional form providing a second-order approximation and is written as follows:

$$\log(y_i) = \beta + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + (v_i - u_i) \tag{3.6}$$

$\log x_{ji} \log x_{hi}$ 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. 3.5 and 3.6, might not be appropriate due to a different type of output. Therefore, we estimated a multi-output distance function and a Translog distance function. The model of the distance function form is written:

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

$$\text{where the interpretation of } \frac{y_h}{y_n} \text{ is } \left(\frac{y_1}{y_n}, \ldots, \frac{y_{n-1}}{y_n}\right) \tag{3.7}$$

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

$$\log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2}\sum_{j=1}^{k}\sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + \sum_{h=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}}$$
$$+\frac{1}{2}\sum_{j=1}^{k-1}\sum_{h=1}^{k-1} \beta_{jh} \log \frac{y_{hi}}{y_{ni}} \log \frac{y_{hi}}{y_{ni}} + \sum_{j=1}^{k}\sum_{h=1}^{k-1} \beta_{jh} \log x_{ji} \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \tag{3.8}$$

As discussed, DEA and SFA have respective advantages and disadvantages; there is therefore no 'best method' for estimating the efficiency frontier (Jacobs *et al.*, 2006). Both methods are appropriate if all conditions are met and if the method allows the researcher(s) to achieve the aims of the study (Jacobs *et al.*, 2006). The empirical studies presented in Chapters 6 and 7 apply both DEA and SFA, plotting the variables used into the functions written above for both methods. Sensitivity analysis in DEA and SFA is performed, and the robustness of the findings is checked by means of validity testing. The validity tests used are set out in the following subsection.

Validity testing

Different combinations of input and output variables are used to test the changes in the efficiency estimates. The internal validity was tested to check the efficiency score estimated as well as the stability between specifications within the method. The external validity was also tested to address the stability of the results between DEA and SFA.

Two-step internal validity testing is conducted prior to the external validity test. For DEA, two model assumptions are first compared using the Kruskal-Wallis test to see whether the difference was statistically significant by reducing the number of inputs and outputs. Second, a Spearman rank correlation test is used to estimate the correlation between DEA input- and output-oriented models. For SFA, a likelihood ratio test investigates, under the null hypothesis, whether there are any difference between SFA and ordinary least squares (OLS) models. Second, a Spearman rank correlation test is used to estimate the correlation between the SFA models (i.e. Cobb-Douglas, Translog, distance function, and Translog distance functions).

External validity is 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 is chosen due to the skewness of the data distribution. Finally, we include models with better estimates of internal and external validity.

Quadrant scores between DEA and SFA

Since the results of the DEA and SFA approaches are not always similar, the identification of health facilities that are efficient or inefficient according to both of the two approaches is required (Jacobs *et al.*, 2006). For this purpose, the DEA and SFA scores are plotted of health facilities and divided the plot into four quadrants using average estimates representing different levels of efficiency (see Figure 3.6).

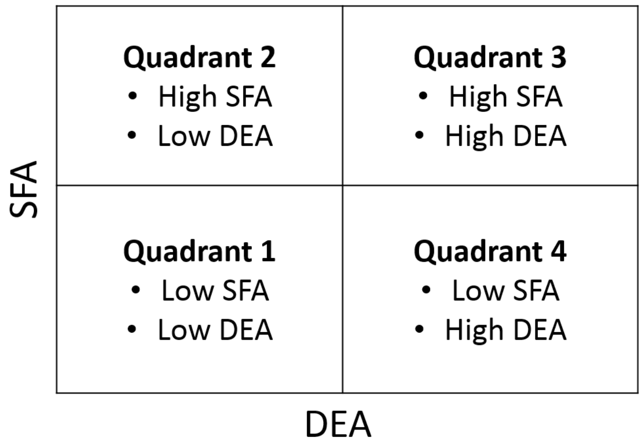


Figure 3.6: Quadrant scoring using DEA and SFA

Components of efficiency

Having discussed above the approaches to measuring efficiency, identification of the specifications of inputs and outputs is needed (see Figure 3.7).

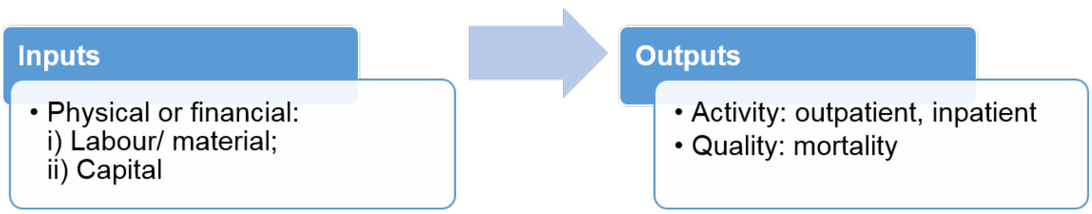


Figure 3.7: Health facility inputs and outputs

There is no best practice method regarding the choice of input and output variables that should be used in efficiency measurement. The implications of using one variable rather than another can indeed be compared; however, there are many variables that can be used to measure input and output.

Inputs can be measured as physical inputs or financial inputs. Applying physical inputs answers questions about whether the output could be optimised by using the optimal mix of labour and capital (Hussey *et al.*, 2009). Physical inputs have the advantages of ease of calculation and comparability, although they have the disadvantage of not always being able to capture monetary aspects of inputs such as health facility expenses (Hadji *et al.*, 2014). Financial inputs answer questions about whether the output could be produced less costly through more efficient use of inputs or substitution of costly inputs (Hussey *et al.*, 2009). Since there are huge discrepancies among salaries and cost of care, financial inputs do not allow this comparison, especially internationally (Hadji *et al.*, 2014).

Previous empirical studies have shown that physical inputs such as number of staff members (labour) and number of beds (proxy of capital) have become the dominant inputs (Hollingsworth, 2003; Worthington, 2004; Hollingsworth, 2008). Number of beds has been used in previous studies as a representative of capital (Mobley & Magnussen, 1998; Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Mitropoulos *et al.*, 2013; Varabyova & Schreyogg, 2013; Chowdhury *et al.*, 2014; Ding, 2014; Ineveld *et al.*, 2015; Matranga & Sapienzab, 2015; Yang & Zeng, 2014); however, Mobley & Magnussen (1998) argued that beds may not appropriately reflect the variation in technology among health facilities. Therefore, a number of studies have used other proxies for capital such as health facility space and specific equipment as main production factors (Heimeshoff *et al.*, 2014). Other studies have used financial inputs of capital such as total cost of capital, or value of equipment (Jacobs, 2001; Besstremyannaya, 2013; Mutter *et al.*, 2013; Chowdhury *et al.*, 2014). In terms of labour and material, previous studies have used number of full-time equivalents (FTE) of physical inputs (physicians, nurses, mix of medical staff, specialists, and other administrative staff) as well as financial inputs (expenses for staff, drugs and medical supplies, as well as price of office space) (Mobley & Magnussen, 1998; Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Mitropoulos *et al.*, 2013; Nedelea & Fannin, 2013; Varabyova & Schreyogg, 2013; Chowdhury *et al.*, 2014; Cordero Ferrera *et al.*, 2014; Heimeshoff *et al.*, 2014; Shreay *et al.*, 2014; Yang & Zeng, 2014; Ineveld *et al.*, 2015; Matranga & Sapienzab, 2015).

Table A.1 in Appendix A summarises input variables that have been used in empirical studies.

There are currently two opposing views regarding the type of output that should be used to evaluate healthcare (Morris *et al.*, 2007). The first argument states that since health is the ultimate output of the health sector, any activities in the health sector should be evaluated in terms of changes in health produced. This could be misleading since changes in health might not reflect the number of services provided. Moreover, health is not a good that can be traded directly, rendering this concept difficult to use in analysing healthcare markets. A final health outcome such as health status is also recognised as an impractical output since the impact of healthcare interventions can only be seen many years later.

The other view states that intermediate outputs, which then will be used by individuals to produce health as the final output, can also be used. Intermediate outputs can then be further separated into two main groups: activity indicators (e.g. amount of care provided), with or without quality adjustment, and financial outputs (e.g. health facility revenue) (Worthington, 2004; Hollingsworth, 2008; Hadji *et al.*, 2014). Activity outputs such as number of outpatient visits, discharges, and inpatient days are predominantly used in healthcare efficiency measurement studies (Hollingsworth *et al.*, 1999; Hollingsworth, 2003; Worthington, 2004; Hollingsworth, 2008). However, using these as output variables might result in losing sight of the main purpose of healthcare, which is to produce health. It should also be noted that this measurement implicitly assumes that there is no difference in effectiveness of healthcare services among organisations. Several studies have therefore used quality outputs such as mortality rates (Varabyova & Schreyogg, 2013; Ding, 2014; Yang & Zeng, 2014; Matranga & Sapienzab, 2015), complications (Ineveld *et al.*, 2015), or re-admission rates (Ding, 2014) as control variables. Whereas most studies use physical performance to ensure homogeneous outcomes, case mix as a weighing device, may give more accurate measures of intermediate output (Hollingsworth, 2008; Mutter *et al.*, 2013; Chowdhury *et al.*, 2014). Table A.2 in Appendix A summarises output variables used in empirical studies. The discussions in this thesis regard both viewpoints as valid, albeit imperfect, measures of outputs since they both have advantages and drawbacks depending on the context of the study.

3.2.3 Stage 3: Identifying factors determining differences in efficiency

Apart from input and output variables, factors beyond the control of health institutions (contextual variables) need to be considered and their impact on efficiency evaluated (Worthington, 2004). Contextual variables are separated into two groups: (1) internal factors: elements within providers' characteristics that affect facility efficiency (e.g. ownership, capacity, and quality); and (2) external factors: those beyond the influence of providers that can impact estimated efficiency (e.g. area economic status, population education level, and geography) (Mobley & Magnussen, 1998; Herr, 2008; OECD, 2010; Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Nedelea & Fannin, 2013; Varabyova & Schreyogg, 2013; Cordero Ferrera *et al.*, 2014; Ding, 2014; Heimeshoff *et al.*, 2014; Shreay *et al.*, 2014; Yang & Zeng, 2014; Matranga & Sapienzab, 2015). We have summarised the contextual factors determining efficiency in healthcare institutions (see Table A.3 in Appendix A).

Large numbers of contextual variables available in the dataset are potentially highly correlated and can lead to problems for multivariate regression techniques (Everitt & Hothorn, 2011). To address this issue, principal components analysis (PCA) is used to create a smaller number of new, uncorrelated variables (Jolliffe & Cadima, 2016). 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 & Hothorn, 2011). We determined the variables grouping prior to PCA analysis for interpretation purposes in the final results. Variables were transformed into a new index variable by categories (i.e. index of health facility disruption, index of quality management, index of poverty, index of access to health facility and index of population education). The contextual variables generated from PCA analysis are presented in Chapters 6 and 7.

To determine the relationship of contextual variables to efficiency, second-stage DEA analysis is applied. Two-stage approach procedures have been widely implemented (Hollingsworth, 2008). First, the relative technical efficiency scores of health facilities are estimated using DEA. Subsequently, efficiency scores acquired from frontier analysis are treated as dependent variables determined by the number of contextual variables. There is some debate regarding regression in second-stage analysis (Hoff, 2007; McDonald, 2009; Simar & Wilson, 2011). Since efficiency scores above 1 are not possible, it is necessary to use a truncated regression model to investigate the relationship between the DEA efficiency scores computed in the first stage and a vector of contextual factors. A problem with the two-stage used in the model is that DEA scores may be serially correlated (Simar, 2007). An alternative method to solve this problem is to use bootstrapping and regress the bootstrapped estimates on contextual variables z to provide inference about β (Simar, 2007; Bogetoft & Otto, 2010). The idea of bootstrap is to sample observations with replacements from one's data set and thereby create a new random data set of the same size of the original. We performed bootstrap using 100 replications to compute the bias-corrected efficiency estimates $\hat{\phi}$. We found mean bias-corrected and confidence interval of efficiency estimates were not significantly different compared to the larger numbers of replications.

Second-stage DEA is written as follows:

$$\hat{\phi}_i = \beta z_i + \varepsilon \tag{3.9}$$

Where in this case $\hat{\phi}$ is the estimated bias-corrected DEA score generated from bootstrap procedure, assumed to be truncated, β is the unknown coefficient, z is the vector of contextual variables, and ε is a random variable.

The two-stage procedure 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.

One-stage SFA is written as follows:

$$u_i = \delta z_i + W_i \tag{3.10}$$

Where u is the technical inefficiency effect in the stochastic frontier model (eq. 3.4), δ is the unknown coefficient, and W is the random variable.

3.3 Data

3.3.1 Dataset

This study employed four national survey datasets; the purpose of each dataset is shown in Table 3.1.

National health facility costing study

The Indonesian Ministry of Health (MoH) conducted a national health facility costing study (HFCS) in 2010. The central objective of this study was to provide a better understanding of the cost of delivering health services across the country. The prospective study was conducted between October 2010 and September 2011 across 15 provinces and 30 districts of Indonesia. Samples of health facilities were selected through a stratified random sampling process (Ensor & Indradjaya, 2012). The survey collected data on the services, resources (infrastructure, equipment, staff, pharmaceuticals, and medical supplies), and expenditures (e.g. office supplies, maintenance, and transportation expenses) for 234 *Puskesmas* (3%) and 202 hospitals (12%) (Kemenkes, 2012e).

National socioeconomic survey

The National Socioeconomic Survey (SUSENAS) is a series of large-scale multi-purpose socioeconomic surveys conducted in Indonesia. It is a district representative sample. In 2011, SUSENAS covered a nationally representative sample composed of 300,000 households from 33 provinces and 497 districts across Indonesia. The survey consisted of a household roster and additional information on healthcare and nutrition, household income, expenditure, labour force experience, etc. This study uses the *Survey Sosial Ekonomi Nasional* 2011 (*Gabungan*), ID number: DDI-00-SUSENAS-2011-M1-GABUNGAN-BPS (BPS, 2011b).

National village potential survey

The Village Potential Statistics (PODES) provide information about village characteristics for all of Indonesia. PODES is a census providing information about village characteristics across Indonesia such as population size, main

Table 3.1: Purpose and method for each dataset

Dataset	Purpose	Method
HFCS	Facility level data to estimate the relative efficiency of health facilities and internal context factors determining efficiency	Ratio and frontier analysis approaches were applied using health facility output and input variables. Bivariate and multivariate statistical analysis were employed to identify health facility characteristics determining differences in efficiency.
SUSENAS	District level data to analyse significant factors in household characteristics that determine efficiency	Empirical analysis using multivariate regressions
PODES	Village level data to identify geographic and infrastructure characteristics, including the availability of healthcare services affecting efficiency.	Empirical analysis using multivariate regressions
INA-CBGs	Individual level data to consider variation in patients' case mix and output-quality measures in hospitals	The average tariff for each case base group for all hospitals was employed to generate case mix index (CMI). Volume of services was then adjusted for the respective CMIs. The output-quality variable was constructed by using mortality ratio for each hospital.

HFCS Health Facility Costing Study, *INA-CBGs* Indonesian-Case Base Groups, *SUSENAS* National Socioeconomic Survey, *PODES* The Village Potential Statistics

source of family income, availability of and access to health facilities, and death rate. In 2011, data were collected from 77,126 villages across 6,651 sub-districts, and 497 districts. An infrastructure census was also conducted to gather information on public infrastructure including health institutions in the village. The health facility types recorded were: primary healthcare, village health post, delivery health post, and integrated health post. This study uses *Pendataan Potensi Desa* 2011, Survey ID number: 00-PODES-2011-M1 (BPS, 2011a).

Indonesian-case base groups dataset

Since 2007, diagnosis-related groups (DRG), namely Indonesian-case base groups (INA-CBGs), have been used to reimburse hospitals under the *Jamkesmas* scheme. The INA-CBGs dataset contains patient-level information related to patient demographics, diagnosis, and reimbursement tariffs. Patient-level data in the INA-CBGs dataset could not be used using multilevel models in this thesis because data is limited to hospitals contracted under the *Jamkesmas* scheme (only 60% of the sample is matched with HFCS dataset as the main dataset). However, the key variables are DRG code, DRG tariff, and type of discharge, which are useful for representing the complexity of patients in hospitals. In order to consider burden of illness and quality, hospital outputs were adjusted by using a case mix index (CMI) and mortality ratio (Witter *et al.*, 2000; AHRQ, 2013).

A higher case mix index (CMI) means that patients with more complex cases were treated in ways that consumed greater amounts of healthcare resources. The adjusted CMI patient volume allows comparability across hospitals. The average tariff for each case base group for all hospitals was used to estimate CMI.

Since there are different tariffs for each hospital class in Indonesia, we used the average tariff for each case base group for all hospitals. Then, CMI for hospital k was calculated using the following equation for outpatient and inpatient services:

$$CMI_i = \frac{\left(\sum_{k=i}^{K} \overline{tariff}_k \times M_{ki}\right) / \sum_{i=1}^{I} M_i}{\left(\sum_{k=i}^{K} \overline{tariff}_k \times \sum_{i=1}^{I} M_{ki}\right) / \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ki}} \quad (3.11)$$

$$\overline{tariff}_k = \frac{\sum_{m_k=1}^{M_k} tariff_k}{M_k}$$

where $\overline{tariff}_k$ is the average tariff for DRG k, and M_{ki} is the number of patients with DRG k in hospital i.

Quality indicators in hospitals were constructed by using the mortality ratio. A ratio smaller than one indicates good quality. Mortality ratio was calculated using the following equation:

$$\begin{aligned} mort\_ratio_i &= \frac{act\_death_i}{exp\_death_i} \\ exp\_death_i &= \sum_{k=1}^{K} \overline{death\_rate_k} \times adm_{ki} \\ \overline{death\_rate_k} &= \frac{death_k}{adm_k} \end{aligned} \tag{3.12}$$

where mortality ratio $mort\_ratio_i$ is the actual number of deaths act_death in hospital i over the expected number of deaths exp_mort in hospital i. Average death rate, $\overline{death\_rate}$, is the number of deaths $death$ for DRG k over the number of admissions adm for DRG k. Number of admissions and bed days were adjusted by the quality indicator (death rate times mortality ratio).

$$\begin{aligned} adj\_admissions_i &= admissions_i \times CMI_i \times (1 - death\_rate_i \times mort\_ratio_i) \\ adj\_beddays_i &= beddays_i \times CMI_i \times (1 - death\_rate_i \times mort\_ratio_i) \end{aligned} \tag{3.13}$$

Hospitals with lower mortality ratio increase the number of hospital discharge, or higher mortality ratio reduce survival rate.

The *Jamkesmas* case mix index can reflect hospitals' case mixes because of its large number of beneficiaries. On average, based on HFCS, *Jamkesmas* patients represented 24% of inpatients and 14% of outpatient visits. Forty-seven percent of *Jamkesmas* beneficiaries were in the bottom three income deciles, 32% in the middle four income deciles, and 20% in the top three income deciles (Marzoeki *et al.*, 2014). The dataset was supplied by the Centre for Health Financing and Insurance at the Indonesian MoH. This study uses the 2011 INA-CBGs dataset, linking it to the HFCS dataset using unique health facility IDs generated by the MoH.

3.3.2 Data management

Data were manipulated and merged in STATA 14 (Stata-Corp, College Station, TX, USA). Ratio analysis, including cost computations, Pabón-Lasso diagram construction, and characteristics analyses were performed using STATA 14. Data were exported into R (http://cran.r-project.org) for all analyses. To assess the pattern of relationships within the data and generate the index score, the package PCAmixdata was applied (Chavent *et al.*, 2012; Chavent *et al.*, 2014). This method can handle quantitative and categorical variables (Kiers, 1991). The efficiency scores were obtained using several 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 for outliers using the FEAR package (Frontier Efficiency Analysis) in R Version 2.0.1 (Wilson, 2008).

3.3.3 Variable description and missing data

Tables A.4 and A.5 in Appendix A describe the key variables, particularly contextual factors, to be used in our empirical studies in hospitals and primary care facilities. The tables also provide descriptive statistics and the number of missing observations in each variable.

When missing data occur, results are potentially biased because they may become unrepresentative and thus lead to misinterpretation of policy conclusions (Marshall *et al.*, 2009). As can be seen in Figures A.1 and A.2 in Appendix A, different missing data patterns were found. In the hospital and *Puskesmas* datasets, the pattern of the missing data was found to be univariate. In hospitals, we found two health facilities with missing data for almost all variables. We therefore dropped those two observations from the hospital sample. INA-CBGs dataset suffered most from missingness because not all hospitals in Indonesia are contracted under *Jamkesmas* scheme. In *Puskesmas*, a univariate pattern was found in variables related to inpatient services such as bed days, bed occupancy rate and length of stay. This was expected, because not all *Puskesmas* provide inpatient services; we thus retained the original dataset. If we consider only the input and output variables used, missing data patterns in hospitals are generally found to be intermittent, where missing variables occur in a random manner in any health facility.

We investigated whether observed variables are associated with missingness, and we concluded the data are missing at random. Tsikriktsis (2005) suggested regression imputation as an appropriate way to address missing data when more than 20% of the data are missing. We performed multiple imputation to impute missing data using a chained equations technique (five imputations were performed) with ‘mice’ library in R statistical software (Buuren & Groothuis-Oudshoorn, 2011). The mice package can handle mixed type of data (i.e continuous, binary, categorical data), thus all predictors were considered for imputation models (list of variables in Table D.1 and E.1 in Appendix). The estimates obtained from imputed data were extracted and used to fill in the missing data.

3.4 Ethical issues

A quantitative secondary analysis study does not require university ethical review (see Figure A.3 in Appendix A). The datasets used in this PhD project are anonymised and publicly available, and permission to use them has been obtained from the Indonesian MoH (see Figures A.4, A.5 and A.6 in Appendix A) and from the Central Bureau of Statistics (BPS) Indonesia (see Figure A.7 in Appendix A). BPS Indonesia is not responsible for the use of data or for interpretations or conclusions based on data usage.

This chapter has reviewed the basis of efficiency measurement, starting from the concept of production and efficiency and followed by the stages required to conduct empirical studies on efficiency. Additionally, techniques for the measurement of efficiency, ratio analysis and frontier analysis as well as the components of efficiency have been reviewed. We have discussed the contextual variables that may influence efficiency, the data used for the empirical studies, and the ethical review.

In order to conduct empirical studies on efficiency in Indonesia, it is essential to understand efficiency in the setting of other LMICs and how efficiency has been measured in LMIC settings to date. The next chapter synthesises current evidence on efficiency and its measurement in LMIC.

Chapter 4

Efficiency Measurement in Health Facilities: Literature Review in Low- and Middle-Income Countries

Having established an understanding of the methodological aspects of efficiency measurement in the previous chapter, we now move to the literature review on the efficiency of health facilities within the context of low- and middle-income countries (LMICs). Such a review is particularly indispensable for policy makers in LMICs who must employ the best evidence to guide efficiency-related decisions. This chapter thus aims to review the methods of measuring efficiency and thus inform future efficiency studies at all levels of health facilities both in public and private settings.

This literature review synthesises the settings of the efficiency measurement studies in LMICs; the techniques, input and output variables, as well as the contextual variables used in the studies; the methodology issues; and the outcomes. The introductory section of this chapter provides background on the healthcare sector and its efficiency in LMICs as well as on the differences between LMICs and high-income countries (HICs). Section 4.2 provides the methods used to synthesise the evidence, while Section 4.3 documents the results of the literature review. The results are then further discussed in Section 4.4, including points of difference within the HIC context. Section 4.4 also sets out policy implications of the results obtained as well as their limitations and several recommendations for further work. The final section offers a summary of the entire chapter.

4.1 Introduction

Improving the efficiency of the utilisation of resources is important in most health systems. It is an issue that is particularly acute in LMICs facing limited resources and pressure on services from a double disease burden and weak health system infrastructure (WHO, 2000; Orach, 2009). LMICs spend USD 266 per capita on health expenditure while high-income countries (HICs) spend USD 5,266 (The World Bank, 2018). Between 1995 and 2014, annual spending in LMICs increased by an average of 10% per annum, placing huge pressure on limited resources (The World Bank, 2016).

Promoting efficiency is important for LMICs to ensure that resources are targeted to promote the goal of universal health coverage (UHC). Efficiency is of great import in both the private and public sectors since the limited public sector capacity in LMICs means that the private sector's role in achieving UHC is particularly crucial (WHO, 2010; The World Bank, 2017). Similarly, improving efficiency in both secondary and primary care can enhance the overall ability of the system to improve population health. Hospitals are often relatively well equipped but inefficiently utilised with, for example, bed occupancy rates that are well below the 85% recommended by the World Health Organization (WHO) (Chisholm & Evans, 2010). Primary care as the system entry point should provide services for most health care needs and control access to specialist services, contributing to improved system efficiency (Starfield, 1994; Starfield *et al.*, 2005; Aldulaimi & Mora, 2017), but in practice, lack of resources and weak management may lead to low utilisation and bypassing.

Most studies on the efficiency of health facilities have been performed in HIC settings. Applying efficiency measurements in LMICs often requires modification of the methods that are used in HIC settings. In HIC settings, inefficiency is sometimes presented as variation in performance resulting from excessive use of inputs to deliver services (Chisholm & Evans, 2010; Ham *et al.*, 2012). However, in LMICs, inefficiency arises from shortages, weak management and poor distribution of resources (Mills, 2014).

The primary objective of this study is to highlight what is known about efficiency methodologies in health facilities in LMICs. The focus is on technical efficiency, defined as the ability of a health facility to use the minimum amount of input to produce a given level of output or to obtain a maximum amount of output from the available input (Palmer & Torgerson, 1999; Coelli *et al.*, 2005).

A variety of techniques have been utilised to measure technical efficiency. Bitran (1992) categorised them as ratio analysis, econometric estimation, stochastic frontier analysis, and data envelopment analysis. Although a number of literature reviews of efficiency techniques have been undertaken in HIC settings (Rosko, 1990; Emrouznejad *et al.*, 2008; O'Neill *et al.*, 2008; Rosko & Mutter, 2008; Afzali *et al.*, 2009), we found only a single review on LMICs; it focused on Iranian hospitals (Kiadaliri *et al.*, 2013). To the best of our knowledge, this review is the first to examine the efficiency methodologies of health facilities across LMICs. The review can therefore inform future efficiency studies across the health system, also providing evidence for policy makers in LMICs to guide efficiency-related decisions.

4.2 Methods

4.2.1 Search strategy

A review of five literature databases was performed along with a manual search of published articles within reference lists and covered publications up to Week 6 of 2018. No time limit was imposed because we wished to capture the entire landscape of efficiency studies.

The PhD candidate searched the following databases: MEDLINE (Ovid), Embase Classic + Embase (Ovid), Global Health (Ovid), and EconLit (EBSCOhost), as well as ProQuest Dissertations and Theses for grey literature. The searches were designed to identify efficiency studies of health facilities in LMICs by combining the search concepts of 'efficiency', 'health facilities' and 'low- and middle- income countries'. The search strategies suggested by Dudley & Garner (2011) for 'low- and middle- income countries' were adopted in this review. The full search strategies and keywords that were used are presented in Appendix B.

4.2.2 Inclusion criteria

Studies that were deemed eligible for inclusion measured efficiency, productivity or performance as a means of comparing services between health facilities. The unit of study is a health facility such as a hospital, primary healthcare facility, or nursing home in either the public or private sector. All types of quantitative analysis studies with empirical information relating to the measurement of the efficiency of services at the health facility level were considered. Because of our focus on LMICs, we excluded studies conducted in countries defined by the World Bank as HICs (countries with per capita incomes of USD 12,616 or more (The World Bank, 2015a). In addition, studies in languages other than English were excluded.

4.2.3 Data collection and analysis

The PhD candidate gathered all of the titles and abstracts retrieved by the electronic searches using a reference management database (EndNote) and removed duplicates. The titles and abstracts were screened on the basis of the inclusion and exclusion criteria, and full-text copies of the included studies were then downloaded and assessed. Once the studies to be included were identified, the data were extracted using a form developed for this purpose. Difficult studies were presented to the candidate's PhD supervisors (Tim Ensor and Sandy Tubeuf) for further discussion. Some articles were manually identified independent of the searching process. For each study, the following items were extracted: the aim, country, geographic region according to the World Bank groupings, type of health facility, sample size, year, method, orientation, input variable(s), output variable(s), contextual variable(s), outcomes, and limitations. Because the included studies were too heterogeneous to conduct a meta-analysis, a narrative synthesis was conducted (Popay *et al.*, 2006). Information from the studies was grouped according to the study characteristics and then examined in a tabulated summary.

4.2.4 Validity of studies

The PhD candidate assessed the methodological validity using a validity tool adapted from an instrument used in a published systematic review of hospitals

(Hadji *et al.*, 2014). The validity tool included thirteen items relating to the sample, indicators and statistical methods (Table B.1 in Appendix B). Each item was given one point if the answer was 'Yes' and zero points if the answer was 'No', yielding a score ranging from 0 to 13 for each study. Studies scoring fewer than 6 points were considered to have low validity, those scoring 6 to 8 to have medium validity, and those scoring 9 or more points to have high validity.

4.2.5 Measurement techniques

Ratio Analysis (RA) has been used to measure efficiency by comparing either input to output ratios (RA of technical efficiency) or the cost of input to output ratios (RA of economic efficiency) (Bitran, 1992). RA is typically limited to one input (e.g. beds) and one output (e.g. bed days). However, it is also possible to perform simultaneous ratio analyses across a range of inputs (Lasso, 1986).

Unlike RA, parametric techniques estimate relationships between one dependent variable and multiple independent variables of inputs or outputs based on a specific functional form (Jacobs *et al.*, 2006). In this review, we divided parametric methods into econometric estimation (EE) and stochastic frontier analysis (SFA). EE estimates technical efficiency or economic efficiency using ordinary least square regression between inputs and outputs. Production function models diagnose factors that are significantly associated with the level of the outputs, and cost function models identify factors that determine the cost (Berman *et al.*, 1989; Somanathan *et al.*, 2000). These average response models evaluate the inefficiency component with a random error (Schmidt, 2008).

4.3 Results

4.3.1 General description of included studies

The literature search identified a total of 6946 potentially relevant studies from five databases, and the manual search identified 12 articles. Once the duplicates were removed, 5376 titles and abstracts were screened, of which 5167 studies were excluded. The most common reasons for exclusion were that the aim of the study was not to assess the efficiency of health facilities and that the setting was not a LMIC. Two hundred and nine potentially relevant studies were retrieved for full-text assessment; 72 studies were excluded from full-text review because the full text was not available or not in English, and 137 studies were included in the analysis (Figure 4.1).

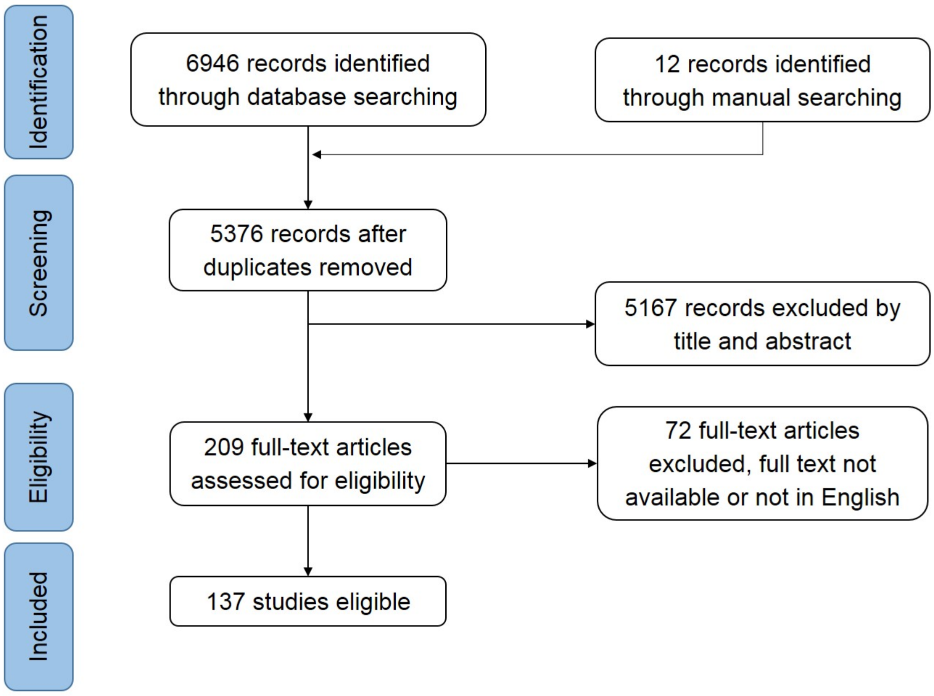


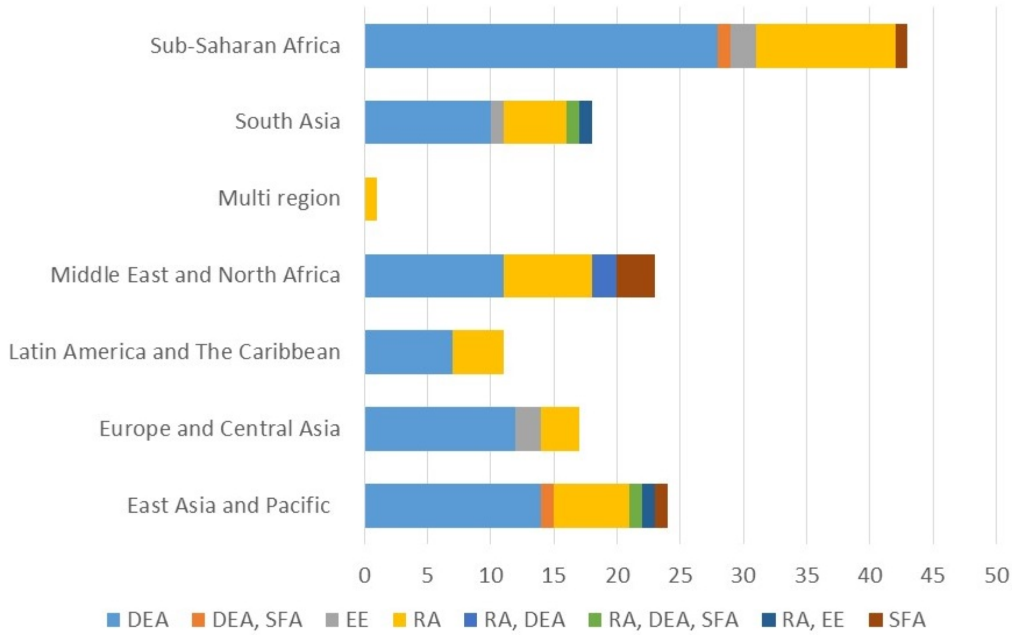
Figure 4.1: Study flow diagram of excluded and included studies

Regarding the validity of studies, of the 137 included studies, 107 studies (78%) had a high validity score and 30 (22%) had a medium validity score. Most of the studies with medium validity had one or more of the following issues: 1) they assessed only one type of health facility, 2) the calculation of the sample size was not clearly justified, and 3) they did not clearly define the study period. Conversely, most of the high-scoring studies had none of the above issues; they were also more likely to use different indicators to measure the impact on efficiency and to justify the statistical method.

4.3.2 Settings

Forty-three studies (31%) were conducted in sub-Saharan Africa (Figure 4.2), with a concentration in Ghana, Kenya, and South Africa. These studies consisted of intra- or inter-country analyses from 48 countries in seven regions. There were five inter-country efficiency studies, four of them conducted in Africa (Mills *et al.*, 1997; Soucat *et al.*, 1997; Levin *et al.*, 2003; Obure *et al.*, 2016); the fifth included several African countries as well as Honduras and Moldova (Brenzel *et al.*, 2015). The primary aim of that study was to improve the quality of information and examine the efficiency in different settings. The representativeness of intra-country analyses varied; for example, the study in Iran used data from only one hospital using five-year panel data (Masoompour *et al.*, 2015). However, a nationwide study of health facilities in Mexico included a total sample of 2,105 facilities (Keith & Prior, 2014).

There is no noticeable difference in the type of methods used in each region (Figure 4.2). DEA remained the most frequently used technique for efficiency measurements in all regions. RA was used in most of the regions, but not in Europe and Central Asia. In addition, only a small number of studies applied SFA and EE. SFA was only used in studies in sub-Saharan Africa, the Middle East and North Africa, and East Asia and the Pacific region, while EE alone was used in studies in South Asia, Europe and Central Asia.



DEA Data envelopment analysis, *RA* Ratio analysis, *EE* Econometric estimation, *SFA* Stochastic frontier analysis

Figure 4.2: Region of studies included and techniques applied

The health facilities were categorised into the following types: hospitals, primary care facilities, and other types of health facilities such as community nutrition centres, dentistry clinics, and dialysis facilities. Eighty-eight studies (64.2%) were conducted in hospitals, 29 studies (21.2%) took place in primary care settings, 11 studies (8.0%) analysed both hospital and primary care facilities, and nine studies (6.6%) were performed in other types of health facilities (Table 4.1). With regard to ownership, the majority of health facilities studied were in the public sector (n=97, 70.8%), 29 studies (21.2%) analysed both public and private health facilities, and only eight studies (5.8%) analysed private health facilities exclusively. Ownership information for the remaining 2.2% of the facilities studied was not available. The characteristics of the included studies appear in Table B.2 in Appendix B.

4.3.3 Techniques

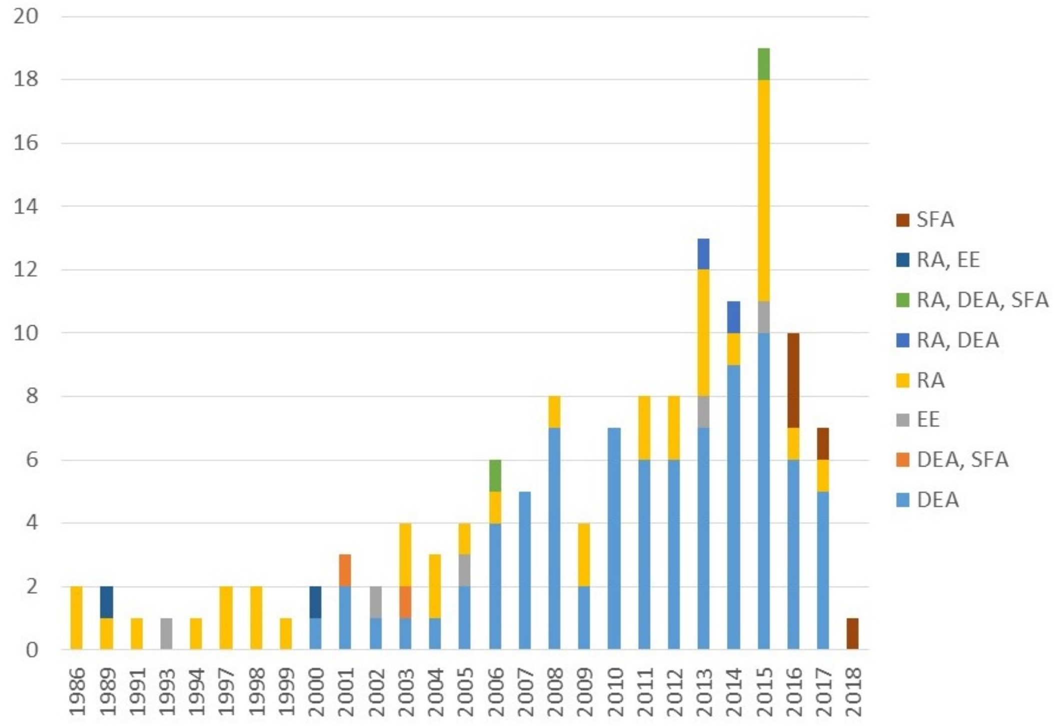
The number of studies using several techniques to measure efficiency has increased dramatically over the past few years (Figure 4.3). Most of the studies (91%) included in this review were published after the year 2000, and most used relatively modern analytical methods. Almost one-third of the studies applied one of two types of RA analysis. The first type is the physical input-to-output ratio (technical efficiency), for example, bed turnover and bed occupancy rates. Ten studies used the Pabón-Lasso model, which applies several RA indicators simultaneously. The second type is the ratio of cost inputs to outputs (economic efficiency), for example, the average cost per admission and the average cost per outpatient visit. The remainder of the studies (n=95, 65.5%) used SFA, DEA or a mix of methods. Fewer than three percent of the studies applied EE exclusively.

The use of DEA in the studies included in this literature review is seen beginning in 2000 (Fig 4.3); DEA has the advantages of being able to handle multiple inputs and outputs and not requiring a functional form to be specified. Of 137 studies, 82 used DEA alone or jointly with a second-stage analysis, including nineteen studies that also included the Malmquist index. It is notable that the studies using DEA were oriented predominantly by input rather than output orientation, while only a small number of studies applied both input and output orientation. Examining different levels of care reveals that the studies in hospitals were mostly input-oriented while those in primary care facilities were distributed equally between input- and output-oriented (Figure 4.4). This is

Table 4.1: Characteristics of efficiency measures

	Number of studies	(%)
Level of care		
Hospital	88	(64.2)
Primary care	29	(21.2)
Hospital and primary care	11	(8)
Other	9	(6.6)
Ownership		
Public	97	(70.8)
Private	8	(5.8)
Public and private	29	(21.2)
Not available	3	(2.2)
Inputs		
Physical	82	(59.9)
Financial	23	(16.8)
Physical and financial	32	(23.4)
Outputs		
Health services	122	(89.1)
Health services and quality	7	(5.1)
Other	8	(5.8)
Statistical/ mathematical methods		
DEA	82	(59.9)
RA	37	(27)
EE	5	(3.6)
SFA	5	(3.6)
RA, DEA, SFA	2	(1.5)
DEA, SFA	2	(1.5)
RA, EE	2	(1.5)
RA, DEA	2	(1.5)
Contextual variables		
Internal	39	(28.5)
External	13	(9.5)
Internal and external	32	(23.4)
None	53	(38.7)
Data source		
Primary data	58	(42.3)
Secondary data	70	(51.1)
Primary and secondary data	9	(6.6)
Time frame		
Cross-sectional	82	(59.9)
Panel	47	(34.3)
Not available	8	(5.8)

DEA Data envelopment analysis, *RA* Ratio analysis, *EE* Econometric estimation, *SFA* Stochastic frontier analysis



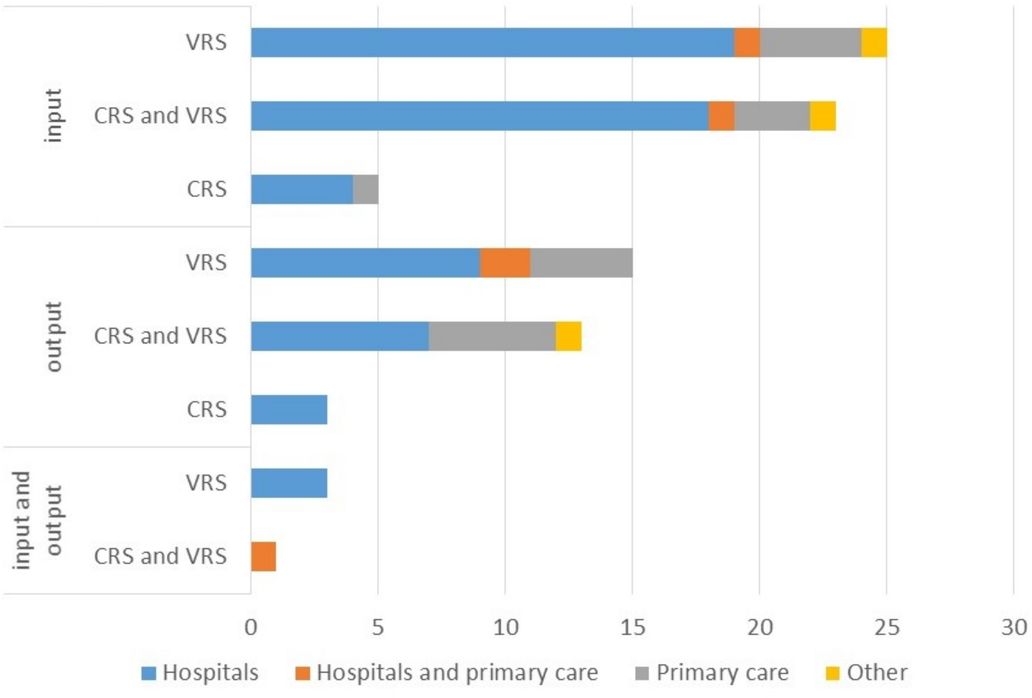
DEA Data envelopment analysis, *RA* Ratio analysis, *EE* Econometric estimation, *SFA* Stochastic frontier analysis

Figure 4.3: Efficiency measurement technique trend

presumably because hospital managers have more control over inputs, which allows them to minimise their use of resources while maintaining the same level of outputs. On the other hand, primary care managers usually have limited control over the level of inputs; their goal is to maximise the resulting outputs. Regarding returns to scale, most of the studies, particularly those conducted in hospitals, used predominantly VRS.

4.3.4 Input variables

Of the 137 efficiency measurement studies in the published literature, 82 studies used counts of physical resources as inputs, 23 studies used financial inputs, and 32 studies used both physical resources and financial inputs (Table 4.1). The physical input variables included different types of capital items (e.g. the number of beds, size of the facility, and the number of pieces of available medical equipment), as well as different types of labour or materials (e.g. the



VRS Variable return to scale, *CRS* Constant return to scale

Figure 4.4: DEA orientation and returns to scale by predominant health facility level of care

number of doctors and nurses and amounts of drugs and medical supplies). The financial inputs included the total expenditures, capital inputs (e.g. cost to reconstruct the health facility, equipment depreciation), and different types of labour/material expenditures (e.g. salaries, drug expenditures, and non-labour expenditures). Other types of inputs were also found, including a service mix as a proxy for the complexity of services and management quality as measured by efforts to satisfy customer expectations (Table 4.2).

4.3.5 Output variables

Most of the measures (89.1%) from the published literature used health services as outputs. The most common health service items in hospitals were 1) the number of outpatient visits, admissions or discharges, and 2) inpatient days (Table 4.3). However, because most of the studies used aggregated outputs, it was not possible to break down services by department. The typical outputs used in primary care settings were outpatient visits and other

Table 4.2: Number and percentage of input variables used by type of health facility

Input variables	Hospitals		Primary care		Hospitals and primary care		Other		Total	
	n	(%)	*n*	(%)	*n*	(%)	*n*	(%)	*n*	(%)
Physical										
Capital										
Beds	73	(27.7)	5	(6.4)	7	(20)	1	(6.3)	86	(21.9)
Size of facility	1	(0.4)	6	(7.7)	1	(2.9)	0	(0)	8	(2)
Medical equipment	2	(0.8)	2	(2.6)	0	(0)	2	(12.5)	6	(1.5)
Department	1	(0.4)	2	(2.6)	1	(2.9)	0	(0)	4	(1)
Number of health facilities	0	(0)	0	(0)	1	(2.9)	0	(0)	1	(0.3)
Labour/ material										
Doctors	47	(17.8)	5	(6.4)	7	(20)	3	(18.8)	62	(15.8)
Nurses/ midwives	34	(12.9)	5	(6.4)	5	(14.3)	2	(12.5)	46	(11.7)
Non-medical staff	20	(7.6)	7	(9)	4	(11.4)	1	(6.3)	32	(8.1)
Total labour	12	(4.5)	5	(6.4)	1	(2.9)	0	(0)	18	(4.6)
Technician staff/ paramedics	17	(6.4)	3	(3.8)	2	(5.7)	0	(0)	22	(5.6)
Medical staff	10	(3.8)	5	(6.4)	3	(8.6)	0	(0)	18	(4.6)
Number or length in hours of activities	1	(0.4)	2	(2.6)	0	(0)	3	(18.8)	6	(1.5)
Drugs and medical supplies	3	(1.1)	4	(5.1)	0	(0)	0	(0)	7	(1.8)
Non-medical supplies	1	(0.4)	0	(0)	0	(0)	0	(0)	1	(0.3)
Financial										
Total expenditure	22	(8.3)	11	(14.1)	0	(0)	3	(18.8)	36	(9.2)
Capital value	4	(1.5)	4	(5.1)	0	(0)	0	(0)	8	(2)
Labour/ materials										
Expenditure for specific item or services	7	(2.7)	7	(9)	0	(0)	1	(6.3)	15	(3.8)
Salary expenditure	6	(2.3)	5	(6.4)	2	(5.7)	0	(0)	13	(3.3)
Other										
Service mix	2	(0.8)	0	(0)	0	(0)	0	(0)	2	(0.5)
Management quality	1	(0.4)	0	(0)	1	(2.9)	0	(0)	2	(0.5)
Total	264	(100)	78	(100)	35	(100)	16	(100)	393	(100)

n number of variable used, % percentage of variable used

services including the number of fully immunised children, the number of individuals enrolled in nutrition services, and the number of prescriptions. In some studies, the outputs were categorised by the type of services (e.g. family planning, child health services) and by condition (e.g. typhoid, malnutrition). Four studies adjusted the number of cases using a case mix index to treat all services equally (Arocena & García-Prado, 2007; Jian *et al.*, 2009; de Castro Lobo *et al.*, 2010; Rajasulochana & Dash, 2012). Two of the studies (Arocena & García-Prado, 2007; de Castro Lobo *et al.*, 2010) used diagnostic-related group (DRG) weighting, and one study (Rajasulochana & Dash, 2012) used the intensity of complicated maternal and neonatal cases. None of the studies used the health outcomes of the population, such as maternal mortality rate or child mortality rate, as outputs. Two studies (Sahin & Ozcan, 2000; Yang & Zeng, 2014) incorporated patient outcomes such as the mortality rate for admitted patients, which were used as undesirable outputs. The quality of services was sometimes used to adjust the outputs; it was proxied by the number of re-admissions (Arocena & García-Prado, 2007), the survival and performance ratios (Ketabi, 2011), and patient satisfaction (Razzaq *et al.*, 2013). Another output measure was financial performance, which was applied by six studies. Financial performance was measured using the health facility revenue (Zaim *et al.*, 2008; Gai *et al.*, 2010; Aboagye & Degboe, 2011; Alaghemandan *et al.*, 2014), purchasing value (Rattanachotphanit *et al.*, 2008), and return on assets and operating margin (Guerra *et al.*, 2012). Detailed methodological characteristics of the included studies can be found in Table B.3 in Appendix B.

Table 4.3: Number and percentage of output variables used by type of health facility

Variable items	Hospitals		Primary care		Hospitals and primary care		Other		Total	
	n	(%)	*n*	(%)	*n*	(%)	*n*	(%)	*n*	(%)
Activity output										
Outpatient visit	68	(24.5)	44	(46.8)	28	(51.9)	6	(31.6)	146	(32.9)
Admission or discharge	70	(25.3)	3	(3.2)	9	(16.7)	0	(0)	82	(18.5)
Inpatient days	61	(22)	0	(0)	6	(11.1)	0	(0)	67	(15.1)
Other services	21	(7.6)	34	(36.2)	4	(7.4)	8	(42.1)	67	(15.1)
Procedure	36	(13)	6	(6.4)	4	(7.4)	3	(15.8)	49	(11)
Session	3	(1.1)	3	(3.2)	0	(0)	0	(0)	6	(1.4)
Financial										
Financial performance	10	(3.6)	2	(2.1)	0	(0)	1	(5.3)	13	(2.9)
Quality output										
Re-admission	1	(0.4)	0	(0)	0	(0)	0	(0)	1	(0.2)
Mortality rate	2	(0.7)	0	(0)	0	(0)	0	(0)	2	(0.5)
% survival rate	1	(0.4)	0	(0)	0	(0)	0	(0)	1	(0.2)
Quality of service	4	(1.4)	1	(1.1)	3	(5.6)	1	(5.3)	9	(2)
Patient satisfaction	0	(0)	1	(1.1)	0	(0)	0	(0)	1	(0.2)
Total	277	(100)	94	(100)	54	(100)	19	(100)	444	(100)

n number of variable used, % percentage of variable used

4.3.6 Contextual variables

More than half (61.3%) of the included studies performed further analysis to explore the determinants of health facility efficiency. On average, three contextual variables were analysed in each study, with the number of contextual variables ranging from one to twelve per study. The typical internal contextual variables used were ownership (e.g. public or private), type of health facility (e.g. general or specialist facility), performance indicators (e.g. bed occupancy rate, average length of stay), quality indicators (e.g. patient satisfaction, mortality rate), and specific health services (Table 4.4). The external contextual variables in use were the geographic location (e.g. region, urban or rural area), demographics (e.g. population size coverage, population education level), economic situation (e.g. provincial income per capita, household asset value), time trend, and market concentration (Table 4.4).

4.3.7 Methodology issues

The analysis of limitations was drawn from the limitations identified by the authors of each study (Figure 4.5).

Thirty-five studies (26%) indicated a lack of availability of quality indicators, leading to an inability to adjust the output variables for quality. Thirty-four studies (25%) stated small sample size as a limitation. On average, the sample size of health facilities examined in the papers was 101, with an average of 74 facilities for analyses conducted in hospitals and 102 facilities in primary care settings. The average number of outputs was 3 (range: 1 to 14); the average number of inputs was also 3 (range: 1 to 11).

Twenty-three studies (17%) indicated that cost and price data were difficult to collect. This challenge led the researchers to use predominantly DEA instead of SFA, which requires financial data. A lack of case mix information to perform output weighting was also noted as a limitation in twenty-four studies (18%).

4.3.8 Outcomes

The studies included in this review reported relative efficiency as a study outcome. Studies using the RA technique explained efficiency by examining

Table 4.4: Number and percentage of contextual variables used by type of health facility

Variable items	Hospitals		Primary care		Hospitals and primary care		Other		Total	
	n	(%)	*n*	(%)	*n*	(%)	*n*	(%)	*n*	(%)
Internal										
Ownership	11	(4.5)	9	(8.7)	2	(8)	3	(16.7)	25	(6.4)
Type of health facility	9	(3.7)	6	(5.8)	4	(16)	1	(5.6)	20	(5.1)
Performance indicators	19	(7.8)	1	(1)	2	(8)	0	(0)	22	(5.6)
Quality indicators	67	(27.6)	22	(21.2)	10	(40)	7	(38.9)	106	(27.2)
Specific health services	16	(6.6)	9	(8.7)	4	(16)	1	(5.6)	30	(7.7)
Size of health facility	17	(7)	0	(0)	0	(0)	0	(0)	17	(4.4)
Financing	8	(3.3)	4	(3.8)	0	(0)	0	(0)	12	(3.1)
Availability of staff	16	(6.6)	3	(2.9)	1	(4)	0	(0)	20	(5.1)
Teaching	9	(3.7)	0	(0)	0	(0)	0	(0)	9	(2.3)
Management	6	(2.5)	2	(1.9)	0	(0)	3	(16.7)	11	(2.8)
Patient mix	5	(2.1)	1	(1)	0	(0)	0	(0)	6	(1.5)
Experience	2	(0.8)	0	(0)	0	(0)	1	(5.6)	3	(0.8)
External										
Geography	25	(10.3)	18	(17.3)	1	(4)	1	(5.6)	45	(11.5)
Demography	11	(4.5)	18	(17.3)	1	(4)	0	(0)	30	(7.7)
Economy	5	(2.1)	3	(2.9)	0	(0)	0	(0)	8	(2.1)
Time	4	(1.6)	6	(5.8)	0	(0)	1	(5.6)	11	(2.8)
Market concentration	9	(3.7)	0	(0)	0	(0)	0	(0)	9	(2.3)
Security	0	(0)	1	(1)	0	(0)	0	(0)	1	(0.3)
Population health status	1	(0.4)	0	(0)	0	(0)	0	(0)	1	(0.3)
Insurance coverage	3	(1.2)	1	(1)	0	(0)	0	(0)	4	(1)
Total	243	(100)	104	(100)	25	(100)	18	(100)	390	(100)

n number of variable used, % percentage of variable used

the variation in ratio indicators among health facilities. In addition, a study that used RA with the Pabón-Lasso model explained efficiency by assessing the position of each health facility in the diagram according to the average bed occupancy and bed turnover rates. The typical DEA and SFA measures presented in the studies were technical efficiency scores, returns to scale measures, rankings of health facilities, and estimates of the input reductions or output increases required to become efficient. Wide variations in the efficiency measurement results were found.

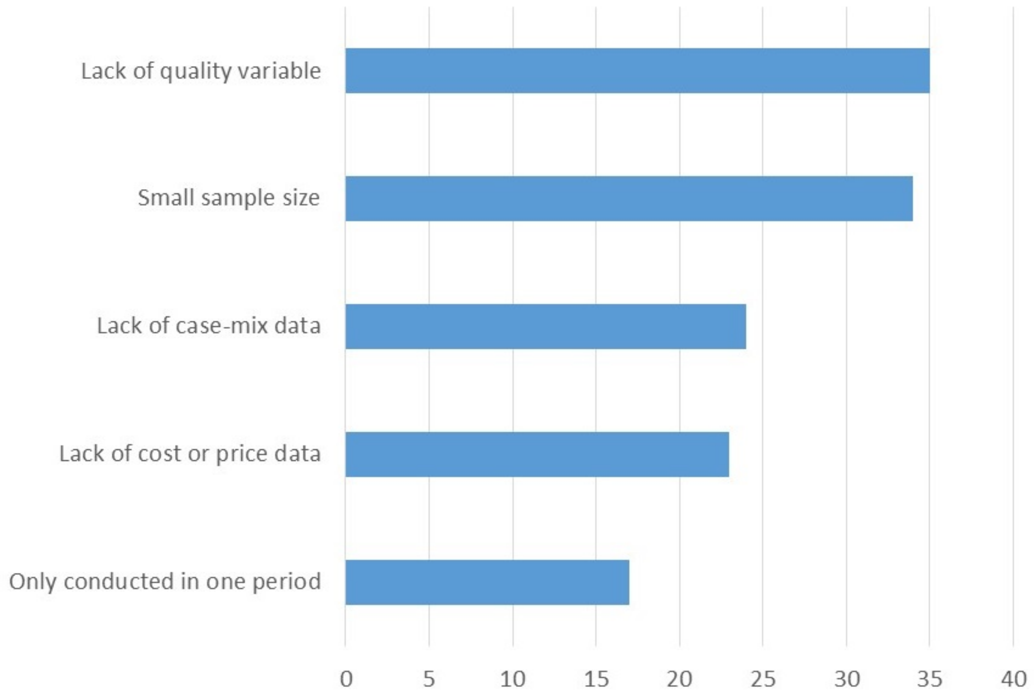


Figure 4.5: Five common limitations highlighted in the studies

4.4 Discussion

4.4.1 Techniques

Most of the studies included relied on methods such as RA and DEA. RA was originally applied because of its advantages: it is simple, easy to compute, low-cost, and can be performed on small samples (Bitran, 1992). Additionally, even though RA cannot address multiple products, it provides useful information for detecting inefficiency. Thus, in specific circumstances involving limitations of time, data, expertise, or budget, policy makers and researchers prefer RA as a means of comparing efficiency across healthcare organisations. This finding is not unique to LMICs; a review of efficiency measurements in the United States found that 44% of the studies used RA as a statistical method (Hussey *et al.*, 2009). However, RA has limitations including its arbitrary assumptions regarding cost allocation and its difficulty with detecting quality and case mix variations among providers (Bitran, 1992). In general the application of RA in HICs is more advanced than in LMICs because it uses adjusted outputs such as severity-adjusted average length of stay (Hussey *et al.*, 2009).

DEA became a popular choice for researchers in both LMICs and HICs to overcome the limitations of RA since 2000 (Hollingsworth, 2008; Hussey *et al.*, 2009). The main advantage of DEA is that it can be used with multiple inputs and outputs. However, both RA and DEA become problematic when there are outliers in the sample.

EE confers the advantage of a better overview of the changes in outputs or total costs in response to changes in the inputs and service mix through the production or cost functions. EE has been applied in HICs since the 1970s, but it only began to be used in LMICs in the late 1980s, when its use was still minimal (Bitran, 1992). Data deficiencies, such as availability as well as inconsistencies between providers, are the primary constraints when using EE. EE is furthermore unable to separate between true inefficiency and random noise (Barnum & Kutzin, 1993; Schmidt, 2008). Most of the studies applying EE in HICs use cost functions, while the application of cost or production functions in LMICs is rare because of the limited availability of cost and price data (Conteh & Walker, 2004).

Efficiency studies in both HICs and LMICs increasingly use SFA; however, DEA remains the dominant technique (Hollingsworth, 2003, 2008). SFA relies on large and detailed sources, especially input prices and other financial information, for data. Cost functions are more commonly applied in SFA than production functions because costs can easily be aggregated into a single measure that is required for an SFA frontier (Cylus *et al.*, 2016). However, this requirement limits the application of SFA when data availability is poor, which is an issue in LMICs in particular. It is important to underscore that only five studies appear to have applied SFA alone, while four used it in conjunction with other methods to compare results. In addition, SFA's complexity may prevent researchers from using it, as results arrived at using this method are difficult for policy makers to interpret.

Each technique has its own advantages and disadvantages; there is no clear consensus about which technique is best. RA of technical efficiency and DEA appear to be the preferred techniques to measure efficiency in LMICs when policy makers need quick, clear, simple, and practical evidence, when cost information is unavailable from routine information systems, and when research resources such as budget and expertise are limited.

4.4.2 Orientation

Regardless of the techniques used to obtain them, efficiency results can be interpreted in multiple ways depending on orientation (Hussey *et al.*, 2009). This review found an equal number of studies that applied input and output orientations. Reallocating excess medical staff and downsizing the capacity of a health facility are examples of improving efficiency based on inputs. However, from an ethical standpoint, this may not be an appropriate way to reduce waste in facilities facing difficulties with resource availability (Kirigia *et al.*, 2008a; Marschall & Flessa, 2011). Output orientation (e.g. improving outreach activities, reducing physical and financial barriers, increasing utilisation rates, etc.) may therefore be a more acceptable stance in the context of LMICs.

In addition, input orientation can be very difficult to apply in health facilities owned by governments. Bureaucratic processes can make the procedures for recruitment or dismissal of employees and the purchase or disposal of assets complex and time-consuming. However, this type of orientation may be feasible if facilities are given increased autonomy with respect to resource management decisions.

4.4.3 Indicators

The results showed that physical inputs such as infrastructure and staff mix were the most frequently used input variables for efficiency measurement in LMICs when the variables related to the services provided were output-based. Only a small percentage of studies used variables related to financial or quality measures as outputs. Similar findings in input and output variables were found in HICs (Hussey *et al.*, 2009).

Although medicines are an input indicator that is intended to be beneficial in detecting underuse and overpricing of generic drugs, irrational use of drugs, and substandard or counterfeit drugs, this type of input variable was lacking in most studies (Chisholm & Evans, 2010).

In relation to outputs, the indicators that were primarily used were unable to detect whether tests and procedures had been applied according to patients' needs. Most of the studies in the literature review failed to account for the severity of the cases treated in various health facilities in measuring the effectiveness of health care services. This omission could lead to misinterpretations of efficiency measurements due to incomparability of the outputs. It is therefore necessary to incorporate quality indicators (e.g. mortality rates, readmission rates), and case mix indicators (e.g. complication case rates, diagnosis group variations) to adjust outputs (Hollingsworth, 2008; Mutter *et al.*, 2013; Varabyova & Schreyogg, 2013; Chowdhury *et al.*, 2014; Ding, 2014; Yang & Zeng, 2014; Ineveld *et al.*, 2015; Matranga & Sapienzab, 2015).

Quality indicators were used in a number of ways to adjust the outputs. Most of the studies in this review applied the inverse of undesirable outputs, for example mortality rate, as an index of quality indicators (Sahin & Ozcan, 2000; Ramanathan *et al.*, 2003); this technique was commonly used in HICs as well. Rather than the mortality rate, two of the LMIC studies used a composite index score for the quality of services, as well as structural and process quality indicators (Aduda *et al.*, 2015; Obure *et al.*, 2016). Quality indicators applied in HIC settings that originate from patient information, such as average length of stay and adverse outcomes (Ding, 2014; Yang & Zeng, 2014; Matranga & Sapienzab, 2015) can prove problematic in LMIC settings because medical records are not reliably accurate (Wong & Bradley, 2009).

4.4.4 Contextual variables

Many studies incorporate contextual variables, and they often use two-stage analyses to identify the determinants of efficiency. The first stage estimates the relative technical efficiency of health facilities using DEA while the second stage is an explanatory regression model, usually a Tobit or truncated regression that predicts the technical efficiency score according to a set of contextual variables (Hoff, 2007; McDonald, 2009; Simar & Wilson, 2011). However, when studies apply SFA to measure efficiency, a two-stage approach is not recommended due to the biases arising from the process and other undesirable statistical properties (Parmeter & Kumbhakar, 2014). Determinants of efficiency are therefore identified using a one-stage approach. Of the nine studies that applied SFA, six studies analysed contextual variables. Four studies (Lekprichakul, 2001; Atilgan, 2016; Chaabouni & Abednnadher, 2016; Wei *et al.*, 2018) applied a one-stage approach while two others (Walker, 2006; Novignon & Nonvignon, 2017) analysed the determinants by comparing the means descriptively and statistically using ANOVA, Pearson, and Nopo matching decomposition procedures.

Contextual variables include both internal and external factors. Internal factors are elements within the health facilities that managers are able to control; external factors are elements outside health facilities that are impossible for health managers to control. In our review, contextual factors typically included ownership status, health facility size, and teaching status as internal factors while geography, demography, and economic status of the population were used as external factors. Studies in HICs generally used similar sets of contextual variables (Lee *et al.*, 2008a; Shreay *et al.*, 2014), with ownership being the most frequently used along with size and capacity, degree of specialisation, market structure and funding issues. Recent studies in HICs have sometimes incorporated quality indicators in the analysis (Hollingsworth, 2003; Worthington, 2004; Herrera *et al.*, 2014).

Public ownership in LMICs was generally found to be correlated with higher efficiency than private ownership, although the findings are mixed. Jehu-Appiah *et al.* (2014) found that public hospitals performed better than private because public hospitals in LMICs operate under significant budget constraints, compelling them to provide medical care at lower costs. However, a study by Hatam *et al.* (2010) in Iran argued that the private sector is more efficient than the public sector because there is no incentive for the public sector to minimise expenses. In HICs, a review by Herrera *et al.* (2014) found that ownership does not seem to affect efficiency. Significant differences in health outcomes and costs were only found between private-for-profit providers and private not-for-profit providers; the latter were found to be more efficient. No significant differences were found in efficiency between public providers and the two categories of private providers.

In addition to ownership, our review found that facility size as measured by the number of beds was associated with efficiency. The findings showed mixed results; some studies found that larger health facility size had a negative association with efficiency (Gok & Sezen, 2012; Sepehrdust & Rajabi, 2013; Jehu-Appiah *et al.*, 2014; Yang & Zeng, 2014), and others found the opposite (Lasso, 1986; Masiye, 2007; Rattanachotphanit *et al.*, 2008). Studies in HICs had similarly mixed results. A study in Greece found no significant association between operational size and efficiency (Mitropoulos *et al.*, 2013), while a study in the United States as well as a review found that a larger organisational size was negatively associated with efficiency (Worthington, 2004; Shreay *et al.*, 2014). A review by Hadji *et al.* (2014) found that the relationship between size and efficiency was U-shaped and that small and large hospitals had higher efficiency than medium-sized hospitals. Other studies in HICs suggested that the effect of the size of the health facility differed according to the location and population (Lee *et al.*, 2008a; Asmild *et al.*, 2013). Larger health facilities were found to be more efficient in urban areas, while smaller health facilities were more efficient in rural areas (Asmild *et al.*, 2013).

Most efficiency analyses included the geographic location of a health facility (e.g. urban or rural region) as an contextual factor. Our review findings differ from those of studies conducted in HICs such as the United States, which have shown that rural hospitals tend to operate with lower costs because fewer severe patient complications arise (Ding, 2014). Heimeshoff *et al.* (2014) also argued that health facilities in rural areas in Germany were significantly more efficient because of a lower density of physicians, leading to a higher occupancy rate. However, these explanations should only be applied in homogeneous situations in which there is equal physical access to health facilities and equal health awareness among the general population.

Nine studies incorporated quality as an contextual variable in the second-stage analysis of healthcare efficiency in LMICs. The indicators used as proxies for quality ranged from a single variable, such as health facility accreditation, patient satisfaction, or mortality rate, to a composite index of quality including structural and process indicators. Results in LMICs showed mixed results; some studies found no trade-offs between quality and efficiency (Somanathan *et al.*, 2000; Alhassan *et al.*, 2015; Obure *et al.*, 2016), and others found trade-offs to vary with size, especially in small- and medium-sized health facilities (Gok & Sezen, 2013; Yang & Zeng, 2014). With respect to HICs, a review by Worthington (2004) found that several studies showed a negative association between quality and efficiency. The researcher hypothesised that improving quality is likely to require additional resources including more advanced and costlier medical technology, thereby reducing efficiency (Worthington, 2004). Market structure in the same review was found to have been measured primarily by means of an index of market competition, which has been increasingly used as a contextual variable in research on efficiency in HICs. However, it is less frequently used in LMICs, and only nine of the studies in the present review incorporated market structure. Findings were similar in LMICs and HICs; results were mixed regarding the association between market competition and efficiency (Worthington, 2004).

Some other potential sources of technical inefficiency in healthcare, such as corruption and fraud, have never been incorporated in either LMIC or HIC settings (Chisholm & Evans, 2010).

This review shows that the efficiency of a health facility is influenced by internal factors but also by external factors that are outside of the control of health sectors. This finding emphasises the need for the inclusion of inter-sectorial actions to improve efficiency.

4.4.5 Analytical framework

The dominant input, output and contextual indicators were identified based on the literature review and availability of variables in dataset. The analytical efficiency framework showing the link between choices of inputs and outputs influence of contextual factors can be seen in Figure 4.6. A clear analytical framework helps understanding of the determinants of efficiency and these elements were applied in the empirical analysis later on.

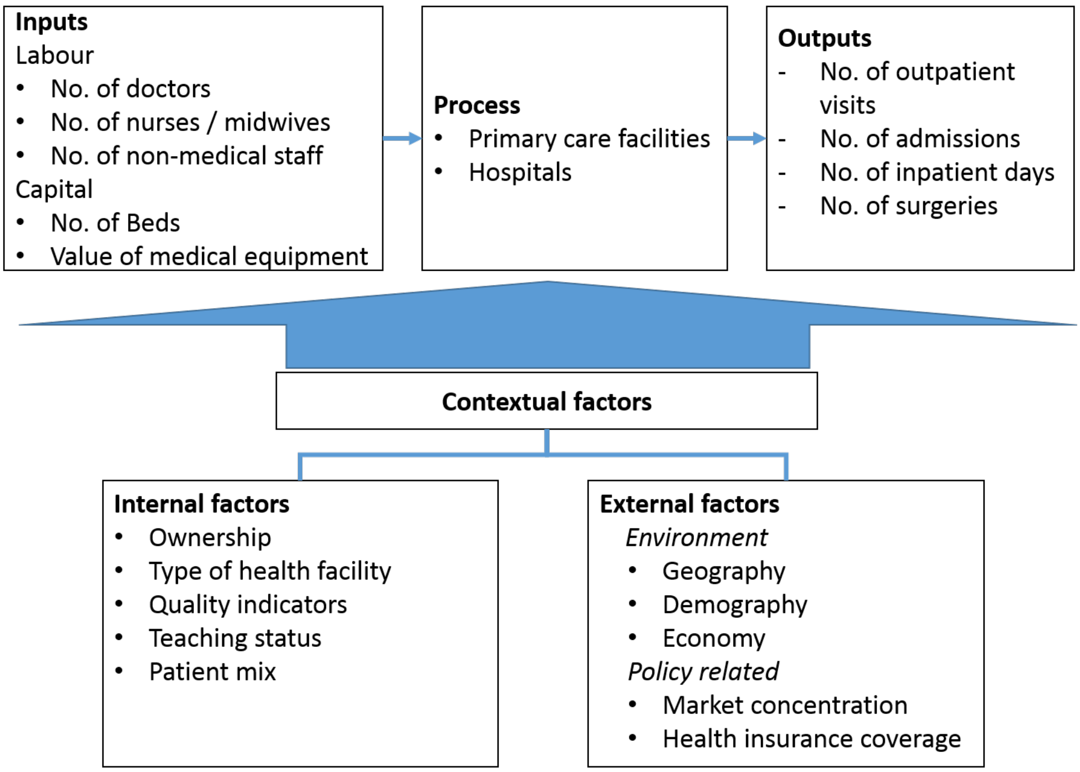


Figure 4.6: Analytical framework

Input indicators represent different types of resources at health facilities to provide various health care services. Factors determining efficiency of health facilities are also affected by contextual factors both internal and external factors. Internal factors are likely to be controlled by health facility managers, while external factors are likely to be controlled by national policy regulation or other stakeholders outside health sector.

4.4.6 Limitations

The findings of this review are subject to some limitations. Potentially relevant studies in languages other than English were excluded. This paper focused on efficiency measures specific to health facilities and excluded efficiency studies in other settings. Moreover, this study focused only on variations in efficiency according to ownership, without accounting for the ways in which efficiency varies with different reimbursement schemes in the public and private sectors. Our objective was to provide a landscaping review, and the quality of the original studies was therefore assessed using a relatively simply validity tool rather than the complex protocols used in Cochrane or Campbell reviews.

4.5 Conclusion

This chapter reviews currently available studies of efficiency measurement in LMICs. This review identified the efficiency methods as well as the contextual factors that have predominantly been used in LMIC efficiency studies. The review provides a comprehensive overview of efficiency measurements for researchers. Researchers performing further work could consider a wider range of sources, including additional sources of grey literature, as well as collaborative work allowing researchers to capture literature in multiple languages.

In the next three chapters, we proceed to the empirical studies, starting with the assessment of performance and the determinants of efficiency in Indonesian primary care facilities and hospitals in Chapter 5. Chapter 6 focuses on the performance of Indonesian primary care facilities, while Chapter 7 analyses the performance of Indonesian hospitals.

Chapter 5

Assessing Health Facility Performance in Indonesia using the Pabón-Lasso Model and Unit Cost Analysis of Health Services

As noted in Chapter 2, healthcare expenditure in Indonesia has grown rapidly. The previous chapter summarised the efficiency measurements that have been undertaken in various low- and middle-income countries. In this chapter, we analyse the performance of Indonesian health facilities, both hospitals and primary care facilities and identify the contextual factors that drive inefficiency. Ratio analysis, unit cost analysis, and the Pabón-Lasso model are used in this study to assess efficiency in health facilities.

The first section of this chapter serves as an introduction offering background on this study. The second section explains the methodology, including an explication of the data used as well as of the analysis. The third section explains the results obtained, followed by a discussion in the fourth section. The chapter then ends with the conclusions of this study.

5.1 Introduction

As seen in Chapter 4, almost one third of studies in low- and middle-income countries have applied the ratio analysis (RA) technique. In specific circumstances in which time, data, expertise, or budget present as limitations, RA is preferred by policy makers and researchers in assessing efficiency within healthcare institutions.

Bitran (1992) categorised two types of ratio analysis of efficiency: technical (physical input to output ratios) and economic (cost of inputs to output ratios). Facilities often use simple ratios (e.g. bed occupancy rate, number of admissions per bed) to evaluate the technical efficiency of health facilities. Lasso (1986) suggests combining bed occupancy rate, bed turnover rate, and average length of stay to provide a fuller picture of health facility performance.

In addition, comparing performance indicators using economic ratio analysis of health facilities can help assess efficiency (Barnum & Kutzin, 1993; Flessa, 1998; Adam *et al.*, 2003; Conteh & Walker, 2004). Accounting methods are appropriate to measure economic efficiency to explain the variance in average costs of services within a given time period (St-Hilaire & Crepeau, 2000). Information regarding cost is useful for planning and budgeting, cost effectiveness analysis, and evaluation of performance in delivering health services (Lindelow & Wagstaff, 2003) . A relatively high unit cost in a health facility may indicate inefficiency, providing valuable information for policy decisions at the facility, local and central government levels (Barnum & Kutzin, 1993; Witter *et al.*, 2000). As illustrated in Chapter 2, large variations in healthcare performance and national heterogeneity suggest that there may be lessons to learn from better-performing health facilities. We combined both types of ratio analysis to identify high-performing health facilities and explored the factors underlying relative performance.

While some studies report on the cost of providing health services in health facilities (Sulistyorini & Moediarso, 2012; Putra *et al.*, 2013; Sari *et al.*, 2013), to the best of our knowledge, there has to date been only one costing study examining primary care in Indonesia to assess the relative efficiency of health facilities (Berman, 1986). One Indonesian study used a Pabón-Lasso model to assess hospital performance and identified strategies to improve efficiency (Iswanto, 2015). However, these methods have never been used to analyse the contextual factors affecting health facilities in Indonesia. Using a national dataset on healthcare facilities across Indonesia, this study measures efficiency in health facilities in a developing country and extends the reach of previous research through its joint application of two relative efficiency measurements.

5.2 Methods

5.2.1 Data

This study assesses the determinants of efficiency in health facilities by analysing data from four sources: 1) a health facility costing study (HFCS), 2) Indonesian-case base groups (INA-CBGs) dataset, 3) the National Socioeconomic Survey (SUSENAS), and 4) village potential statistics (PODES)

We used hospital identifiers to merge the HFCS and INA-CBGs datasets. We merged the SUSENAS dataset using district identifiers both for hospitals and *Puskesmas*. The PODES dataset was merged using district identifiers for hospitals and sub-district identifiers for *Puskesmas*. Our merged dataset from these four sources comprises 89 variables for 200 hospitals, as well as 65 variables for 234 *Puskesmas*. However, we did not analyse the 139 *Puskesmas* without inpatient services since the parameters of the Pabón-Lasso model only apply to inpatient services. There was no multiple imputation for missing values, apart from the case mix index to adjust hospital unit costs.

5.2.2 Pabón-Lasso model analysis

Lasso (1986) developed a graphical technique to plot health facilities in four sectors using a combination of efficiency indicators. There are three main indicators: (1) average bed occupancy rate, which is represented on the horizontal axis and measures the percentage of time an average bed was occupied in the year; (2) average bed turnover rate, which is represented on the vertical axis and measures the average annual number of discharges per bed in the year; and (3) average length of stay, which is represented by the gradient of a straight line from the origin to the observation and measures the average duration of inpatient admissions (Lasso, 1986). We applied the Pabón-Lasso graphical model (1986) to assess health facility efficiency by plotting two indicators: the number of admissions per bed and the bed occupancy rate. These indicators divide the figure into four sectors representing different levels of efficiency (Figure 5.1): health facilities in Sector 1 (lower left) have low throughput (number of admissions per bed) of patients and long periods during which beds are empty; health facilities in Sector 2 (upper left) treat a large number of patients per bed but have long periods in which beds are unoccupied; health facilities in Sector 3 (upper right) treat patients with high throughput and high occupancy; and health facilities in Sector 4 have beds with low throughput and longer patient stays. Instead of showing the average length of stay line in the figure, we applied the Pabón-Lasso model to examine the contextual variation across the providers' settings (e.g. bed size, ownership, and location).

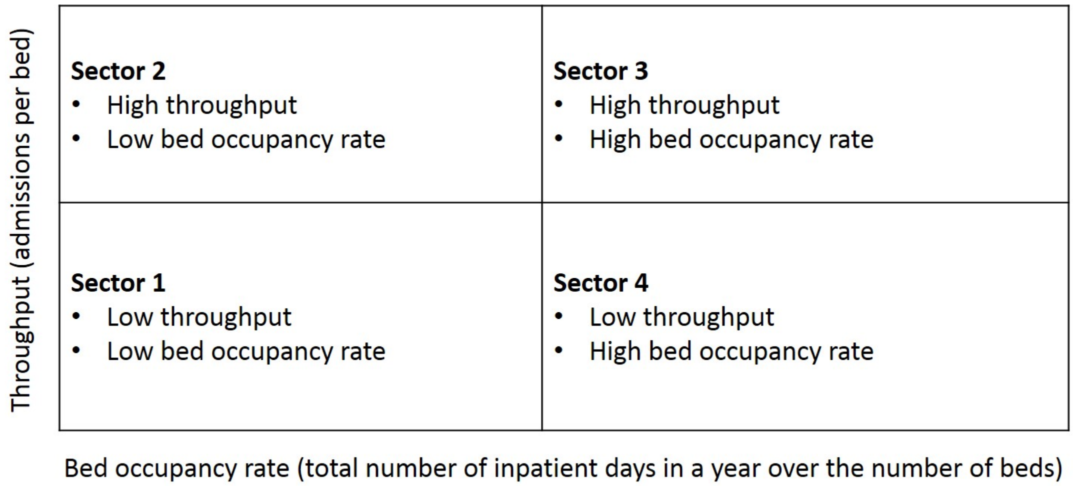


Figure 5.1: Pabón-Lasso model

We found that the mean as cut-offs for the sectors is a reasonable measure of the central tendency with a pretty even distribution of high and low performers on each side. This technique was applied to the four-sector approach used in the thesis.

5.2.3 Costing method

We estimated the total costs and unit costs of hospitals and *Puskesmas*. Unit cost refers to the average cost of providing a single service. Step-down and bottom-up approaches are equally valid for estimating unit cost (Mogyorosy & Smith, 2005). The selection of the appropriate method frequently relies on the aggregation level of the data (Smith & Barnett, 2003). The bottom-up approach requires more detailed data such as patient-level data, which could not be obtained for this study (Smith & Barnett, 2003). Therefore, we used the step-down approach, a common technique to calculate unit cost that offers an optimal balance between accuracy and practicality (Conteh & Walker, 2004;

Mogyorosy & Smith, 2005). Overhead cost was allocated to intermediate and final cost centres (e.g. outpatient visits and inpatient admissions) to calculate cost per outpatient visit, cost per inpatient admission, and cost per bed day (Conteh & Walker, 2004; Mogyorosy & Smith, 2005).

The first step was cost centre classification, with two final cost centres and several intermediate cost centres. The final cost centres are the inpatient and outpatient departments; the supportive cost centres provide support for patient care, including administration, nonclinical support (e.g. kitchen, transport and laundry) and clinical support (e.g. radiology, pharmacy and operating theatre).

The direct costs, including staffing, materials and capital, were allocated to each cost centre. Staffing costs reflect individuals' basic salaries and financial incentives such as insurance and family allowances. Materials, including medical supplies and drugs, were valued using the Indonesia Monthly Index of Medical Specialities (MIMS) database. This study included buildings, vehicles, equipment and furniture as capital costs, excluding the cost of land. An economic approach was used to estimate capital costs, covering both depreciation and the opportunity cost of investing (Shepard *et al.*, 2000). The health facility costing study dataset collected information about buildings' value per square metre to obtain the annualised value of buildings. Capital costs were annualised using a 3% discount rate, as recommended by the WHO (Edejer *et al.*, 2003). Since figures on the life span of equipment and capital assets were not available in Indonesia, we estimated these using the American Hospital Association's depreciated hospital assets guidelines, which provide complete and detailed information on each item (AHA, 2008). The life span of equipment varied from 1 to 20 years, with an average of 8.7 years.

The direct cost of supportive cost centres was then allocated to the final cost centres. Table 5.1 summarizes the detailed criteria used to allocate these costs. All final cost centres were divided by the total number of outpatient visits or inpatient admissions at the health facility to calculate the unit cost of services. The 2011 exchange rate was used to convert Indonesian rupiah (IDR) into US dollars (USD) (1 USD= 8733.44 IDR) (OANDA, 2015).

5.2.4 Analyses of characteristics

The objective of this empirical study is to analyse the relationship between contextual factors and efficiency of health facilities, hospitals and *Puskesmas*

Table 5.1: Allocation base criteria

Cost Item	Allocation base
Administration	Floor area
Maintenance	Estimated actual cost
Office expenses	Estimated actual cost
Transport expenses	Estimated actual cost
Fixed capital cost	Floor area
Equipment	Estimated actual cost
Staff cost	Time
Food and linen	Number of beds
Drug and medical supplies	Proportion of drug value based on patient surveys from each department

guided by the analytical framework in Chapter 4. To achieve this, bivariate analysis (i.e. ANOVA, Chi-Square test and simple linear regression) was applied to explain the difference of health facility characteristics in the Pabón-Lasso model and unit costs. Furthermore, a three-stage analysis was performed to identify the high-performing health facilities. First, a combination of ratio analyses was applied; where high-performing health facilities have low unit costs (below the mean) and are located in the high utilisation sector in the Pabón-Lasso model (Sector 3). Thus, the main outcome of the analysis is a binary variable taking a value of 1 for a high-performing health facility, and 0 for a non high-performing health facility.

Second, the relationships between performance and various contextual factors were quantified using logistic regression. Factors exhibiting an acceptable significance level (P value $<$0.25) in the bivariate analysis were included in the multivariate logistic regression analyses to determine their independent contributions to the factors of health facility performance (Sperandei, 2014). Third, in this multivariate analysis, forward-step wise selection was performed: The variables were included one by one in the model, using a P value of $<$0.05 as the criterion for inclusion. This yielded a reduced final model. Checks for multicollinearity were also performed. A variance inflation factor of $>$10 was used to denote significant multicollinearity. The area under the receiver operating characteristic (ROC) curve was used to estimate the ability of the models to discriminate between high-performing and other health facilities. Cost computations, Pabón-Lasso diagram construction, and characteristic analyses were performed using STATA 14 (Stata-Corp, College Station, TX, USA).

5.3 Results

5.3.1 Health facility characteristics

Tables 5.2 and 5.3 present the characteristics and activities of the health facilities studied. On average, hospitals received 81,873 outpatient visits and 8,984 inpatient admissions. This output was produced using an average of 42 doctors, 155 nurses, 153 support staff, and 159 beds per hospital. *Puskesmas*, including their village satellites, produced on average 22,372 outpatient visits and 591 admissions. *Puskesmas* produced these outputs using 3 doctors, 29 nurses and midwives, 17 support staff, and 10 beds on average. There was a wide variation in the number of medical staff in hospitals and *Puskesmas*. The nurse-to-doctor ratio was 4:1 in hospitals and 10:1 in *Puskesmas*.

Table 5.2: Characteristics and activities of hospitals

Characteristic or statistic	Hospitals n= 200		Public hospitals n= 122		Private hospitals n= 78	
	Mean	**(SD)**	**Mean**	**(SD)**	**Mean**	**(SD)**
Number of doctors	42	(40)	44	(47)	39	(27)
Number of nurses and midwives	155	(147)	184	(168)	111	(90)
Number of support staff	153	(146)	167	(149)	131	(139)
Number of beds	159	(123)	187	(139)	115	(76)
Number of outpatient visits	81873	(126874)	98382	(132275)	56051	(114014)
Number of admissions	8984	(6941)	10784	(7630)	6177	(4470)
Number of inpatient days	35749	(33380)	43257	(37549)	23370	(19742)
Bed occupancy rate	60%	(31%)	63%	(35%)	54%	(22%)

5.3.2 Pabón-Lasso model

Hospitals

Figure 5.2 shows four Pabón-Lasso models for hospitals; the vertical and horizontal lines represent the mean values of the bed occupancy rate and

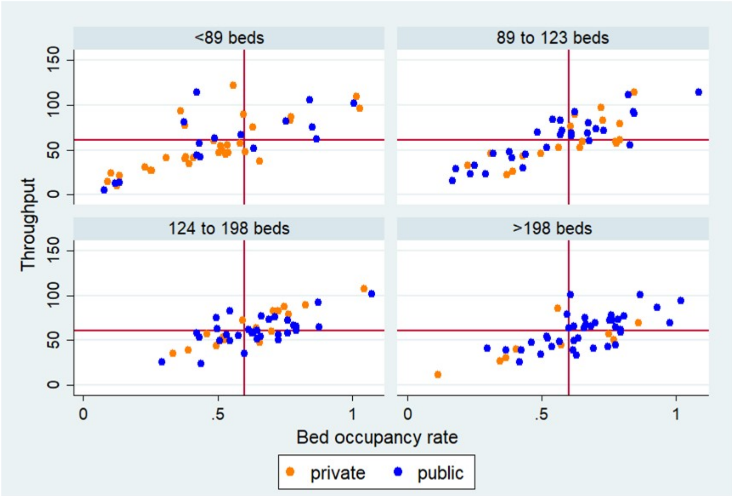
Table 5.3: Characteristics and activities of *Puskesmas*

Characteristics or statistics	Puskesmas n= 229		Puskesmas in urban areas n= 64		Puskesmas in rural areas n= 165	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Number of doctors	3	(4)	4	(7)	2	(3)
Number of nurses and midwives	29	(40)	33	(50)	28	(36)
Number of support staff	17	(21)	23	(30)	15	(16)
Number of beds	10	(5)	9	(3)	11	(6)
Number of outpatient visits	22372	(15504)	32164	(16170)	18672	(13667)
Number of admission	591	(493)	608	(491)	594	(495)
Number of inpatient days	1079	(1069)	1212	(1038)	1050	(1082)
Bed-occupancy rate	30%	(25%)	34%	(33%)	29%	(22%)

admissions per bed. Thirty-six percent of hospitals overall were in the high utilisation sector of the Pabón-Lasso model (Sector 3), it indicates hospitals reached a high efficiency with a minimum waste of beds. Thirty-nine percent appeared in the low utilisation sector (Sector 1), where the number of beds is higher relative to current demand. Some small hospitals ($<$ 89 beds) in sector 2 indicate patients requiring short-term hospitalisation and excess beds unoccupied. Some hospitals ($>$198 beds) located in sector 4, indicate long-term hospitalisation of the patients due mainly to the nature of the diseases treated in large hospitals. We found wide variance in smaller hospitals and narrow variance in larger hospitals. The Pabón-Lasso models show that private hospitals and those with fewer beds had a greater tendency to be in the low utilisation sector than public and larger hospitals. Hospitals in the high utilisation sector tended to exhibit specific characteristics: they had more full-time-equivalent nonspecialist medical doctors, had population with lower education levels, and were located on Java or Bali (Table C.1 in Appendix C).

Puskesmas

Figure 5.3 contains four Pabón-Lasso models for *Puskesmas*; 33% of all *Puskesmas* with inpatient services were located in the high utilisation sector of the Pabón-Lasso model (Sector 3), while 54% were located in the low utilisation sector (Sector 1). *Puskesmas* predominantly fall into sector 1 indicating a inefficient usage of resources, particularly in *Puskesmas* with seven to nine beds. Whereas, larger *Puskesmas* ($>$12 beds) were found to be more efficient. There were only small number of *Puskesmas* located in



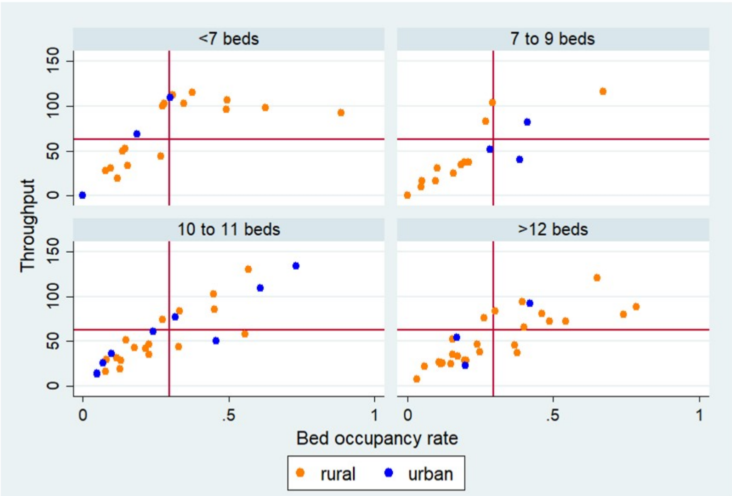
Note: Two outlier observations have been excluded from the figure for reader-friendly purposes.

Figure 5.2: Pabón-Lasso models of hospitals by ownership and number of beds

sector 4 (characterised by a long average length of stay) because the main role of *Puskesmas* is to treat less severe cases. We found no significant differences in utilisation based on rural/ urban location or number of beds in the Pabón-Lasso models. However, *Puskesmas* in the low utilisation sector faced significantly more water disruptions than *Puskesmas* in the high utilisation sector (Table C.2 in Appendix C).

5.3.3 Total cost

Figure 5.4 represents the cost structure of health facilities. From the sample, it was found that health care provision in hospitals and *Puskesmas* cost USD 3.8 million (median USD 2.9 million) and USD 205,000 USD (median USD 189,000) on average per year, respectively. The total costs of Class A hospitals were more than 11 times that of Class D hospitals. Cost structures varied by health facility type. Staffing costs, including both salaries and incentives, were the largest component of total costs in all types of facilities. Private hospitals had the lowest proportion of staff costs (35%) and *Puskesmas* without inpatient services had the highest (57%).



Note: Two outlier observations have been excluded from the figure for reader-friendly purposes.

Figure 5.3: Pabón-Lasso models of *Puskesmas* by location and number of beds

Material costs, including pharmaceuticals and medical supplies, also constituted a significant share of total costs, ranging from 24% in *Puskesmas* without inpatient services to 39% in private hospitals. Capital costs accounted for approximately 14% of total costs in hospitals and 19 % in *Puskesmas*. We found no specific pattern in total cost structures based on hospital size, although *Puskesmas* with and without inpatient services did show similar cost structures.

5.3.4 Health care unit costs

Hospitals

The average unit cost per patient in hospitals based on outpatient visits, inpatient admissions, and bed days were USD 44, USD 299, and USD 82, respectively (Table 5.4). The unit costs were positively skewed; thus, the associated medians of unit costs were lower: USD 24, USD 248, and USD 68 for outpatient visits, inpatient admissions, and bed days, respectively.

There are important variations in the unit costs of services according to hospital ownership. Private hospitals had statistically significant higher

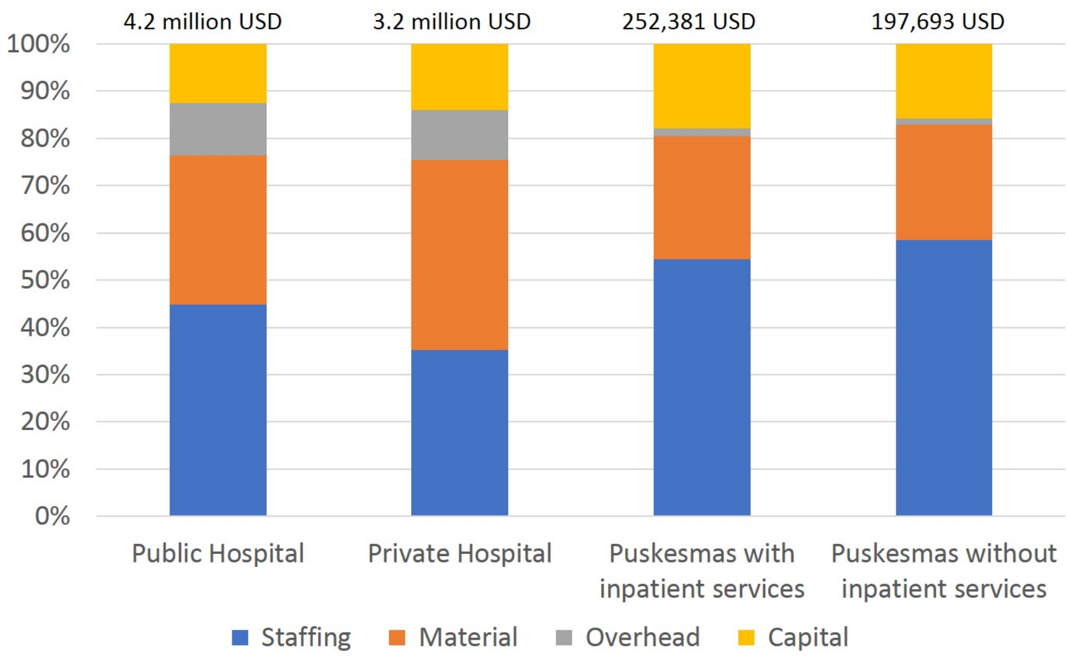


Figure 5.4: Total cost structure by health facility type

unit costs than public hospitals. The costs of outpatient services in private hospitals were almost double those in public hospitals; the costs of both inpatient services and bed days were more than 1.2 times higher.

Hospital size is also associated with unit costs. Large hospitals, such as Class A and B hospitals, had lower unit costs based on outpatient visits and bed days compared to Class C and D hospitals. Class B hospitals had statistically significantly lower unit costs compared with Class C and D hospitals. This finding was contrary to expectations, since Class B hospitals tend to handle more complex case than Class C and D hospitals. Given the small sample size of Class A hospitals, unit costs showed a wide variance. Hospital size was therefore re-categorised into three groups proxied by number of beds (Lasso, 1986; AHRQ, 2013): small hospitals (with fewer than 100 beds), medium hospitals (between 100 and 199 beds), and large hospitals (more than 200 beds). Large hospitals had statistically significant lower outpatient unit costs than medium and small hospitals. Small hospitals had higher inpatient and bed day unit costs, but these figures were not statistically significant. The difference in case mix unit cost showed that almost all types of hospitals treated patients with less severe cases (showed in negative values). However, Class A public hospitals and private hospitals were found to treat more severe cases compared to other types of hospitals. Table C.3 in Appendix C shows the relationship between unit costs and hospital characteristics.

Puskesmas

The average unit cost per patient in *Puskesmas* with inpatient services for outpatient visits, inpatient admissions, and bed days were USD 11, USD 135, and USD 83, respectively (Table 5.5). Unit costs were positively skewed, so the associated medians of unit costs were lower: USD 9, USD 112, and USD 61 for outpatient visits, inpatient admissions, and bed days, respectively . The availability of services such as inpatient services, basic emergency obstetric and new born care (BEmONC), and evening opening hours did not have a significant impact on unit costs. However, the size of *Puskesmas*, proxied by number of beds and availability of emergency services was found to be negatively correlated with outpatient unit cost: larger *Puskesmas* had lower outpatient unit costs than small *Puskesmas* (Table C.4 in Appendix C).

5.3.5 Characteristics of high-performing health facilities

The institutions' characteristics were examined by comparing the contextual factors of the high- and non-high-performing health facilities (see Table 5.6).

Hospitals

Bivariate analysis showed the 40 high-performing hospitals to have specific characteristics that were lacking in the 152 other hospitals: they were predominantly larger, more likely to be publicly owned, and more likely to be non-profit providers. High-performing hospitals treated more elderly patients and more patients who were part of the insurance scheme for the poor. In terms of quality, most of the indicators were inconclusive, but hospitals accredited by the Indonesian hospital accreditation commission performed better. Regarding external factors, high-performing hospitals were generally located in deprived areas where a high proportion of the population was poor, a low proportion of the population had a secondary school or higher education, and the population had relatively low household expenditures. Additionally, hospitals in areas with greater coverage through the insurance scheme for the

Table 5.4: Unit cost per hospital patient by hospital type

Unit cost of services		n	OP	(95% CI) IQR	IP	(95% CI) IQR	Bed days	(95% CI) IQR	ΔCasemix unit cost OP	ΔCasemix unit cost IP	ΔCasemix unit cost Bed days
Hospital	Mean	200	44	(34 to 51)	299	(266 to 321)	82	(73 to 89)	-2	-19	-1
	Median		24	16 to 39	248	162 to 363	68	48 to 101	-3	-13	-2
Ownership											
Public hospital	Mean	122	33	(24 to 39)	276	(238 to 307)	74	(65 to 83)	-3	-34	-3
	Median		20	14 to 32	230	159 to 319	61	41 to 94	-3	-20	-4
Private hospital	Mean	78	62	(42 to 81)	335	(281 to 374)	95	(79 to 107)	0	4	2
	Median		31	22 to 57	261	188 to 420	77	57 to 113	-3	0	4
Hospital class											
Class A	Mean	2	18	(-35 to 71)	331	(-1221 to 1883)	52	(-186 to 290)	5	140	22
	Median		18	13 to 22	331	209 to 453	52	33 to 71	5	140	22
Class B	Mean	52	23	(17 to 27)	282	(220 to 312)	69	(55 to 76)	1	-46	4
	Median		18	12 to 24	230	148 to 380	60	41 to 82	0	-7	0
Class C	Mean	101	51	(35 to 64)	324	(273 to 367)	90	(77 to 104)	-1	-13	-5
	Median		25	18 to 45	253	176 to 381	73	50 to 110	-3	-23	-5
Class D	Mean	44	50	(30 to 70)	267	(225 to 310)	80	(67 to 92)	-7	-14	0
	Median		29	19 to 56	248	156 to 351	69	52 to 101	-4	-9	-2
Hospital size											
Small hospital(<100 beds)	Mean	49	76	(47 to 103)	334	(261 to 400)	98	(79 to 115)	-13	4	2
	Median		35	24 to 72	249	158 to 396	83	53 to 119	-6	-5	1
Medium hospital(100-199 beds)	Mean	51	46	(30 to 56)	334	(255 to 386)	95	(74 to 114)	0	-22	-7
	Median		32	15 to 39	266	175 to 351	77	50 to 104	-3	-19	-5
Large hospital(> 200 beds)	Mean	50	33	(18 to 47)	261	(217 to 298)	68	(59 to 77)	4	-8	-2
	Median		21	14 to 23	239	159 to 363	62	41 to 77	-3	-18	-3

OP Outpatient, *IP* Inpatient, *IQR* interquartile range, Δ *Case mix unit cost* difference between non-adjusted unit cost and unit cost adjusted by case mix

Table 5.5: Unit cost per *Puskesmas* patient by type of health facility

Unit cost of services		Puskesmas with inpatient services							Puskesmas without inpatient services		
		n	OP	(95% CI) IQR	IP	(95% CI) IQR	Bed days	(95% CI) IQR	n	OP	(95% CI) IQR
Puskesmas	Mean	95	11	(10 to 13)	135	(109 to 161)	83	(62 to 104)	139	10	(9 to 12)
	Median		9	5 to 14	112	72 to 152	61	30 to 90		7	5 to 11
BEmONC services											
With BEmONC	Mean	49	12	(10 to 14)	148	(115 to 182)	89	(62 to 117)	18	9	(6 to 12)
	Median		10	6 to 15	119	83 to 181	62	39 to 90		6	5 to 9
Without BEmONC	Mean	34	13	(9 to 17)	105	(73 to 137)	66	(43 to 89)	104	11	(9 to 13)
	Median		9	5 to 15	89	47 to 147	59	25 to 95		7	5 to 12
Emergency services											
with emergency services	Mean	67	11	(9 to 13)	134	(107 to 161)	81	(60 to 102)	30	14	(8 to 19)
	Median		9	5 to 15	116	72 to 152	58	31 to 87		10	5 to 16
without emergency services	Mean	13	18	(10 to 27)	132	(-83 to 348)	96	(1 to 190)	91	10	(8 to 12)
	Median		10	7 to 29	91	73 to 231	89	61 to 136		7	5 to 10
Evening services											
Open in the evening	Mean	38	10	(8 to 12)	153	(108 to 198)	95	(59 to 131)	14	12	(7 to 17)
	Median		9	5 to 15	127	74 to 190	62	34 to 103		10	7 to 20
Closed in the evening	Mean	42	14	(11 to 18)	113	(91 to 135)	66	(50 to 82)	108	11	(8 to 13)
	Median		10	6 to 18	110	72 to 144	58	28 to 87		7	5 to 11
Puskesmas size											
Beds Q1 (<7beds)	Mean	23	14	(9 to 19)	130	(47 to 213)	92	(14 to 170)		NA	NA
	Median		10	5 to 18	93	77 to 132	62	32 to 87		NA	NA
Beds Q2 (7 to 9 beds)	Mean	17	14	(9 to 19)	151	(110 to 192)	87	(58 to 116)		NA	NA
	Median		10	6 to 15	131	83 to 217	69	57 to 89		NA	NA
Beds Q3 (10 to 12 beds)	Mean	26	11	(8 to 14)	154	(88 to 220)	98	(45 to 151)		NA	NA
	Median		8	6 to 15	118	64 to 180	58	34 to 113		NA	NA
Beds Q4 (>12 beds)	Mean	29	8	(6 to 10)	112	(77 to 147)	63	(39 to 87)		NA	NA
	Median		6	3 to 11	103	45 to 144	46	24 to 87		NA	NA
Puskesmas location											
Urban	Mean	19	8	(5 to 10)	188	(80 to 296)	119	(30 to 208)	45	9	(5 to 12)
	Median		7	3 to 10	115	83 to 181	52	35 to 125		5	4 to 9
Rural	Mean	75	12	(10 to 15)	123	(100 to 146)	75	(56 to 93)	90	11	(9 to 13)
	Median		10	5 to 15	110	70 to 147	61	28 to 90		7	5 to 14

OP Outpatient, *IP* Inpatient, *BEmONC* Basic emergency obstetric and newborn care, *NA*= Not applicable

Table 5.6: Characteristics of high-performing health facilities

Contextual factor	Hospital	Puskesmas
Internal	• Class A or B hospital • Publicly owned • Large number of elderly patients • Large number of patients with poor insurance scheme • Fewer patients without insurance scheme • Accredited hospital	• Fewer electricity disruption
External	• Low total household expenditure • High % of poverty in the population • High population coverage through poor insurance scheme • Low % of pop with secondary school and higher education • Lower population coverage through civil servants and private insurance schemes	• Large population coverage • Low ratio of primary care per population

poor were more efficient than hospitals in other areas (Table C.5 in Appendix C).

Given the rich data available and the framework developed in Chapter 4, sensitivity analysis was conducted and two different models using logistic regression were developed to identify and understand the contextual factors that have driven the high-performing hospitals (Table 5.8). Accreditation, greater numbers of elderly patients, larger hospital size, public ownership, lower population educational levels and coverage through the health insurance scheme for the poor were independent predictors of high-performing hospitals in the multivariate analysis. Accreditation hospitals and greater population coverage through the health insurance scheme for the poor were the predictors in Model 1. Accredited hospitals had triple the odds of being high-performing than other hospitals. For every additional 1% of the population covered under the health insurance scheme for the poor, a hospital's odds of being high-performing rose by 3%. Model 2 shows hospitals with a higher proportion of elderly patients, Class A or B classification, public ownership and lower population educational level to be more likely to be among the high-performing hospitals. For every additional 1% of patients older than 65, a hospital's odds of being among the high-performing hospitals rose by 6%. Class A and B hospitals had 2.6 times higher odds of being high-performing than Class C and D hospitals. Public hospitals had four times higher odds to be high-performing than private hospitals. In addition, for every additional 1% of the population with only a primary education level, a hospital's odds of being high-performing rose by 5%.

Both models are useful for different stakeholders. The Ministry of Health would be more interested in model 1 results where the quality of hospitals and national insurance coverage are the primary policy focus. Health facility managers are likely to focus on model 2 results because they have some control over most of the variables. To find the best model, ROC was used as it facilitates discrimination between models. Model 2 increased the ROC area to 0.784 from 0.656 in Model 1, indicating that model 2 has a more accurate model fit. Model 2 also explains more variables both external and internal factors of hospitals. The results suggest that type and ownership of hospitals are related to accreditation where large public hospital are more likely to be accredited. Also, the higher proportion of population with primary school degree reflects a poor population.

Table 5.8: Independent contributions of high-performing hospital characteristics according to multivariate analysis

Variables	Odds ratio	(95% CI)	P value	ROC area of model	(95% CI)
Model 1					
Accredited	3.39	(1.39 to 8.25)	0.007	0.656	(0.58 to 0.72)
% Poor insurance	1.03	(1.01 to 1.06)	0.012		
cons	0.05	(0.02 to 0.15)	0.000		
Model 2					
% Patients over 65	1.06	(1.01 to 1.12)	0.028	0.784	(0.72 to 0.84)
Class A/B	2.59	(1.06 to 6.33)	0.038		
Publicly owned	3.91	(1.27 to 12.03)	0.017		
% Primary school	1.05	(1 to 1.1)	0.049		
% Poverty	1.04	(0.98 to 1.11)	0.181		
cons	0.00	(0 to 0.03)	0.000		

Puskesmas

The bivariate analysis suggests that the 17 high-performing *Puskesmas* had specific common characteristics that are different from those of the 76 non-high-performing *Puskesmas*: high-performing *Puskesmas* experienced fewer electrical and medicinal disruptions. Regarding external contextual factors, high-performing *Puskesmas* were generally in areas where a lower proportion of the population had a primary school educational level and where the *Puskesmas* served larger populations (see Table C.6 in Appendix C).

The multivariate analysis suggests four independent predictors of high-performing *Puskesmas* (see Table 5.9). *Puskesmas* with fewer electrical disruptions and medicinal disruptions had five times greater odds of being among the high-performing *Puskesmas* than others. For every additional 1 USD of household expenditure per month, a *Puskesmas's* odds of being high-performing declined by 2%. Also, for every additional 10,000 people covered, a *Puskesmas's* odds of being high-performing rose by 25 to 40%. Models 1 and 2 both have strong discriminatory power, with an ROC area of 0.8. However, given more variables can explain the efficiency of primary care facilities, model 2 is preferred.

Table 5.9: Independent contributions of high-performing *Puskesmas* characteristics according to multivariate analysis

Variables	Odds ratio	(95% CI)	P value	ROC area of model	(95% CI)
Model 1					
Electrical disruptions	0.22	(0.06 to 0.88)	0.033	0.796	(0.69 to 0.88)
Population in 10,000	1.25	(1.01 to 1.55)	0.041		
cons	0.33	(0.09 to 1.2)	0.093		
Model 2					
Medicinal disruptions	0.19	(0.04 to 0.97)	0.046	0.817	(0.71 to 0.9)
Household expend.	0.98	(0.96 to 1)	0.017		
Population in 10,000	1.40	(1.06 to 1.87)	0.020		
On Java or Bali	0.27	(0.04 to 1.68)	0.160		
cons	20.03	(0.48 to 827.67)	0.114		

5.4 Discussion

The ratio analysis, unit cost analysis, and Pabón-Lasso model are useful means to assess efficiency in health facilities (Lasso, 1986; Barnum & Kutzin, 1993). To the best of our knowledge, this study is the first to use both methods, and as such it has drawn more robust results.

5.4.1 Utilisation

Bed occupancy rate is a basic indicator to assess health facility performance, with an 80-90% occupancy rate taken to indicate high efficiency (Chisholm & Evans, 2010; Chatterjee *et al.*, 2013). Neither hospitals nor *Puskesmas* in Indonesia have achieved that target; the highest bed occupancy rate found was 60% in Indonesian hospitals and 34% in *Puskesmas*. Similarly, Somanathan *et al.* (2000) found the average occupancy rate for primary care facilities in Sri Lanka to be under 50%. In addition, using the Pabón-Lasso model, only a few facilities were identified to be in the high utilisation sector. Studies in Colombia, Iran, and Mali have shown approximately 20% to 45% of facilities to be in the high utilisation sector (3) (Lasso, 1986; Mohammadkarim *et al.*, 2011; Asbu *et al.*, 2012; Mehrtak *et al.*, 2014). These results indicate excess bed capacity in health facilities given the current level of utilisation.

To avoid surplus inputs, it is critical to find optimal health facility sizes. We found that the size of hospitals and *Puskesmas*, proxied by number of beds, did affect efficiency. The most interesting finding using the Pabón-Lasso model was the pattern in health facility size in each sector: the largest proportion of high-performing health facilities were of medium size (between 94 and 205 beds).

5.4.2 Variation in costs

Our costing results show healthcare facilities in Indonesia to be costlier than WHO estimations, especially at the hospital level (Gkountouras *et al.*, 2011). The costs per bed day and outpatient visit estimated at hospitals in this study were two and four times higher, respectively, than the WHO estimation. Furthermore, the cost per outpatient visit at primary care facilities without inpatient services in this study was double the WHO estimation. However, the costs of outpatient visits at Indonesian primary care facilities with inpatient services are similar to the WHO estimation. This suggests that the expectation of health service costs can still be reduced through efficiency.

Staffing was the largest component of health facility costs. Studies in developing countries suggest that personnel costs account for between 41%

and 74% of all costs across health facilities (Green *et al.*, 2001; Minh *et al.*, 2010). Chatterjee *et al.* (2013) also found that private hospitals in India had lower staffing costs than public hospitals. The main reasons for the lower proportion of staffing costs in private hospitals are that private hospitals offer salary structures below the market rate, have more flexibility in using staff, and are more dependent on part-time contract staff (Ensor & Indradjaya, 2012; Chatterjee *et al.*, 2013).

Wide variations in unit costs were found across facilities partly because of differing patterns of utilisation. This further supports the finding of high inpatient unit costs in primary care facilities due to the low levels of output (Somanathan *et al.*, 2000). Somanathan *et al.* (2000) also found higher inpatient costs in large facilities because these facilities treat more complex cases; however, our results indicate that large facilities tend to have lower inpatient costs regardless of case mix.

5.4.3 Internal factors

Ownership is particularly important when examining efficiency, especially given the important differences in characteristics highlighted in Table 5.8. Although a recent review by Herrera *et al.* (2014) showed no conclusive results as to whether public or private hospitals perform better, we found that public hospitals were more frequently efficient than private hospitals. This finding is in agreement with Herr (2008) who found both for-profit and not-for-profit private hospitals to be less efficient than public hospitals. There are several possible explanations for this result. Public hospitals usually have more resources such as staff, beds, and medical technologies, and they can therefore treat more patients than can private hospitals (Lee *et al.*, 2008b; Asbu *et al.*, 2012). Another explanation is that public hospitals have more opportunity to reinvest their profits in high-tech medical equipment and training medical personnel, while private hospitals likely to pay higher than public to attract and retain physicians (Helmig & Lapsley, 2001; Lee *et al.*, 2008b). Our comparison of public and private hospitals showed that public hospitals were generally located in deprived areas and treated more patients with access to the insurance scheme for the poor. Thus, the insurance scheme for the poor reduces financial barriers to health care access and increases utilisation levels. In addition, the Indonesian insurance scheme for the poor uses the prospective payment mechanism, which gives health providers strong incentives to operate efficiently (Hsu, 2010). Therefore, apart from protecting people who may face financial catastrophic health expenditures, universal health coverage in Indonesia affects health facility efficiency.

Health managers may argue that meeting a minimum quality standard entails higher costs. However, our study addressed service quality, and found health facilities that are accredited and do not suffer electricity disruptions to perform better. To increase its health system efficiency, Indonesia will need to confront several challenges. In 2011, 18% of *Puskesmas* predominantly in the eastern part of the country, had no electricity; slightly more than 40% of *Puskesmas* had no technician on staff; and almost half of hospitals in Indonesia had not been accredited (Kemenkes, 2012a,b).

5.4.4 External factors

Assessing health facilities based on geographical location is important for policy decisions, especially those related to a nation's distribution of health facilities (Pham, 2011; Pavitra, 2013). As did Barnum & Kutzin (1993), we found health facilities on Java to be more efficient compared to those on other islands. High-performing health facilities were efficient in areas with easy access to health facilities. These factors suggest that a better transport and health facility infrastructure is important to reduce physical barriers to health care access.

Governments provide satellite *Puskesmas* in rural areas to bring healthcare closer to the population. However, large infrastructure investments in the *Puskesmas* network without adequate number of health workers would lead to inefficiency (The World Bank, 2008). Therefore, the system requires better resource allocation, for example for outreach activities, suitable vehicles, and maintenance, in order to improve efficiency in health facilities (Mills *et al.*, 1993).

In addition, consistent with the findings of Rosko & Mutter (2010) and Nedelea & Fannin (2012), we also found a negative association of household expenditure on health facilities efficiency. This result may be explained by the fact that *Puskesmas* and public hospitals are likely to be utilised by lower income population.

5.4.5 Limitations

This study has some limitations due to the nature of the data and methods used. First, only public primary care facilities with inpatient services were included; thus, the results might not apply to primary care facilities without inpatient services. Second, at this stage, the analysis of health facility characteristics was performed using ratio analysis, a simple method based on utilisation to help clarify the relationship between variables. Third, lack of health outcome data such as mortality ratio meant that the analysis conducted could not measure the quality of services and adjust output accordingly. Output quality is considered in Chapter 7. In future research, it would be useful to identify whether inefficiency stems from overuse of resources or from inappropriate medical treatment.

To mitigate the above mentioned limitations, the use of frontier techniques in efficiency measurement may help to identify inefficiency in multiple inputs and outputs. Future research could utilise regression analysis to explore factors that cause inefficiency and propose a practical way to overcome these inefficiencies. This study should also be replicated in private primary care and using longitudinal data, which would highlight changes in efficiency due to policy changes or interventions. In addition, longitudinal data would help address outlier data and determine whether the outliers identified here are true outliers or simply measurement errors. However, this study shows that it is feasible to undertake national-level assessments with different types of health facilities using simple methods that are easy to use and replicate.

5.5 Conclusion

This study suggests that there is considerable scope for improving the efficiency of health facilities in Indonesia. Few health facilities were located in the high utilisation sector of the Pabón-Lasso model, and wide variation in unit costs was found. The significant variation in unit costs and utilisation can present a powerful basis for benchmarking and identifying relatively efficient units. This study not only identifies the high-performing health facilities and their specific characteristics, but also provides information as to how efficiency can be improved. Benchmarking using unit cost analysis and the Pabón-Lasso model technique are valuable tools that policy makers can understand relatively easily and use in routine monitoring of health facility performance.

The next chapter focuses on primary care facility performance using frontier analysis, with the aim to explain relative efficiency in these facilities. In Chapter 7, hospital performance is also assessed by means of frontier analysis.

Chapter 6

Assessing Primary Care Performance in Indonesia: An Application of Frontier Analysis Techniques

Chapter 2 explained the primary care setting in Indonesia as well as conditions that may influence primary care facility performance. Building on that information, we now look more deeply into primary care and identify the factors associated with relative efficiency. Chapter 5 provided a general overview of Indonesian health facility performance using ratio analysis (RA). However, due to the nature of the data and methods used it was only feasible to include public primary care with inpatient services. Moreover, the RA technique cannot identify whether inefficiency stems from non-optimal input or non-optimal output, nor can it determine how inefficient primary care facilities can improve their efficiency levels. Frontier analysis is therefore needed to account for the above mentioned limitations of RA as well as to provide benchmarks for efficient primary care.

The present chapter is organised as follows. Section 6.1 provides a description of public primary care facilities in Indonesia. Section 6.2 outlines the methodological approaches employed to analyse technical efficiency, including data envelopment analysis (DEA) and stochastic frontier analysis (SFA), as well as validity testing. This section also describes the dataset and the variables used as the input, output, and contextual variables. Section 6.3

presents the results, while implications for policy and practice are discussed in Section 6.4.

6.1 Introduction

Healthcare utilisation in Indonesia is sub-optimal. The average contact rate in Indonesian public primary care facilities (*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 (Cashin *et al.*, 2002; Ensor & Indradjaya, 2012; OECD/WHO, 2014). Moreover, undesirable health outcomes in Indonesia are more common than in other Asian countries with similar or lower GDP per capita; for example, Indonesia's maternal mortality ratio, at 133 per 100,000 live births, is poor compared to 117 in the Philippines, 54 in Vietnam, and 31 in Sri Lanka (The World Bank, 2015b). Apart from other factors, such as income distribution and geography, the sub-optimal healthcare utilisation and outcomes in Indonesia indicate inefficiency of health facility services (Giokas, 2001).

Making better use of primary care resources is important because primary care facilities play an important role in achieving universal health coverage and improving the health of the population (Hsieh *et al.*, 2013; Ikegami, 2016). Primary health care also contributes to improving equity for the poor, allowing them to access care at reasonably low cost (Starfield *et al.*, 2005; Kruk *et al.*, 2010; Stigler *et al.*, 2016). Most essential care and health interventions can be delivered at the primary care level, and primary care facilities have a responsibility to initiate public health care activities, including disease prevention and health promotion (Starfield, 1994). However, more than half of the studies on efficiency in healthcare facilities worldwide have been conducted in hospitals; those conducted in primary care facilities represent a mere 10% to 20% (Hollingsworth, 2008; Hussey *et al.*, 2009).

In general, two main approaches have been used within the literature to measure efficiency: data envelopment analysis (DEA) techniques and stochastic frontier analysis (SFA). Most studies to date measure technical efficiency alone using a single technique and do not include contextual variables (Hollingsworth, 2008; Hussey *et al.*, 2009). The aims of this chapter are: 1) to examine the relative efficiency of primary healthcare facilities using frontier analysis, 2) to identify factors determining the relative efficiency of primary care facilities, and 3) to investigate the possible causes of differences in efficiency scores. We applied both DEA and SFA to study the variations in efficiency among Indonesian primary care facilities as well as the factors determining the efficiency levels found.

6.2 Methods

6.2.1 Data

This study analysed 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. We used this data to estimate the relative efficiency of *Puskesmas* (community-based primary care facilities) and identify internal factors influencing efficiency. Second, we used data from the 2011 National Socioeconomic Survey (SUSENAS), which provides household characteristics at the district level including the educational levels of all adults in the household and information on health insurance coverage. Third, we used data from the 2011 Village Potential Statistics (PODES), a census providing information about village characteristics across Indonesia such as population size, job types, and access to health facilities. We merged the SUSENAS dataset and the MoH health facility survey data using district identifiers for primary care facilities; the PODES dataset was merged with the MoH health facilities survey using sub-district identifiers for primary care facilities.

6.2.2 Input and output variables

The efficiency analysis was based on a vector of inputs measuring labour and capital in primary care facilities based on the analytical framework in Chapter 4. Five different inputs were 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 assets. Three outputs were considered: (1) the number of bed days, (2) the number of outpatients in the general clinic, and (3) the number of outpatients in maternal and child health care (MCH). The choice of the inputs and outputs illustrated in Table 6.1 was guided by those used in previous efficiency measurement studies undertaken in primary care facilities (Marschall & Flessa, 2009; Kirigia *et al.*, 2011; Blaakman *et al.*, 2014; Cordero Ferrera *et al.*, 2014; Alhassan *et al.*, 2015) and covered all primary care facility production inputs and outputs, health worker roles, 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. However, we found no significant difference between two DEA model specifications with and without the number of bed days.

Table 6.1: Input and output variables

Variables	Definition	Measurement	Data source
Input variables			
Doctors	Doctors	Total number of doctors	HFCS
Nurses	Nurses	Total numbers of nurses	HFCS
Midwives	Midwives	Total number of midwives	HFCS
Nurses_midwives	Nurses and midwives	Total number of nurses and midwives	HFCS
Other staff	Non-medical staff	Total number of non-medical staff	HFCS
Value of medical asset	The annualised value of medical assets in US dollars	$A_i = \frac{rV_iN_i}{(1-\frac{1}{(1+r)^{L_i}})}$ A_i =annualised value of medical assets i V_i =replacement cost using a standardised price list N_i =number of medical asset i L_i =useful life r = discount rate (3%)	HFCS
Output variables			
Patients - generalist	Outpatient visits in general clinic	Total number of attendances in general clinic within a year	HFCS
Patients - maternal and child health	Outpatient visits in maternal and child health care	Total number of attendances in maternal and child health care within a year	HFCS
All patients	patients_gen and patients_mch	Total number of outpatient visits in general clinic and maternal and child health care combined	HFCS

HFCS Health facility costing study

6.2.3 Contextual variables

The analysis examined contextual factors affecting health institutions and evaluated their impact on facility efficiency levels (Worthington, 2004). We selected the contextual variables in consultation with previous literature review in Chapter 4 and according to the availability of data. Contextual variables were grouped into two categories: (1) internal factors: elements specific to providers that affect facility efficiency (e.g. size and capacity, quality, and type of patients); (2) external factors: elements beyond the influence of a provider that can impact on facility efficiency (e.g. economic status, education level, and geography) (Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Mitropoulos *et al.*, 2013; Nedelea & Fannin, 2013; Varabyova & Schreyogg, 2013; Cordero Ferrera *et al.*, 2014; Ding, 2014; Heimeshoff *et al.*, 2014; Shreay *et al.*, 2014; Yang & Zeng, 2014; Matranga & Sapienzab, 2015).

Our large dataset with many contextual variables that are potentially highly correlated could have led to problems with the use of multivariate regression techniques (Everitt & Hothorn, 2011). To address this issue, principal components analysis (PCA) was used to create a smaller number of uncorrelated new variables by category (Jolliffe & Cadima, 2016). We thus transformed 15 variables into four new index variables. The PCA results are presented in Table 6.2, and all contextual variables are available in Table 6.3.

In addition to PCA variables, the initial general model contained all of the identified contextual variables. We ran several models, checked for multicollinearity and finalised a vector of contextual variables.

6.2.4 DEA

We applied DEA with bootstrap procedure to estimate the efficiency scores for each of the providers in the sample. Variable returns-to-scale (VRS) were applied to run input- and output-oriented models to estimate the individual primary care facility efficiency scores, assuming that not all primary care facilities are operating at an optimal scale. In this study, output orientation was chosen to identify the factors determining efficiency because healthcare resources, including workforce and capital investment in primary care facilities, tend to be fixed and controlled by the government (Mahendradhata *et al.*, 2017).

The empirical DEA model is given by Eq. 6.1

$$\begin{aligned}
&\max \phi, \\
&\text{subject to} \\
\sum_{i=1}^{n} \lambda_i x_{ji} \leq x_{jo} \qquad & j = 1, 2, .., m; \\
\sum_{i=1}^{n} \lambda_i y_{ri} \geq \phi y_{ro} \qquad & r = 1, 2, ..., s; \\
\sum_{i=1}^{n} \lambda_i = 1 \qquad \lambda_i \geq 0 \qquad & i = 1, 2, ..., n
\end{aligned} \tag{6.1}$$

where i = primary care facility; 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 primary care facility$_i$, that the sum of λ equals to one; ϕ = represents the efficiency of primary care facility. The right-hand side is one of the n primary care facilities that are under evaluation; the left-hand side represents the convex combinations of observed values of inputs and outputs.

We developed a number of alternative model specifications, using combination of inputs and outputs. Models I1, I4, O1 and O4 used all inputs (capital and disaggregated medical staff), with five inputs: medical assets value, number of nurses, number of midwives, number of doctors and number of other staff. Since the value of medical assets data were not reliable because of the wide variation, models I2, I5, O2 and O5 used four inputs without capital: number of nurses, number of midwives, number of doctors and number of other staff. The restricted models (I3, I6, O3 and O6) used aggregate number of nurses and midwives with three inputs: doctors, other staff and aggregate number of nurses and midwives. Models I1, I2, I3, O1, O2 and O3 used two different type of outputs: number of general outpatients and MCH services. Since both outputs provide similar types of services, models I4, I5, I6, O4, O5 and O6 used one output: aggregate number of outpatients and MCH services.

Table 6.2: PCA variables

Description	PCA Coef.	New variable
Cons	0.00	Index of less disruption
Water disruption	-0.31	
Without water disruption	0.70	
Electricity disruption	-0.18	
Without electricity disruption	0.92	
Medicine disruption	-0.37	
Without medicine disruption	0.46	
Salary disruption	-0.77	
Without salary disruption	0.30	
Incentive disruption	-0.39	
Without incentive disruption	0.56	
Cons	-0.00	Index of less management
Case meetings at least 6 months	-0.50	
Case meetings less frequent	0.33	
With mentoring	-0.35	
Without mentoring	1.18	
With monitoring of work hours	-0.31	
Without monitoring of work hours	1.36	
Cons	-2.91	Index of access to health facility
Hospital per pop	-3.60	
Primary per pop	1.07	
Easy access to Hospital	2.82	
Easy access to Primary care fac	3.04	
Cons	-0.85	Index of higher education
Secondary school	8.72	
Higher education	10.58	
Primary school	-6.64	

6.2.5 SFA

In this study, we estimated technical inefficiency using Cobb-Douglas and Translog production functions. We aggregated the outputs and did not use weighting because of similar types of services. As mentioned in Chapter 3, combining the number of total treatments provided in different areas of services (i.e. sum of general and MCH outpatient visits) might not be appropriate due to the differing types of outputs. It is for these reasons that we also considered Cobb-Douglas and Translog distance functions.

The empirical model of Cobb-Douglas function form is given by Eq. 6.2.

Table 6.3: Contextual variables

Variables	Definition	Measurement	Data source
Internal factors			
Index of less disruption	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	HFCS
Index of less management	Index of management	Principal component analysis score of regular meetings about service performance, regular meetings to discuss cases, mentoring clinical staffs, and monitoring of employee working hours	HFCS
Patients aged 0 to 4	Proportion of patients under 5 years old	Total number of patients under 5 years old divided by total number of all patients	HFCS
Facilities with inpatient services	Availability of inpatient services	Whether inpatient services are available: 1 if available, and 0 if not available	HFCS
External factors			
Jamsostek ins	Employee insurance scheme	Proportion of households covered by *Jamsostek* insurance (scheme for employees)	SUSENAS
Askes ins	Civil servant insur- ance scheme	Proportion of households covered by *Askes* insurance (scheme for civil servants)	SUSENAS
Jamkesmas ins	Poor insurance scheme	Proportion of households covered by insurance scheme for the poor	SUSENAS
Urban	Urban area	Whether primary care facility is in an urban area: 1 if yes, 0 if no	
On Java or Bali	Java or Bali island	Whether primary care facility is on Java or Bali island: 1 if yes, 0 if no	HFCS
Index of access to health facility	Index of health facilities availability	Principal component analysis score of (smaller) number of hospitals 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
Index of higher education	Index of population education level	Principal component analysis score of district population proportion with primary school education, less than secondary education, and less than higher education	SUSENAS
Population	Number of population	2011 population in sub-district	PODES

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + (v_{i-}u_i) \tag{6.2}$$

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 the technical inefficiency of primary care facility i.

Using the same justification in Section 6.2.4 we tailored number of model specifications. Three specifications developed for Cobb-Douglass function (C1, C2 and C3). C1 used five inputs: assets, nurses, midwives, doctors and other staff. C2 used four inputs: nurses, midwives, doctors and other staff. C3 used three inputs: doctors, other staff and aggregate number of nurses and midwives. All Cobb-Douglas function forms used one output: the aggregate number of general outpatients and of MCH services.

The empirical model of Translog function form is given by Eq. 6.3.

$$\log(y_i) = \beta + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + (v_i - u_i) \tag{6.3}$$

$\log x_{ji} \log x_{hi}$ represents the interaction of the corresponding inputs j and h of the i-th primary care facility. We tailored three specifications of Translog function form (T1, T2 and T3). T1 used five inputs: assets, nurses, midwives, doctors and other staff. T2 used four inputs: nurses, midwives, doctors and other staff. T3 used three inputs: doctors, other staff and aggregate number of nurses and midwives. All Translog function forms used one output: the aggregate number of general outpatients and of MCH services.

The empirical model of multi-output distance function form is given by Eq. 6.4.

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

$$\text{where the interpretation of } \frac{y_h}{y_n} \text{ is } \left(\frac{MCH}{General}\right) \tag{6.4}$$

We tailored the multi-output distance function form with different specifications (CD1, CD2 and CD3). CD1 used five inputs: assets, nurses, midwives, doctors and other staff. CD2 used four inputs: nurses, midwives, doctors and other staff. CD3 used three inputs: doctors, other staff and aggregate number of nurses and midwives. All multi-output distance function forms used two outputs: the number of general outpatients and the number of MCH services.

The empirical model of multi-output Translog distance function form is given by Eq. 6.4.

$$\log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k}\beta_j \log x_{ji} + \frac{1}{2}\sum_{j=1}^{k}\sum_{h=1}^{k}\beta_{jh}\log x_{ji}\log x_{hi} + \sum_{h=1}^{k-1}\beta_h \log\frac{y_{hi}}{y_{ni}}$$
$$+\frac{1}{2}\sum_{j=1}^{k-1}\sum_{h=1}^{k-1}\beta_{jh}\log\frac{y_{hi}}{y_{ni}}\log\frac{y_{hi}}{y_{ni}} + \sum_{j=1}^{k}\sum_{h=1}^{k-1}\beta_{jh}\log x_{ji}\log\frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \tag{6.5}$$

We tailored the multi-output Translog distance function form with different specifications (TD1, TD2 and TD3). TD1 used five inputs: assets, nurses, midwives, doctors and other staff. TD2 used four inputs: nurses, midwives, doctors and other staff. TD3 used three inputs: doctors, other staff and aggregate number of nurses and midwives. All multi-output Translog distance function form used two outputs: number of general outpatients and MCH services.

6.2.6 Validity testing

We tested for internal validity, focusing on the stability of the results within each method, and external validity, addressing the stability of the results achieved between DEA and SFA. Various combinations of input and output variables were used to test the changes in the efficiency estimates (see Table 6.4).

Two-step internal validity testing was conducted prior to the external validity test. With DEA, two model assumptions were first compared using the Kruskal-Wallis test to determine whether differences were statistically significant by reducing the number of inputs and outputs. Second, a Spearman rank correlation test was used to estimate the correlation between DEA input- and output-oriented models. With SFA, a likelihood ratio test was first used to detect the presence of any difference between the SFA and ordinary least squares (OLS) models. Second, a Spearman rank correlation test was used to estimate the correlation between the SFA models (i.e. Cobb-Douglas, Translog and distance functions).

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.

6.2.7 DEA and SFA quadrant scores

Since the results of the DEA and SFA approaches were not always similar, it appeared important to identify the primary care facilities that were shown to be efficient and inefficient in both 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.

6.2.8 Contextual variable analysis

Second-stage DEA analysis

Two-stage approach procedures have been widely implemented (Bernet *et al.*, 2008; Marschall & Flessa, 2009, 2011; Blaakman *et al.*, 2014; Alhassan *et al.*, 2015) to find factors determining efficiency. In this study, we first used bootstrap DEA to estimate the relative technical efficiency of health facilities. Subsequently, regression models predicting the efficiency scores were applied according to a set of contextual variables that were expected to influence the technical efficiency of health facilities.

There is some debate about the use of regression for this second-stage analysis (Hoff, 2007; McDonald, 2009; Simar & Wilson, 2011). Since efficiency scores above 1 are not possible, it is appropriate to use a truncated regression model to investigate the relationship between the DEA efficiency scores computed in the first stage and a vector of contextual factors. Truncated regression is appropriate because it provides consistent estimations in the second stage, where models using Tobit or ordinary least squares (OLS) are consistent only if several assumptions hold. First, it is assumed that all of the coefficients on the contextual variables are non-negative, which might not be the case in our study, as we have no *a priori* direction of the effects. Second, the assumption that input and contextual variables are independent is not likely to hold; for example, primary care in urban areas might use more doctors and nurses. Third, the assumption of constant variance for the noise is not likely to hold here as output is likely to be more variable in larger facilities than in small facilities constrained by capacity (Simar & Wilson, 2011).

Table 6.4: Model specifications

Variables	DEA*												SFA**											
	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 variables																								
Assets	X			X			X			X			X			X			X			X		
Nurses	X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X	
Midwives	X	X		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	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	X	X	X
Nurses and midwives			X			X			X			X			X			X			X			X
Output variables																								
General outpatients	X	X	X				X	X	X				X	X	X				X	X	X			
MCH services	X	X	X				X	X	X				X	X	X				X	X	X			
General outpatients and MCH services				X	X	X				X	X	X				X	X	X				X	X	X

*I1-I6 are input-oriented and O1-O6 are output-oriented DEA models.

**CD1-CD3 are multi output distance functions, C1-C3 are Cobb-Douglas functions, TD1-TD3 are Translog distance functions, and T1-T3 are Translog functions.

X indicates that the variable is included in the models.

Second-stage DEA is written as follows:

$$\hat{\phi}_i = \beta z_i + \varepsilon \tag{6.6}$$

where in this case $\hat{\phi}$ represents the estimated bias-corrected DEA score generated from bootstrap procedure, assumed to be truncated, β is the unknown coefficient, z is the vector of contextual variables refers to internal and external factors that can be seen in Table 6.3, and ε is a random variable. A variance inflation factor was used to denote significant multicollinearity, and we found moderately correlated with coefficient less than 2.

One-stage SFA analysis

The two-stage procedures in SFA models have been found to be biased because of misspecified or under-dispersed distribution (Battese & Coelli, 1995; Wang & Schmidt, 2002; Kumbhakar *et al.*, 2015). A one-stage procedure was therefore applied to study the determinants influencing inefficiency, defined by

$$u_i = \delta z_i + W_i \tag{6.7}$$

where u is the technical inefficiency in the stochastic frontier model, δ is the unknown coefficient, z_i is a vector of contextual variables associated with technical inefficiency, using the same list as in the second-stage analysis in DEA (Table 6.3) and W is the random variable.

6.2.9 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 several 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). Because DEA efficiency scores are sensitive to the presence of outliers, a data cloud method was implemented to check for outliers using the FEAR (Frontier Efficiency Analysis) package in R version 2.0.1 (Wilson, 2008). Kruskall-Wallis test was applied and no statistical differences of efficiency scores between with and without outliers. We imputed using the chained equations technique with the 'mice' library in R statistical software (Buuren & Groothuis-Oudshoorn, 2011). We used T-test and Chi-square test, we found no statistical difference between the complete and imputed data (see Table D.1 in Appendix D). To include 49 observations from the sample of inputs and outputs that were missing or equal to zero, we performed multiple imputation.

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 also exceed the product of the number of inputs and outputs (Bowlin, 1998; Bogetoft & Otto, 2010). We had 234 facilities, which exceeded the minimum sample of health facilities needed.

6.3 Results

6.3.1 Primary care statistics

Table 6.5 presents the characteristics and activities of primary care facilities. There was wide variation in the number of outputs and inputs. On average, *Puskesmas* (primary care facilities), including their satellites in villages, provided 18,600 general outpatient visits and 3,800 MCH care visits. The facilities produced these outputs with an average of four doctors, 31 nurses and midwives, and 19 other staff.

6.3.2 Technical efficiency

We omitted the Translog distance function in this study because it did not fit our data, with the model showing nearly perfect multicollinearity.

Table 6.6 shows the summary statistics of efficiency in different models; smaller average scores imply lower facility efficiency. The mean efficiency score in output-oriented DEA was lower than in SFA. The spread of DEA efficiencies was much larger than in SFA efficiencies.

The output-oriented efficiency is the maximal number of services (output) given the number of health workers (inputs). The average scores of 0.3 in DEA (O6) and 0.6 in SFA (T3) suggested that we could expand the outputs by 245% and by 69% without spending additional resources. In absolute terms,

Table 6.5: Primary care descriptive statistics

Variables	Overall
Input variables	
Doctors (mean (sd))	3.31 (4.27)
Nurses (mean (sd))	16.15 (20.90)
Midwives (mean (sd))	14.03 (20.60)
Other staff (mean (sd))	18.30 (20.72)
Value of asset_med (mean (sd))	24342.79 (24410.67)
Output variables	
Patients - generalist (mean (sd))	17597.60 (12533.28)
Patients - maternal and child health (mean (sd))	3698.56 (3738.02)

n sample size, *sd* standard deviation

using DEA and SFA, primary care facilities could expand to 43,000 and 12,000 general outpatient visits per year without increasing the number of health staff.

Regarding internal validity testing, a likelihood ratio test showed that all SFA models rejected the null hypothesis that OLS and SFA are the same at the 5% level. Spearman rank correlation was found between the DEA models ranging from 0.21 to 0.33 and between the SFA models from 0.91 to 0.99 (see Table 6.8).

Comparing all models, we found that the correlation between DEA and SFA efficiency ranged from 0.63 to 0.79. The disaggregation of health workers as well as services in the output definition might considerably reduce the efficiency correlation. Finally, we included the two models (Models O6 and T3 in Table 6.8) with the strongest external validity estimates. The preferred specifications of the models included the number of doctors, the number of nurses and midwives, and the number of other staff as inputs, and the aggregated total number of outpatient and MCH care visits as outputs.

Figure 6.1 provides a scatter plot of primary care facilities; the vertical and horizontal lines represent the mean values of DEA and SFA. 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) according to both techniques. The results for the remaining 23% of health facilities are inconclusive (Quadrant 2 and 4). The statistics of the quadrant scores between DEA and SFA are presented in Table 6.7.

Table 6.6: DEA and SFA efficiency scores in primary care

Statistic	N	Mean	St. Dev.	Min	Median	Max
DEA						
I1	234	0.59	0.25	0.05	0.60	0.99
I2	234	0.57	0.27	0.04	0.51	0.99
I3	234	0.55	0.27	0.03	0.48	0.98
I4	234	0.59	0.26	0.05	0.56	0.99
I5	234	0.57	0.27	0.04	0.49	0.98
I6	234	0.55	0.28	0.03	0.48	0.98
O1	234	0.37	0.21	0.02	0.32	0.83
O2	234	0.35	0.21	0.02	0.31	0.83
O3	234	0.33	0.20	0.02	0.28	0.84
O4	234	0.32	0.20	0.02	0.26	0.78
O5	234	0.30	0.19	0.02	0.25	0.74
O6	234	0.29	0.18	0.02	0.24	0.80
SFA						
CD1	234	0.55	0.19	0.10	0.57	0.88
CD2	234	0.55	0.19	0.10	0.57	0.89
CD3	234	0.55	0.19	0.10	0.56	0.88
C1	234	0.53	0.20	0.08	0.54	0.89
C2	234	0.53	0.20	0.08	0.54	0.89
C3	234	0.53	0.20	0.08	0.55	0.89
T1	234	0.62	0.14	0.22	0.65	0.87
T2	234	0.59	0.17	0.16	0.62	0.88
T3	234	0.59	0.16	0.17	0.61	0.88

I1-I6 are input-oriented and O1-O6 are output-oriented DEA models
CD1-CD3 are multi output distance functions, C1-C3 are Cobb-Douglas functions, and T1-T3 are Translog functions.

6.3.3 Contextual factors

The results of the two-stage DEA model and the one-stage SFA model are presented in Table 6.9. The signs of the coefficients between the SFA and DEA were consistent with the exception of the proportion of patients under five years old. The index of less disruption in health facilities, index

Table 6.7: Statistics by efficiency quadrant

	1	2	3	4	p
n	104	38	88	4	
O6 (mean (sd))	0.14 (0.06)	0.24 (0.03)	0.47 (0.13)	0.58 (0.02)	<0.001
T3 (mean (sd))	0.38 (0.11)	0.63 (0.05)	0.74 (0.07)	0.42 (0.10)	<0.001
Doctors (mean (sd))	3.45 (3.61)	3.45 (3.00)	3.57 (5.67)	4.50 (5.00)	0.971
Nurses (mean (sd))	18.54 (25.49)	18.97 (22.75)	13.86 (16.52)	5.50 (5.20)	0.301
Midwives (mean (sd))	14.90 (17.92)	17.71 (20.58)	13.90 (26.32)	4.25 (3.95)	0.622
Other staff (mean (sd))	19.16 (19.65)	16.34 (9.13)	20.22 (25.90)	29.75 (37.46)	0.606
Patients - generalist (mean (sd))	8295.25 (3605.36)	17093.97 (5126.58)	28769.48 (12132.16)	16067.06 (22090.62)	<0.001
Patients - maternal and child health (mean (sd))	1882.01 (1485.08)	4086.68 (2983.81)	5838.04 (4773.71)	2185.33 (2370.63)	<0.001
Index of less disruption (mean (sd))	-0.34 (1.31)	0.21 (1.51)	0.33 (1.19)	-0.37 (1.03)	0.003
Index of less management (mean (sd))	-0.02 (1.11)	0.02 (1.21)	0.05 (1.20)	-0.60 (0.18)	0.736
Patients aged 0 to 4 (mean (sd))	0.15 (0.06)	P 0.12 (0.05)	0.13 (0.06)	0.14 (0.06)	0.020
Facilities with inpatient services (n(%))	46 (44.2)	16 (42.1)	32 (36.4)	1 (25.0)	0.645
Jamsostek ins (mean (sd))	0.03 (0.03)	0.04 (0.05)	0.06 (0.06)	0.03 (0.04)	0.002
Askes ins (mean (sd))	0.11 (0.04)	0.12 (0.04)	0.13 (0.06)	0.15 (0.04)	0.004
Jamkesmas ins (mean (sd))	0.24 (0.15)	0.22 (0.15)	0.23 (0.13)	0.33 (0.22)	0.510
Urban (n(%))	17 (16.3)	7 (18.4)	39 (44.3)	1 (25.0)	<0.001
On Java or Bali (n(%))	22 (21.2)	23 (60.5)	47 (53.4)	2 (50.0)	<0.001
Index of access to health facility (mean (sd))	0.13 (1.77)	-0.24 (0.62)	-0.03 (1.37)	-0.50 (0.76)	0.505
Index of higher education (mean (sd))	-0.55 (1.19)	-0.05 (1.32)	0.66 (1.81)	0.25 (2.86)	<0.001
Population in 1,000 (mean (sd))	31.91 (28.76)	46.67 (31.19)	56.43 (50.31)	27.49 (32.93)	<0.001

O6 is an output-oriented DEA model. T3 is a Translog function.
n sample size, *sd* standard deviation

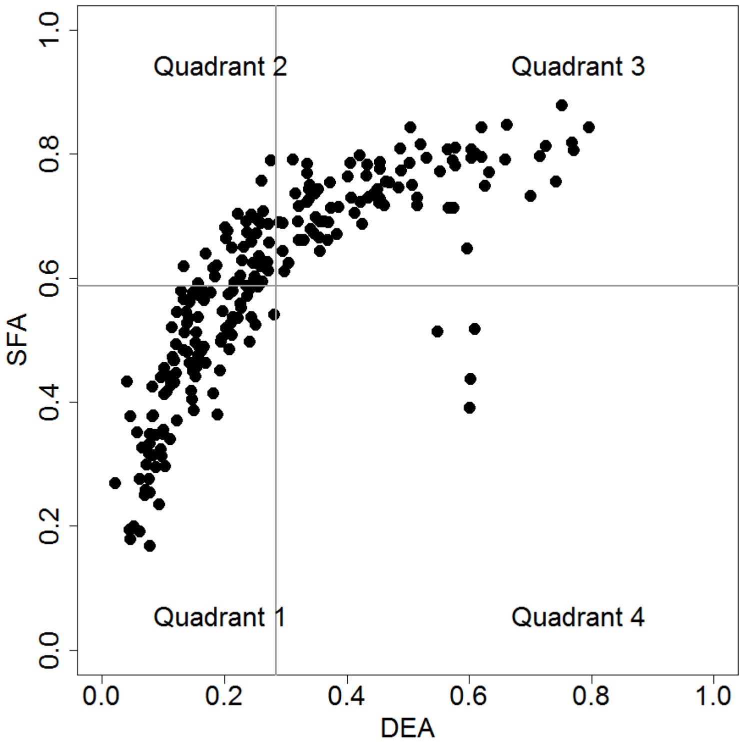


Figure 6.1: Quadrant scatter plot of estimated DEA and SFA scores in primary care facilities

of management, proportion of patients under five years old, availability of inpatient services, coverage of civil servant insurance scheme, and education were inconclusive in all models. The results indicated that geographic and demographic characteristics, and health insurance coverage were likely to influence efficiency.

Given the rich data available and the framework developed in Chapter 4, two logistic regression models were used to explain factors determining efficiency of primary care facilities. The results of the truncated regression for DEA efficiency scores indicated that none of the internal factors were likely to influence efficiency. Health insurance coverage, location on Java or Bali, location in an urban area, and access to health facilities were positively associated with efficiency. For each 10% increase in the proportion of population with poor insurance scheme coverage, there was a 0.02 (Model 1) and 0.03 (Model 2) increase in the predicted value of efficiency. Geographic location yielded different interpretations. The predicted value of the efficiency score was 0.09 (Model 1 and Model 2) points higher for primary care facilities

Table 6.8: 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																				
I2	0.95	1																			
I3	0.91	0.96	1																		
I4	0.98	0.94	0.9	1																	
I5	0.94	0.98	0.95	0.95	1																
I6	0.89	0.94	0.98	0.91	0.96	1															
O1	0.33	0.3	0.29	0.3	0.27	0.26	1														
O2	0.28	0.26	0.24	0.24	0.23	0.21	0.93	1													
O3	0.2	0.18	0.21	0.16	0.15	0.17	0.86	0.93	1												
O4	0.35	0.32	0.31	0.33	0.3	0.28	0.95	0.86	0.78	1											
O5	0.29	0.28	0.27	0.26	0.26	0.24	0.87	0.94	0.87	0.9	1										
O6	0.23	0.22	0.24	0.2	0.19	0.22	0.8	0.86	0.93	0.82	0.92	1									
CD1	0.04	0.03	0.04	0.01	0.01	0.02	0.63	0.7	0.77	0.6	0.69	0.77	1								
CD2	0.03	0.03	0.04	0.01	0.01	0.02	0.63	0.7	0.77	0.59	0.7	0.77	1	1							
CD3	0.04	0.04	0.04	0.01	0.02	0.02	0.64	0.7	0.77	0.6	0.71	0.77	1	1	1						
C1	0.04	0.03	0.04	0.01	0.01	0.02	0.66	0.72	0.79	0.62	0.72	0.79	0.99	0.99	0.99	1					
C2	0.04	0.03	0.04	0.01	0.01	0.02	0.66	0.72	0.79	0.62	0.72	0.79	0.99	0.99	0.99	1	1				
C3	0.04	0.03	0.04	0.02	0.01	0.02	0.66	0.73	0.8	0.63	0.73	0.79	0.98	0.98	0.99	1	1	1			
T1	0.03	0.03	0.04	0	0.01	0.02	0.65	0.72	0.77	0.62	0.72	0.77	0.9	0.91	0.91	0.91	0.91	0.91	1		
T2	0.03	0.02	0.03	0.01	0.01	0.01	0.66	0.72	0.78	0.63	0.73	0.78	0.93	0.93	0.93	0.94	0.94	0.94	0.97	1	
T3	0.02	0.01	0.03	-0.01	-0.01	0.01	0.66	0.73	0.79	0.63	0.74	0.79	0.94	0.94	0.95	0.95	0.95	0.95	0.97	0.99	1

I1-I6 are input-oriented and O1-O6 are output-oriented DEA models.

CD1-CD3 are multi output distance functions, C1-C3 are Cobb-Douglas functions, and T1-T3 are Translog functions.

Table 6.9: Results of regression on explanatory variables in primary care facilities

Variables	DEA				SFA			
	Model 1		Model 2		Model 1		Model 2	
	Est	SE	Est	SE	Est‡	SE	Est‡	SE
Internal factors								
Index of less disruption	0.01	0.01	0.01	0.01	0.05	0.04	0.03	0.05
Index of less management	0.00	0.01	0.00	0.01	0.00	0.04	0.02	0.05
Patients aged 0 to 4†	-0.02	0.02	-0.02	0.02	0.01	0.09	0.02	0.12
Facilities with inpatient services	-0.02	0.02	-0.02	0.02	0.03	0.11	-0.02	0.12
External factors								
Jamsostek ins†	0.09	0.03 ***	0.07	0.04	0.46	0.15 **	0.21	0.18
Askes ins†	0.03	0.02	0.03	0.03	0.06	0.11	0.01	0.16
Jamkesmas ins†	0.02	0.01 **	0.03	0.01 ***	0.10	0.04 *	0.13	0.05 **
Urban	0.07	0.03 *	0.06	0.03 *	0.50	0.14 ***	0.43	0.15 **
On Java or Bali	0.09	0.03 ***	0.09	0.03 ***	0.54	0.13 ***	0.47	0.16 **
Index of access to health facility			0.02	0.01 *			0.08	0.04 *
Index of higher education			0.00	0.01			0.07	0.07
Population (in 100,000)			0.04	0.04			0.50	0.25 *
Constant	0.13	0.05 **	0.10	0.06	1.96	0.28 ***	1.98	0.36 ***
R2	0.24		0.26		0.11		0.11	
sigma	0.16	0.01 ***	0.15	0.01 ***				
sigmaSq					0.35	0.05 ***	0.34	0.05 ***
gamma					0.82	0.09 ***	0.81	0.09 ***
Log Likelihood	102.22		105.34		-190.24		-183.90	

Significance level: ***0.001, **0.01, *0.05
† The unit is a proportion of variable multiply by 10 (one unit represent 10%).
‡ The coefficients are multiplied by -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

on Java or Bali than on other islands. The predicted value of the efficiency score was significantly higher for health facilities in urban areas.

Model 2 shows full model by adding access to health facility, education level and population. By comparing model 1 and model 2, *Jamsostek* insurance coverage becomes inconclusive. Results suggest that *Jamsostek* beneficiaries are located in areas with a better access to health facilities and large populations.

The estimations of the SFA were multiplied by -1; the results can thus be directly interpreted as effects on the efficiency estimates. On average, primary care facilities in urban areas were 0.50 and 0.43 points (Model 1 and Model 2, respectively) more efficient than primary care facilities in rural areas. A

10% increase in health insurance coverage scheme for the poor showed an increase of approximately 0.10 point in the predicted value of efficiency. The predicted value of the efficiency score was also significantly higher for primary care facilities in areas with better access to health facilities.

6.4 Discussion

6.4.1 Technical efficiency

Efficiency measurement is required for ensuring that health resources for services are spent as effectively as possible. Given the advantages and disadvantages of each method, there is no consensus about which method best estimates efficiency. Giuffrida & Gravelle (2001) argued that the different settings of the organisations evaluated may yield different efficiency results and that it is therefore important to investigate the results and use more than one method according to healthcare facility type. The choice of the method(s) should depend on the purpose of the analysis, the sample size, the perceived availability of data, and the characteristics of the units evaluated (Huang & McLaughlin, 1989).

The basic assumptions used for the specification of the models may also influence the estimated results (Hollingsworth, 2003). In DEA models, it has been found that the application of VRS and a greater number of inputs and outputs yields higher efficiency scores (Giuffrida & Gravelle, 2001).

Giuffrida & Gravelle (2001) found that the correlation of the efficiency scores between DEA and SFA was lower than the correlation between different DEA models. The correlations differed according to the models used. The returns-to-scale assumption used in the DEA also affected the correlation between the DEA and SFA results, although the effects were mixed.

Health facilities as shown in Figure 6.1 can be categorised into three main groups. The first group consists of health facilities in which the efficiency scores are sensitive to the technique used (Quadrants 2 and 4), the second group consists of the health facilities that appear to be efficient using both techniques (Quadrant 3), and the last group is composed of the health facilities that appear inefficient using both techniques (Quadrant 1). Following Jacobs *et al.* (2006), inferences should not be drawn from facilities in the first or second groups as they are considered as outliers. Meanwhile, facilities in the third group should be subjected to more critical scrutiny, in such forms as performance assessment and determinants of inefficiency, in order to improve their efficiency.

6.4.2 Contextual variables affecting efficiency

We used both DEA and SFA to check the robustness of the association of contextual variables with estimated efficiency (Nedelea & Fannin, 2012). On the whole, in the factors determining efficiency were found to be similar. Health insurance coverage, geographic location, and access to health facilities all had significant effects on efficiency, while quality (as proxied by disruption index and management index) and patient mix had no significant effect on efficiency in health facilities. However, the relationship between the civil servant health insurance coverage scheme and efficiency was inconsistent between SFA and DEA. This difference might be due to how the techniques establish and shape the efficiency frontier, as well as the techniques for determining how far individual observations lie from the frontier: DEA attributes all frontier distance differences between facilities to inefficiency, while SFA splits the variance into an inefficiency component and a random component (Jacobs *et al.*, 2006; Varabyova & Schreyogg, 2013).

In this study, high-performing primary care facilities were most often found in affluent areas, particularly in urban areas and on the islands of Java and Bali. As has been shown elsewhere, health facilities in rural areas were found to perform less well than those in urban areas (Ramanathan *et al.*, 2003; Pavitra, 2013). Rural areas with low population density and inferior access were associated with reduced use of services and efficiency (Soucat *et al.*, 1997; Ramanathan *et al.*, 2003; Rattanachotphanit *et al.*, 2008; Pavitra, 2013). Nevertheless, other studies have suggested that primary care facilities located in rural areas have higher technical efficiency than those located in urban areas (Dandona *et al.*, 2005; Alhassan *et al.*, 2015). This might be caused by higher utilisation of primary care by the patients of low socioeconomic status who largely populate such areas (Dandona *et al.*, 2005). Primary care facilities in urban areas, however, must compete with private sector health facilities, which are seen as providing better services than those facilities in the public sector (Alhassan *et al.*, 2015).

Regarding geographical location, the work of Berman *et al.* (1989) supports our findings that better performing primary care facilities are on Java. Java is the most densely populated island in Indonesia and has a more developed infrastructure (BPS, 2015). Health facilities found to be efficient were more likely to be in regions with better healthcare resources, indicated by, for example, a strong ratio of population to health workers and facilities (Puenpatom & Rosenman, 2008). Notably the populations on Java and Bali islands and in urban areas have higher educational and economic status. We found an inconclusive impact of population education on efficiency, but other studies have proven education to be a key input for population health and to be positively associated with the efficiency of health facilities (Spinks & Hollingsworth, 2009; Varabyova & Schreyogg, 2013).

Our results demonstrate an association between high-performing primary care facilities and high levels of health insurance coverage among the population, especially those covered under the insurance scheme for the poor. Health insurance protects people from financial catastrophe and reduces financial barriers to healthcare access. Increasing health insurance coverage encourages health care demand and improves both the efficiency of healthcare 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 regulations between insurance schemes; civil servants are permitted to register in private primary care facilities, where the quality of care is perceived to be higher (Mundiharno & Thabrany, 2012).

6.4.3 Policy implications

Investment in primary care for public health programmes and prevention activities would save lives, increase quality of life, harvest economic benefits in the form of reduced health care costs, and increase efficiency (Langenbrunner *et al.*, 2014). As discussed above, efficiency measurement is crucial in the decision-making process to ensure that the resources invested are spent as intended. There are different methods to measure efficiency; policymakers need to understand the advantages and disadvantages of each of these methods and integrate efficiency measurement into regular monitoring of the Indonesian health system.

We found waste of health resources at several levels, especially in facilities located in rural areas. However, downsizing or closure of health facilities would be neither practical nor ethical as an intervention: an increase in the difficulty of physical access would likely reduce overall demand. Poor transportation infrastructure is the main reason for inadequate use of health facilities (Marschall & Flessa, 2009). Inadequate transportation to health facilities has been identified as the main barrier to maternal services, and provision of incentives could help reduce transportation costs and increase use of services (Sarma, 2009; Keya *et al.*, 2014; Fleming *et al.*, 2017). However, providing incentives may not be a sustainable strategy; therefore, investments in areas such as public transportation systems, expanded medical services and referral transport systems, could reduce barriers in access to health services (Prinja *et al.*, 2014; Sagrestano *et al.*, 2014).

Our study suggests that quality has no significant association with technical efficiency. However, continued improvement of quality of care remains important; the availability of basic equipment in primary care facilities in Indonesia is often poor, especially in rural areas (Mahendradhata *et al.*, 2017). Health facilities have mentioned inadequate supplies and inadequate staffing as hurdles to improving efficiency (Dandona *et al.*, 2005).

6.4.4 Limitations

This study focused on public primary care facilities in Indonesia and has therefore not taken private health facilities into account. Therefore, generalisation of the findings to other LMICs, particularly Africa, may be a challenge where health facilities managed by non-government organisations are found more frequently (Vogel *et al.*, 2012; Yagub & Mtshali, 2015). The extent to which our findings would apply to private facilities certainly requires further investigation. Although there are many private facilities in Indonesia, most of them are small and the majority of the health workers there also work in the public sector (Heywood & Harahap, 2009).

Not all output activities in primary care facilities were captured in this study as it largely focused on curative care activity. Consideration of preventive care was limited to MCH care, including antenatal care, postnatal care, and immunisation. The number of bed days was omitted because fewer than half of the primary care facilities in the sample offered inpatient services. However, the inclusion of bed days was tested in the models and no significant difference between the models with and without bed days was found. The types of primary care facilities were also not controlled in the analysis as it was assumed that the technology was homogeneous.

Data from 2011 were used in this study. We suggest that this study should be replicated using longitudinal data to highlight changes in efficiency due to recent policy changes, especially the national health insurance reform that was initiated in 2014.

6.5 Conclusions

The results of this empirical study indicate a wide variation in efficiency among primary care facilities. Geographical location, population health insurance coverage, and access to health facilities were the principal factors determining the primary care facilities' levels of efficiency. High-performing primary care facilities were generally located in affluent areas or in areas with high coverage under the insurance scheme for the poor; those located in urban areas, and those located on Java and Bali Islands were also found to perform better than others. Another notable finding is that health facilities' efficiency cannot be explained by either quality or patient mix. Routine efficiency measurement is therefore recommended to be incorporated into regular health system monitoring.

Having analysed primary care facilities efficiency in this chapter, we move to the assessment of hospital performance in Chapter 7.

Chapter 7

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

In the previous chapters, we discussed the performance of both hospitals and primary care facilities using Pabón-Lasso model analysis, as well as frontier analysis in the case of primary care facility performance. This chapter aims to assess the determinants of hospitals' efficiency and focuses on the assessment of hospitals' performance.

This chapter is organised as follows. Section 7.1 serves as an introduction and provides an explanation of hospitals' efficiency in Indonesia as well as of the aim of this chapter. Section 7.2 explains the frontier analysis techniques used in this study, namely data envelopment analysis (DEA) and stochastic frontier analysis (SFA), and presents the variables and the dataset. The results of the study are presented in Section 7.3, followed by a discussion in Section 7.4.

7.1 Introduction

Hospitals represent the largest share of healthcare spending in Indonesia, accounting for 38% of total public health expenditures (Rokx, 2009). Between 2005 and 2014, Indonesian hospitals' expenditures increased by 23 percentage points. However, the average hospital bed occupancy rate (total number of inpatient days in a year over the number of beds) in Indonesia was just above 60% between 2004 and 2012, which is far lower than the recommended occupancy levels of 85–90% (Kemenkes, 2006; Rokx, 2009; Chisholm & Evans, 2010; Kemenkes, 2011b; Soewondo *et al.*, 2011; TNP2K, 2015; CHEPS *et al.*, 2016; Mahendradhata *et al.*, 2017).

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

Chapter 5 of this study shows that, according to the Pabón-Lasso model, 37% of hospitals are in the high utilisation sector, while another 37% appear in the low utilisation sector. Chapter 5 also provides evidence of variation in hospital performance across Indonesia. This chapter aims to investigate the possible causes for the variations in the hospitals' efficiency scores. Further frontier analysis has been conducted to provide a benchmark of hospital efficiency as well as to determine the functional relationships between efficiency and its potential contextual factors.

7.2 Methods

7.2.1 Data

This study assesses the determinants of efficiency in hospitals by analysing data from four sources. The first source is a survey of health facilities that was carried out by Indonesia's Ministry of Health (MoH) between October 2010 and September 2011. We used these data to estimate the relative efficiency of hospitals and to identify internal factors determining efficiency. Second, we used data from the 2011 National Socioeconomic Survey (SUSENAS), which provides household characteristics at the district level such as the standard of education of all adults in the household and health insurance coverage. Third, we used data from the 2011 Village Potential Statistics (PODES), a census providing information about village characteristics across Indonesia such as population size, job types, and access to health facilities. Fourth, we used data from the 2011 Indonesian case base groups (INA-CBGs), which provide patient-level data to generate case mix index (CMI) and mortality ratio. We merged the SUSENAS and PODES datasets and the MoH health facility survey data using district identifiers for hospitals; the INA-CBGs dataset was merged with hospital unique ID.

7.2.2 Input and output variables

The efficiency analysis was 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 in Chapter 4 undertaken in hospitals and included hospitals' production inputs and outputs differentiated by the various 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). Validity testing was also conducted to guide the choice of input and output variables as discussed in Section 7.2.6. We found SFA analysis to be sensitive to outpatient visits, and showed no inefficiency. A possible explanation for this might be related to wide outpatient standard deviation, resulting perhaps from the heterogeneity of outpatients which, unlike admissions that are limited to availability of beds. We therefore excluded outpatient visits in the SFA analysis.

Six inputs were considered: (1) the number of doctors, (2) the number of nurses, (3) the number of other staff, (4) the number of full-time equivalent (FTE) non-specialist doctors, (5) the number of FTE specialist doctors, and (6) the number of beds. Eight outputs are considered: (1) the number of outpatient visits, (2) the adjusted number of admissions (adjusted by the admission mortality ratio), (3) the adjusted number of bed days (adjusted by the admission mortality ratio), (4) the number of surgeries, (5) the number of outpatient visits, the adjusted number of admissions, and the number of surgeries, (6) the number of outpatient visits, the adjusted number of bed days and the number of surgeries, (7) the adjusted number of admissions, and the number of surgeries, (8) the adjusted number of bed days and the number of surgeries (Table 7.1).

The numbers of outpatients and bed days and the volume of admissions were adjusted for their respective CMIs (case mix indices) as a proxy of severity of cases treated, and the mortality ratio was applied as a proxy for quality in each hospital. The detailed explanation of casemix and quality adjustments can be seen in Section 3.3.1. Since standard SFA models are limited to only one output, weighting was used to aggregate different type of outputs. Unit cost ratio of admission, bed day and surgery to outpatient visit were applied as proxy of weight, 12.6, 3.5 and 3.5 respectively (Ensor & Indradjaya, 2012). Previous costing study in China found unit cost of surgery and bed day were not significantly different, thus we used the same weight value for bed day and surgery (Adam *et al.*, 2014). To address the limitation of using sum of number of treated patients, we also considered multi-output distance function model to estimate technical efficiency.

Table 7.1: Input and output variables

Variable	**Definition**	**Measurement**	**Data source**
Input variables			
doctors	Doctors	Total number of doctors	HFCS
nurses	Nurses and midwives	Total number of nurses and midwives	HFCS
other prof	Non-medical staff	Total number of non-medical staff	HFCS
non-spec FTE	Non-specialist doctors	Full-time equivalent non-specialist doctors	HFCS
spec FTE	Specialist doctors	Full-time equivalent specialist doctors	HFCS
beds	Beds	Total number of beds	HFCS
Output variables			
outpatients	Outpatient visit	Total number of outpatient visits per year x outpatient case mix index	HFCS
adj_admissions	Adjusted admissions	Total number of admissions x inpatient case mix index x (1-death rate x mortality ratio)	HFCS
adj_beddays	Adjusted bed days	Total number of bed days x inpatient case mix index x (1-death rate x mortality ratio)	HFCS
tot_surgery	Total surgery	Total number of surgeries per year	HFCS
out.admis.surg	Outpatient, adjusted admissions and total surgery	Total number of outpatients + adj_admissions + tot_surgery	HFCS
out.beddays.surg	Outpatient, adjusted bed days and total surgery	Total number of outpatients + adj_beddays + tot_surgery	HFCS
admis.surg	Adjusted admissions and total surgery	adj_admissions + tot_surgery	HFCS
beddays.surg	Adjusted bed days and total surgery	adj_beddays + tot_surgery	HFCS

HFCS Health facility costing study

7.2.3 Contextual variables

The analysis selected internal and external contextual factors in hospitals based on previous literature review in Chapter 4, then evaluated their impact on hospital efficiency levels (Worthington, 2004). The contextual variables were grouped into two categories: (1) internal factors (e.g. size and capacity, ownership, and patient type) and (2) external factors (e.g. insurance coverage, population education level, and geography) (Mobley & Magnussen, 1998; Herr, 2008; Besstremyannaya, 2013; Gok & Sezen, 2013; Kirigia & Asbu, 2013; Mitropoulos *et al.*, 2013; Nedelea & Fannin, 2013; Varabyova & Schreyogg, 2013; Cordero Ferrera *et al.*, 2014; Ding, 2014; Heimeshoff *et al.*, 2014; Shreay *et al.*, 2014; Yang & Zeng, 2014; Matranga & Sapienzab, 2015).

As in the analysis of primary care facilities in Chapter 6, PCA was used to create a smaller number of uncorrelated new variables, thus avoiding the problems that could have arisen with multivariate regression techniques (Jolliffe & Cadima, 2016). In this way, we transformed 16 variables into five new index variables. The PCA results are presented in Table 7.2.

In addition to PCA variables, the initial general model contained all of the identified contextual variables: hospital class, teaching status, ownership, patient type, district population, geographical location, and health insurance coverage. We ran several models, checked for multi-collinearity and finalised a vector of contextual variables. All contextual variables are included in Table 7.3.

Table 7.2: PCA variables in hospitals

Description	PCA Coef.	New variable
Cons	0.00	Index of disruption
Water disruption	0.40	
Without water disruption	-0.63	
Electricity disruption	0.27	
Without electricity disruption	-0.74	
Medicine disruption	0.45	
Without medicine disruption	-0.41	
Salary disruption	1.17	
Without salary disruption	-0.12	
Incentive disruption	0.60	
Without incentive disruption	-0.37	
Cons	0.00	Index of less management
Case meetings at least every 6 months	-0.79	
Case meetings less frequent	0.63	
With mentoring	-0.14	
Without mentoring	3.46	
Cons	-1.71	Poverty index
Family in agriculture	2.38	
Poor population	11.14	
Cons	-4.11	Index of access to health facility
Hospital per pop	2.08	
Primary per pop	1.50	
Easy access to hospital	4.25	
Easy access to primary care facility	4.79	
Cons	-1.18	Index of higher education
Secondary school	6.79	
Higher education	8.88	
Primary school	-5.75	

Table 7.3: Contextual variables

Variables	Definition	Measurement	Data source
Internal factors			
Index of disruption	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
Index of less management	Index of less management	Principal component analysis score of regular meetings to discuss cases, and mentoring of clinical staff	HFCS
% patients 1-4 years	Proportion of patients between 1 and 4 years old	Total number of patients aged 1 to 4 years divided by total number of all patients	HFCS
% NCD patients	Non-communicable diseases	Proportion of non-communicable diseases treated	HFCS
Class A/B	Class A or B	Hospital class: 1 if Class A or B, 0 if Class C or D	HFCS
Public hospital	Public ownership	Hospital ownership: 1 if public, 0 if private	HFCS
Teaching hospital	Teaching status	Whether hospital has an MoU or partnership with medical education university: 1 if yes, 0 if no	HFCS
External factors			
Askes ins	Civil servant insurance scheme	Proportion of households covered by *Askes* insurance (scheme for civil servants)	SUSENAS
Jamkesmas ins	Poor insurance scheme	Proportion of household covered by insurance scheme for the poor	SUSENAS
Index of access to health facility	Index of health facilities availability	Principal component analysis score of fewer hospitals for population, number of primary care facilities for population, proportion of villages that have easy access to hospitals, and proportion of villages that have easy access to primary care facilities.	PODES
On Java Bali	On Java or Bali island	Whether primary care facility is on Java or Bali Island: 1 if yes, 0 if no	HFCS
Population	Population	District population in year 2011	PODES
Poverty index	Index of population economy	Principal component analysis score of smaller proportion of families working in agriculture and smaller proportion of poor population	PODES and SUSENAS
Index of higher education	Index of population education level	Principal component analysis score of district population proportion with primary school education, less than secondary education, and less than higher education	SUSENAS

HFCS Health facility costing study, *SUSENAS* National Socioeconomic Survey, *PODES* village potential statistics

7.2.4 DEA

A bootstrap DEA procedure was implemented to estimate the efficiency scores for each of the providers in the sample. Variable returns to scale (VRS) were applied to run input- and output-oriented models to estimate the individual hospital efficiency scores. As in the analysis of primary care facilities (Section 6.2.4), we chose output orientation to identify factors determining efficiency. Given that inputs such as workforce and capital investment are generally not under hospital managers' control, especially in the case of public hospitals (Mahendradhata *et al.*, 2017), managers should focus on maximising outputs with the available inputs.

The empirical DEA model is given by Eq. 7.1

$$\begin{aligned} &\max \phi, \\ &\text{subject to} \\ &\sum_{i=1}^{n} \lambda_i x_{ji} \leq x_{jo} \qquad j = 1, 2, .., m; \\ &\sum_{i=1}^{n} \lambda_i y_{ri} \geq \phi y_{ro} \qquad r = 1, 2, ..., s; \\ &\sum_{i=1}^{n} \lambda_i = 1 \qquad \lambda_i \geq 0 \qquad i = 1, 2, ..., n \end{aligned} \tag{7.1}$$

where i = hospital; 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 hospital$_i$, that the sum of λ equals to one; ϕ = represents the efficiency of hospital. The right-hand side is one of the n hospital that is under evaluation; the left-hand side represents the convex combinations of observed values on the inputs and outputs.

We developed a number of alternative model specifications, using combination of inputs and outputs. Models I1, I2, I4, I5, I7, I8, I10, I11, O1, O2, O4, O5, O7, O8, O10 and O11 used all inputs (capital and disaggregated medical staff), with five inputs: number of nurses, number of other staff, FTE of non-specialist doctors, FTE of specialist doctors and number of beds. Models I3, I6, I9, I12, O3, O6, O9 and O12, used aggregate number of doctors, with four inputs: number of doctors, number of nurses, number of other staff and number of beds. Based on analytical framework in Chapter 4, inpatient services are mainly measured using two indicators, number of bed days and admissions. Therefore we tailored the first two specifications using different inpatient indicators. Models I1 and O1 used three outputs: number of outpatients, number of adjusted admissions and number of surgeries. Models I2, I3, O2 and O3 used three outputs: number of outpatients, number of adjusted bed days and number of surgeries. Since standard SFA can only use one output, we aggregated number of outputs. Models I4 and O4 used one output: aggregate number of outpatients, adjusted admissions and surgeries. Models I5, I6, O5 and O6 used one output: aggregate number of outpatients, adjusted bed days and surgeries. We compared like with like without number of outpatient visits in regards to the SFA that failed to identify inefficiency as discussed in Section 7.2.2. Models I7 and O7 used two outputs: number of adjusted admissions and number of surgeries. Models I8, I9, O8 and O9 used two outputs: number of adjusted bed days and number of surgeries. Models I10 and O10 used one output: aggregate number of adjusted admissions and surgeries. Models I11, I12, O11 and O12 used one output: aggregate number of adjusted bed days and surgeries.

7.2.5 SFA

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, given by Eq. 7.2.

$$\log(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + (v_{i-} u_i) \tag{7.2}$$

Where j represents the number of independent variables, i the hospital, y_i the output of the i-th hospital, x_i the input j of the i-th hospital, 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 the technical inefficiency of hospital i.

Using the same justification in Section 7.2.4, we tailored number of model specifications. Three specifications of Cobb-Douglass function form (C1, C2 and C3). Models C1 and C2 used five inputs: number of nurses, number of other staff, FTE of non-specialist doctors, FTE of specialist doctors and number of beds. Models C3 used four inputs: number of doctors, number of nurses, number of other staff and number of beds). Model C1 used one output: aggregate number of adjusted admissions and surgeries. Models C2 and C3 used one output: aggregate number of adjusted bed days and surgeries.

However, the Cobb-Douglas form is restrictive because it assumes constant elasticity of substitution. We therefore also estimated a Translog stochastic production frontier model.

The empirical model of translog function form is given by Eq. 7.3.

$$\log(y_i) = \beta + \sum_{j=1}^{k} \beta_j \log x_{ji} + \frac{1}{2} \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \log x_{ji} \log x_{hi} + (v_i - u_i) \tag{7.3}$$

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

We tailored three specifications of translog function form (T1, T2 and T3). Models T1 and T2 used five inputs: number of nurses, number of other staff, FTE of non-specialist doctors, FTE of specialist doctors and number of beds. Model T3 used four inputs: number of doctors, number of nurses, number of other staff and number of beds. Model T1 used one output: aggregate number of adjusted admissions and surgeries. Models T2 and T3 used one output: aggregate number of adjusted bed days and surgeries.

In addition, anticipating that the sum of the number of treated patients in the Translog function might not be appropriate for our outputs (i.e. outpatient visits and inpatient admissions), we estimated a multi-output distance function and a Translog distance function.

The empirical model of multi-output distance function form is given by Eq. 7.4.

$$\begin{gathered} \log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ji} + \sum_{h=1}^{k-1} \beta_h \log \frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \\ \text{where the interpretation of } \frac{y_h}{y_n} \text{ is } \left(\frac{MCH}{General}\right) \end{gathered} \tag{7.4}$$

We tailored three specifications of multi-output distance function form (CD1, CD2 and CD3). Models CD1 and CD2 used five inputs: number of nurses, number of other staff, FTE of non-specialist doctors, FTE of specialist doctors and number of beds. Model CD3 used four inputs: number of doctors, number of nurses, number of other staff and number of beds. Model CD1 used two outputs: number of adjusted admissions and number of surgeries. Models CD2 and CD3 used two outputs: number of adjusted bed days and number of surgeries.

The empirical model of multi-output translog distance function form is given by Eq. 7.4.

$$\log\left(\frac{1}{y_{ni}}\right) = \beta_0 + \sum_{j=1}^{k}\beta_j \log x_{ji} + \frac{1}{2}\sum_{j=1}^{k}\sum_{h=1}^{k}\beta_{jh}\log x_{ji}\log x_{hi} + \sum_{h=1}^{k-1}\beta_h \log\frac{y_{hi}}{y_{ni}}$$
$$+\frac{1}{2}\sum_{j=1}^{k-1}\sum_{h=1}^{k-1}\beta_{jh}\log\frac{y_{hi}}{y_{ni}}\log\frac{y_{hi}}{y_{ni}} + \sum_{j=1}^{k}\sum_{h=1}^{k-1}\beta_{jh}\log x_{ji}\log\frac{y_{hi}}{y_{ni}} + (v_{i-}u_i) \tag{7.5}$$

We tailored three specifications of multi-output translog distance function form (TD1, TD2 and TD3). Models TD1 and TD2 used five inputs: number of nurses, number of other staff, FTE of non-specialist doctors, FTE of specialist doctors and number of beds. Model TD3 used four inputs: number of doctors, number of nurses, number of other staff and number of beds. Model TD1 used two outputs: number of adjusted admissions and number of surgeries. Models TD2 and TD3 used two outputs: number of adjusted bed days and number of surgeries.

7.2.6 Validity testing

We tested for internal and external validity largely as described in Section 6.2.6. Table 7.5 illustrates the combinations of input and output variables used to test changes in the efficiency estimates.

In the first step of internal validity testing, the presence of inefficiency was confirmed by the high values of the contribution of the inefficiency (σ_u) to the total error (γ). In the second step, a Spearman rank correlation test was used to estimate the correlation between the SFA models (i.e. distance function and Translog distance function).

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 Pearson correlations have been used in previous research (Jacobs, 2001).

Table 7.5: Model specifications

	DEA*																								SFA**											
	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	CD1	CD2	CD3	C1	C2	C3	TD1	TD2	TD3	T1	T2	T3
Input																																				
doctors			X			X			X			X			X			X			X			X			X			X			X			X
nurses	X	X	X	X	X	X	X	X	X	X	X	X	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	X	X	X	X	X	X	X	X	X	X	X	X
non spec FTE	X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X	
spec FTE	X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		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	X	X	X	X	X	X	X	X	X	X	X	X
Output																																				
outpatients	X	X	X										X	X	X																					
adj_admissions	X						X						X						X						X						X					
adj_beddays		X	X					X	X					X	X					X	X					X	X					X	X			
tot surgery	X	X	X				X	X	X				X	X	X				X	X	X				X	X	X				X	X	X			
out.admis.surg				X												X																				
out.beds.surg					X	X											X	X																		
admis.surg										X												X						X						X		
beds.surg											X	X											X	X					X	X					X	X

* I1-I12 are input-oriented and O1-O12 output-oriented DEA models.

** CD1-CD3 are multi-output distance functions, C1-C3 are Cobb-Douglas functions, TD1-TD3 are Translog distance functions, and T1-T3 are Translog functions in SFA models.

X indicates that the variable is included in the model.

7.2.7 DEA and SFA quadrant scores

For the reasons explained in Section 6.2.7 with regard to primary care facilities, we plotted the DEA and SFA scores of hospitals and divided the plot into four quadrants representing different levels of efficiency.

7.2.8 Contextual variable analysis

Second-stage DEA analysis and one-stage SFA analysis were performed as discussed in Section 6.2.8. Second-stage DEA is written as follows:

$$\hat{\phi}_i = \beta z_i + \varepsilon \tag{7.6}$$

where in this case $\hat{\phi}$ represents the estimated bias-corrected DEA score generated from bootstrap procedure, assumed to be truncated, β is the unknown coefficient, z is the vector of contextual variables refers to internal and external factors that can be seen in Table 7.3, and ε is a random variable. A variance inflation factor was used to denote significant multicollinearity, and we found moderately correlated with coefficient between 1 and 5.

A one-stage SFA procedure was applied to study the determinants influencing inefficiency, defined by

$$u_i = \delta z_i + W_i \tag{7.7}$$

where u is the technical inefficiency in the stochastic frontier model, δ is the unknown coefficient, z_i is a vector of contextual variables associated with technical inefficiency, using the same list as in the second-stage analysis in DEA (Table 7.3) and W is the random variable.

7.2.9 Data management

The data in this study were managed as discussed in Section 6.2.9. As in the results of our study of primary care facilities in Chapter 6, we did not find significant differences in efficiency scores with and without outliers using Kruskal-Wallis test. Therefore, in order to prevent loss of valuable information, we did not drop the outliers.

Hospitals are assumed to obtain inputs and produce outputs according to the standardised figures provided by the Indonesian Ministry of Health (Kemenkes, 2014a). Therefore, we replaced zero values with missing values. Complete data were available for 138 hospitals from a total of 200 hospitals (31% missing). When data are missing, results may be biased due to unrepresentativeness, which can lead to misinterpretation in policy conclusions (Marshall *et al.*, 2009). Tsikriktsis (2005) suggested regression imputation as an appropriate way to proceed when more than 20% of the data are missing. Missing data are assumed to be missing at random, where the probability of missing data depends on observed data. We imputed using the chained equations technique with the 'mice' library in R statistical software (Buuren & Groothuis-Oudshoorn, 2011). T-test and Chi-Square test were used and there was no statistical difference between the complete and imputed data, with the exception of mortality ratio (see Table E.1 in Appendix E).

With regard to the minimum number of DEA observations, we applied the rule according to which the number of hospitals must exceed three times the sum of inputs and outputs, and must also 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 hospitals, m the number of inputs and n the number of outputs. After the imputation, 200 hospitals remained, which number exceeded the minimum sample needed.

7.3 Results

7.3.1 Hospital statistics

Table 7.6 presents hospital characteristics and activities. There was wide variation in the number of inputs and outputs per facility. Hospitals produced an average number of 70,586 outpatient visits, 8,943 admissions, and 2,017 total surgeries with an average of 42 doctors, 178 nurses and midwives, and 139 other staff.

7.3.2 Technical efficiency

The analysis eventually omitted the distance function and the Translog distance function because of small inefficiency values from all of the residual variations; for this reason, these functions failed to reject the hypothesis that SFA is no different from ordinary least squares (OLS) (Bogetoft & Otto, 2010; Kumbhakar *et al.*, 2015).

Table 7.6: Hospital descriptive statistics

Variables	Overall
Input variables	
Doctors (mean (sd))	42.30 (40.28)
Non-Spec FTE (mean (sd))	15.35 (9.94)
Spec FTE (mean (sd))	19.75 (20.46)
Nurses (mean (sd))	177.62 (141.86)
Other staff (mean (sd))	139.26 (130.83)
Output variables	
Beds (mean (sd))	158.71 (123.14)
Outpatients (mean (sd))	70586.07 (108423.62)
Bed days (mean (sd))	35563.32 (33075.01)
Admissions (mean (sd))	8943.55 (6891.41)
Tot surgery (mean (sd))	2016.55 (2248.73)

FTE Full-Time Equivalent, *n* sample size, *sd* standard deviation

Table 7.7 shows summary statistics of efficiency between two models; smaller average scores represent lower facility efficiency. The efficiency scores in DEA were consistently lower than in SFA; the spread of DEA efficiency range was almost identical to that of SFA efficiency.

Output-oriented efficiency is the maximal number of services (outputs) given the number of workforce and capital (inputs). The average scores of 0.49 in DEA (O10) and 0.64 in SFA (T1) suggest that we could expand the outputs by 104% and 56% respectively with current levels of all resources. In absolute terms, hospitals could expand by 73,467 (according to DEA) or 39,705 (according to SFA) outpatient visits, as well as by 9,309 (DEA) or 5,031 (SFA) admissions per year, without increasing the number of staff or beds.

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 0.47 to 0.83 and between the SFA models from 0.90 to 0.95 (see Table 7.8).

Comparing all models, we found that the correlation between DEA output orientation and SFA efficiency ranged from 0.16 to 0.76. The external validity correlation estimates suggested that the disaggregation of doctors would increase the efficiency correlation. Finally, we included two models (Models

O10 and T1 in Table 7.8) with a high internal validity estimate and a high external validity estimate, respectively. The preferred input specifications of the models included the full-time equivalent of non-specialist doctors, the full-time equivalent of specialist doctors, the number of nurses and midwives, the number of other staff and the number of beds. The preferred specifications were the aggregate number of admissions and the number of surgeries.

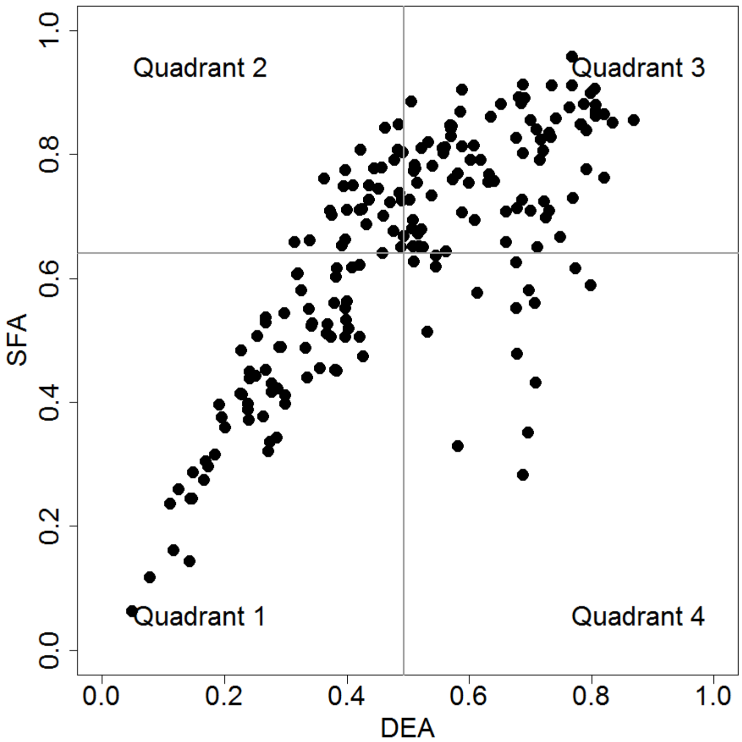


Figure 7.1: Quadrant scatter plot of DEA and SFA scores estimated in hospitals

Figure 7.1 shows the scatter plot of hospitals; the vertical and horizontal axes represent the mean according to DEA and SFA. It appears that 34% of hospitals are low-performing health facilities (in the bottom-left, Quadrant 1) while 43% are high-performing (in the upper-right, Quadrant 3) according to both techniques. The scores of the remaining 24% of health facilities are inconclusive (Quadrants 2 and 4). The statistics of the quadrant scores between DEA and SFA are presented in Table 7.9. Regardless of the substantial variations found, hospitals in Quadrant 3 generally have higher average numbers of outputs than hospitals in other quadrants. As for the outputs produced, outpatient visits and admissions were found to have significantly different means among the four quadrants. High-performing hospitals were found to have 2.3 times more admissions than low-performing hospitals. Hospitals in Quadrant 3 have higher levels of inputs on average when compared to hospitals in other quadrants, and high-performing hospitals have 10% more of beds compared to low-performing hospitals. Additionally, the ratio of admissions per doctor in the high-performing hospitals in Quadrant 3 was double of those in low-performing hospitals.

The possible associations between contextual characteristics and efficiency scores are assessed in the following subsection.

7.3.3 Contextual factors

The results of the two-stage DEA models and the one-stage SFA models are presented in Table 7.10. Generally, internal and external contextual factors were found to be significantly associated in the DEA and SFA models. The directions of the coefficients for the variables were mostly consistent through all models.

With regard to internal factors, larger hospital size (Class A or B) were found to be positively associated with efficiency scores. Ownership was found to be significant only in DEA model, with public ownership negatively associated with efficiency. The quality of each facility as proxied by hospital disruption index and management index was not found to be significant.

As for external factors, three were found to be associated with efficiency: hospital location in an area with high population health insurance coverage through the scheme for civil servant, hospital location on Java or Bali, and lower education level. Each 10% increase in the proportion of population with civil servant insurance scheme coverage led to a 0.09-point and 1.43-point increase in predicted efficiency in the DEA and SFA models. One-unit index increases in higher education were associated with a 0.07-point and 1.06 decrease respectively, in predicted efficiency according to DEA and SFA.

Table 7.7: DEA and SFA efficiency scores in hospitals

Statistic	N	Mean	St. Dev.	Min	Median	Max
I1	200	0.60	0.17	0.19	0.60	0.89
I2	200	0.56	0.17	0.16	0.57	0.85
I3	200	0.61	0.16	0.18	0.61	0.92
I4	200	0.44	0.19	0.12	0.41	0.79
I5	200	0.45	0.18	0.11	0.40	0.80
I6	200	0.44	0.19	0.13	0.39	0.89
I7	200	0.58	0.17	0.08	0.57	0.88
I8	200	0.54	0.18	0.15	0.54	0.85
I9	200	0.61	0.16	0.18	0.60	0.92
I10	200	0.56	0.17	0.08	0.55	0.87
I11	200	0.53	0.18	0.13	0.52	0.88
I12	200	0.60	0.16	0.18	0.59	0.91
O1	200	0.55	0.19	0.10	0.56	0.83
O2	200	0.53	0.18	0.09	0.53	0.84
O3	200	0.55	0.18	0.11	0.54	0.85
O4	200	0.32	0.20	0.03	0.27	0.84
O5	200	0.32	0.19	0.03	0.26	0.79
O6	200	0.30	0.19	0.03	0.25	0.79
O7	200	0.52	0.19	0.07	0.53	0.83
O8	200	0.51	0.18	0.09	0.51	0.85
O9	200	0.53	0.18	0.11	0.53	0.84
O10	200	0.49	0.19	0.05	0.50	0.87
O11	200	0.49	0.18	0.09	0.48	0.86
O12	200	0.52	0.18	0.10	0.51	0.85
C1	200	0.62	0.20	0.06	0.65	0.95
C2	200	0.69	0.13	0.23	0.73	0.94
C3	200	0.68	0.15	0.20	0.71	0.94
T1	200	0.64	0.19	0.06	0.68	0.96
T2	200	0.63	0.20	0.12	0.63	0.95
T3	200	0.65	0.19	0.14	0.67	0.93

I1-I12 are input-oriented and O1-O12 output-oriented DEA models.
C1-C3 are Cobb-Douglas functions, and T1-T3 are Translog functions in SFA models.

Table 7.8: Spearman rank correlation coefficients across various model specifications

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	C1	C2	C3	T1	T2	T3
I1	1																													
I2	0.84	1																												
I3	0.74	0.82	1																											
I4	0.82	0.77	0.66	1																										
I5	0.81	0.83	0.72	0.97	1																									
I6	0.68	0.65	0.75	0.86	0.87	1																								
I7	0.93	0.78	0.7	0.75	0.75	0.63	1																							
I8	0.83	0.97	0.83	0.76	0.82	0.64	0.81	1																						
I9	0.72	0.8	0.99	0.65	0.71	0.74	0.71	0.83	1																					
I10	0.91	0.76	0.68	0.79	0.77	0.64	0.98	0.79	0.7	1																				
I11	0.8	0.95	0.82	0.77	0.84	0.66	0.79	0.98	0.82	0.78	1																			
I12	0.7	0.78	0.97	0.65	0.71	0.75	0.7	0.81	0.99	0.69	0.82	1																		
O1	0.79	0.68	0.59	0.49	0.49	0.39	0.71	0.64	0.57	0.67	0.6	0.55	1																	
O2	0.61	0.77	0.66	0.43	0.5	0.34	0.53	0.73	0.63	0.5	0.7	0.62	0.8	1																
O3	0.57	0.69	0.82	0.38	0.46	0.45	0.5	0.66	0.8	0.47	0.64	0.78	0.72	0.86	1															
O4	0.55	0.58	0.44	0.5	0.52	0.38	0.43	0.52	0.4	0.41	0.53	0.4	0.74	0.7	0.59	1														
O5	0.53	0.66	0.52	0.5	0.58	0.42	0.42	0.6	0.48	0.39	0.62	0.49	0.69	0.78	0.68	0.95	1													
O6	0.43	0.54	0.53	0.39	0.48	0.47	0.32	0.48	0.49	0.29	0.5	0.5	0.62	0.68	0.72	0.84	0.88	1												
O7	0.75	0.64	0.59	0.45	0.46	0.37	0.8	0.67	0.6	0.76	0.64	0.59	0.92	0.72	0.67	0.61	0.57	0.51	1											
O8	0.59	0.75	0.66	0.41	0.48	0.32	0.57	0.77	0.66	0.55	0.74	0.65	0.76	0.96	0.84	0.63	0.71	0.61	0.77	1										
O9	0.57	0.68	0.83	0.37	0.45	0.45	0.55	0.7	0.84	0.52	0.68	0.82	0.7	0.83	0.97	0.54	0.62	0.66	0.71	0.86	1									
O10	0.75	0.62	0.58	0.48	0.48	0.38	0.79	0.65	0.59	0.79	0.64	0.58	0.88	0.68	0.63	0.62	0.57	0.48	0.95	0.73	0.67	1								
O11	0.55	0.71	0.65	0.39	0.46	0.3	0.54	0.73	0.65	0.52	0.73	0.64	0.7	0.91	0.8	0.65	0.74	0.62	0.71	0.95	0.83	0.73	1							
O12	0.53	0.64	0.82	0.36	0.44	0.43	0.51	0.66	0.82	0.49	0.67	0.83	0.66	0.8	0.95	0.53	0.62	0.67	0.67	0.83	0.98	0.65	0.84	1						
C1	0.4	0.2	0.28	0.04	-0.01	-0.02	0.45	0.22	0.29	0.45	0.19	0.27	0.6	0.39	0.43	0.25	0.16	0.17	0.66	0.42	0.45	0.69	0.43	0.45	1					
C2	0.37	0.37	0.44	0.1	0.14	0.06	0.34	0.38	0.43	0.33	0.35	0.41	0.48	0.58	0.6	0.23	0.3	0.26	0.47	0.6	0.61	0.49	0.61	0.61	0.73	1				
C3	0.39	0.39	0.51	0.12	0.16	0.11	0.37	0.4	0.5	0.36	0.38	0.48	0.49	0.59	0.65	0.22	0.3	0.28	0.5	0.61	0.67	0.52	0.63	0.68	0.73	0.97	1			
T1	0.47	0.28	0.35	0.1	0.06	0.05	0.52	0.3	0.36	0.52	0.27	0.34	0.66	0.46	0.48	0.31	0.23	0.21	0.73	0.5	0.5	0.76	0.5	0.5	0.95	0.68	0.69	1		
T2	0.37	0.41	0.45	0.07	0.12	0.02	0.37	0.42	0.45	0.36	0.4	0.43	0.5	0.64	0.63	0.25	0.33	0.28	0.52	0.67	0.64	0.55	0.7	0.65	0.69	0.9	0.9	0.71	1	
T3	0.35	0.38	0.5	0.08	0.12	0.05	0.35	0.38	0.49	0.35	0.36	0.47	0.47	0.59	0.66	0.21	0.29	0.26	0.48	0.62	0.68	0.51	0.65	0.69	0.71	0.92	0.94	0.69	0.93	1

I1-I12 are input-oriented and O1-O12 output-oriented DEA models.

C1-C3 are Cobb-Douglas functions, and T1-T3 are Translog functions in SFA models.

Table 7.9: Statistics by efficiency quadrant

	1	2	3	4	p
n	67	32	85	16	
O10 (mean (sd))	0.28 (0.09)	0.43 (0.05)	0.65 (0.10)	0.65 (0.09)	$<$0.001
T1 (mean (sd))	0.43 (0.13)	0.73 (0.06)	0.79 (0.08)	0.52 (0.12)	$<$0.001
Doctors (mean (sd))	43.70 (26.04)	34.39 (15.63)	46.60 (55.02)	29.42 (25.62)	0.271
Nurses (mean (sd))	172.25 (104.22)	185.15 (75.94)	176.26 (153.71)	192.28 (272.89)	0.948
Other prof (mean (sd))	129.09 (98.21)	157.12 (92.28)	147.58 (157.26)	101.94 (159.82)	0.452
Beds(mean (sd))	148.75 (93.72)	138.34 (55.02)	168.67 (141.14)	188.19 (204.69)	0.428
Outpatients (mean (sd))	81228.55 (137706.84)	52227.93 (46052.92)	74666.92 (112995.98)	50211.47 (93941.96)	0.564
Admissions (mean (sd))	5360.00 (3439.06)	8886.42 (3473.93)	12263.91 (9877.86)	7486.63 (8279.22)	$<$0.001
Tot surgery (mean (sd))	1385.16 (1415.18)	2178.31 (2058.81)	2472.88 (2623.07)	1912.62 (2820.58)	0.028
Index of disruption (mean (sd))	0.09 (1.39)	0.16 (1.47)	-0.17 (1.56)	0.20 (1.21)	0.556
Index of less management (mean (sd))	-0.20 (0.80)	0.25 (1.31)	0.08 (1.03)	-0.09 (1.32)	0.177
% Patients aged 1 to 4 (mean (sd))	9.34 (5.19)	8.45 (4.27)	9.32 (4.53)	8.43 (4.31)	0.730
% NCD patients (mean (sd))	36.45 (15.34)	43.00 (14.92)	38.67 (14.34)	32.68 (14.47)	0.088
Class A/B (n (%))	13 (19.4)	7 (21.9)	30 (35.3)	4 (25.0)	0.146
Public (n (%))	43 (64.2)	26 (81.2)	45 (52.9)	8 (50.0)	0.030
Teaching (n (%))	22 (32.8)	11 (34.4)	28 (32.9)	3 (18.8)	0.699
Jamsostek ins (mean (sd))	0.07 (0.06)	0.05 (0.05)	0.07 (0.07)	0.07 (0.06)	0.270
Askes ins (mean (sd))	0.15 (0.06)	0.11 (0.06)	0.12 (0.06)	0.14 (0.06)	0.021
Jamkesmas ins (mean (sd))	0.19 (0.13)	0.21 (0.14)	0.23 (0.16)	0.18 (0.14)	0.326
Index of access to health facility (mean (sd))	0.15 (1.73)	-0.04 (1.78)	-0.05 (1.27)	-0.26 (0.40)	0.728
On Java or Bali (n (%))	17 (25.4)	10 (31.2)	45 (52.9)	7 (43.8)	0.005
Population in ’000 (mean (sd))	616.96 (643.89)	496.41 (472.67)	890.23 (856.86)	754.92 (581.59)	0.028
Poverty index (mean (sd))	-0.35 (1.14)	0.43 (1.43)	0.16 (1.24)	-0.26 (1.05)	0.010
Index of higher education (mean (sd))	0.50 (1.49)	-0.53 (1.40)	-0.22 (1.68)	0.12 (1.64)	0.008

O10 is an output-oriented DEA model score.

T1 is a Translog multi-output distance function score. *FTE* Full-Time Equivalent, *n* sample size, *sd* standard deviation

Table 7.10: Regression on explanatory variables results in hospitals

Variables	DEA			SFA		
	Est.	SE		Est.[‡]	SE	
Internal factors						
Index of disruption	0.01	0.01		0.10	0.09	
Index of less management	0.01	0.01		0.30	0.17	
Patients aged 1 to 4 [†]	0.01	0.01		0.14	0.30	
NCD patients [†]	-0.01	0.03		0.12	0.08	
Class A/B	0.12	0.04	**	0.94	0.46	*
Public hospital	-0.12	0.04	***	-0.57	0.39	
Teaching hospital	-0.01	0.03		0.01	0.30	
External factors						
Jamsostek ins [†]	0.02	0.03		-0.07	0.33	
Askes ins [†]	0.09	0.04	*	1.43	0.70	*
Jamkesmas ins [†]	0.00	0.01		-0.12	0.13	
Index of access to health facility	0.01	0.01		0.07	0.08	
On Java or Bali	0.08	0.03	**	1.34	0.64	*
Population (in 1,000,000)	0.02	0.02		0.58	0.34	
Poverty index	0.00	0.02		-0.15	0.21	
Index of higher education	-0.07	0.02	***	-1.06	0.47	*
Constant	0.32	0.09	***	1.73	0.84	*
R2	0.21			0.49		
sigma	0.18	0.01				
sigmaSq				0.70	0.33	
gamma				0.95	0.03	
Log Likelihood	68.99			-79.69		

Significance level: ***0.001, **0.01, *0.05.
[†] The unit is a proportion of the variable multiplied by 10 (one unit represents 10%).
[‡] The coefficients are multiplied by -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.

7.4 Discussion

7.4.1 Technical efficiency

As discussed in Chapter 6, efficiency measurements are required for ensuring that health resources for services are spent as efficiently as possible. Given that there is no consensus on the best method for doing so, several specifications must be developed and both DEA and SFA applied to determine whether the results are sensitive to the analytic methods (Jacobs, 2001). Though we found, like previous researchers (Jacobs, 2001; Xu *et al.*, 2015), that DEA efficiency scores were more likely than SFA models to change with different input and output variables, we also found SFA to be sensitive to specific outputs; we were thus unable to apply the specifications applied in DEA.

The correlation of efficiency scores between SFA and DEA may reveal inconsistency, with DEA showing a hospital to be fully efficient and SFA showing it to be inefficient or vice versa (Chirikos & Sear, 2000; Mathiyazhagan, 2007). 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 indicated that SFA efficiency scores tend to be higher than DEA efficiency scores. Previous studies carried out in China, Thailand, and the United Kingdom that applied both methods together also showed SFA average efficiency to be higher than in DEA (Jacobs, 2001; Xu *et al.*, 2015). By contrast, an international comparison of technical efficiency measures found DEA scores corrected with bootstrap to be slightly higher than SFA scores (Varabyova & Schreyogg, 2013).

Hospitals are divided into three main groups in Figure 7.1. The first group consists of hospitals whose efficiency scores were sensitive to the technique used (Quadrants 2 and 4), the second group consists of hospitals that were shown to be efficient using both techniques (Quadrant 3), and the last group contains the hospitals where both techniques showed to be inefficient (Quadrant 1). Inferences should not be drawn from the scores of hospitals placed in the first and second groups; rather, they should be considered as outliers (Jacobs *et al.*, 2006). Techniques such as performance assessment and determination of the causes of inefficiency, should be used to improve the efficiency of hospitals in the third group.

7.4.2 Contextual variables affecting efficiency

Both DEA and SFA were applied to check the robustness of the association between contextual variables and estimated efficiency (Nedelea & Fannin, 2012). Our results show that the two methods, they generally produced similar results regarding the factors determining efficiency, and did point in the same direction. The high-performing hospitals tended to share several characteristics: they were predominantly large; they more likely to present in deprived areas with low levels of education; and they were located on Java or Bali. The few difference illustrated by these results might be due to differing interpretations of inefficiency; as discussed in Chapter 6, only SFA considers a random component in measurement (Jacobs *et al.*, 2006; Varabyova & Schreyogg, 2013).

Hospital size was one of the internal factors found to be associated with efficiency. Studies by Colombi *et al.* (2017) and Xenos *et al.* (2017) found that large hospitals are more efficient than small hospitals. Large health facilities have also been found to have better utilisation and higher bed occupancy rates than small facilities (Mobley & Magnussen, 1998). This result can be explained by the fact that larger hospitals tend to be better managed and to reallocate wisely human resources using performance targets; in addition, they have better and more innovative, information technology capabilities (Mitropoulos *et al.*, 2013; Shettian, 2017). However, Mitropoulos *et al.* (2013) found lower levels of efficiency in both medium and large hospitals. The mixed results among previous studies may support the argument that the effect of the size of the health facility differs depending on location, with larger hospitals found to be more efficient in urban areas and smaller hospitals found to be more efficient in rural areas (Asmild *et al.*, 2013).

Regarding ownership, results in this Chapter contrasts with the findings that we presented in Chapter 5, where private hospitals appeared significantly less efficient than public hospitals. There are several possible explanations for this result. A recent study showed that private hospitals perform better than public hospitals in terms of efficiency and cost because the private sector has more flexibility in managing health workers and purchasing medications and medical equipment (Guerrini *et al.*, 2017). Private hospitals may also make savings by hiring part-time contract staff (Ensor & Indradjaya, 2012; Chatterjee *et al.*, 2013). The findings of the current study are consistent with Herrera and colleagues' (2014) review, which showed mixed results as to whether public or private hospitals perform better. Differences in the efficiency levels of public and private hospitals might also be due to the differences in their payment mechanisms. A study by Barbetta *et al.* (2007) found convergence in the efficiency scores of not-for-profit private hospitals and public hospitals after they instituted a common DRG-based payment system.

In addition to ownership, teaching hospital classification was found to have a negative, although insignificant, association with efficiency. Healthcare services, however, are not the only objective of teaching hospitals, which are also responsible for teaching and research; treatment in teaching hospitals may thus last longer than medically required (Xenos *et al.*, 2017). These results are consistent with the findings of other studies in which teaching hospitals' costs are higher than those of non-teaching hospitals because they provide sub-specialised healthcare services, severe cases referred from other hospitals, and a disproportionately large share of medical graduate residencies (López-Casasnovas & Saez, 1999; Medin *et al.*, 2011). This result must therefore be interpreted with caution. Additional indicators such as teaching and research costs, number of citations, and publications must be considered to assess teaching hospitals' efficiency levels (Medin *et al.*, 2011).

This study did not find an association between the proportion of patients with NCDs and efficiency. Treating NCDs demands more health resources because of the complexity and severity of patients' conditions (Herr, 2008; Medin *et al.*, 2011), and the prevalence of chronic diseases such as cardiovascular disease and diabetes is increasing. Most patients with such diseases require regular follow-up visits and hospitalisation, which generally increases utilisation (Gonçalves *et al.*, 2015; IHME, 2016; Khanal, 2017). One viable explanation for our results might be the lower awareness of the share of patients with chronic NCDs for the need to undertake routine health check-ups.

With respect to external factors, our results regarding geography match those of earlier studies by Barnum (1987) and Berman *et al.* (1989) in which Javan hospitals were found to perform better than hospitals on other islands. We also found hospitals on Java and Bali to be more efficient than those on the other islands. These results suggest that the relatively good transportation and health facility infrastructure on Java are important to reduce physical barriers to health care access. In addition, poor performance on the other islands may result from low demand for health services, popular preference of alternatives to hospitals, low quality of services, or over-bedding (Barnum & Kutzin, 1993).

Another important finding of this study is the positive association between the health insurance coverage and efficiency; as with the similar result in Chapters 5 and 6 but different insurance scheme, this suggests that the health insurance reduces financial barriers to health care access and increases utilisation. Another aspect to be considered is the fact that hospitalisation is positively associated with people with less education and those in weaker economic positions, as patients in these groups face more frequently risk factors such as obesity, smoking and sedentary lifestyle (Gonçalves *et al.*, 2015). However, studies by Rosko & Mutter (2010) and Nedelea & Fannin (2013) in the United States found that the effect of Medicaid admissions on efficiency was inconclusive.

We found an inconclusive association between access to health facilities and hospital efficiency. This study has been unable to demonstrate that better access to health facilities increases hospital efficiency. This rather contradictory result may be due to the fact that areas with better access to hospitals also have relatively high hospital concentrations. Higher concentration leads to lower demand in individual hospitals, therefore decreasing technical efficiency (Cellini *et al.*, 2000; Nedelea & Fannin, 2013). When patients experience difficulty in accessing primary care facilities and lack trust in the quality of primary care facilities, they often by-pass primary care services and access hospital emergency services directly (Yip & Hsiao, 2014; Gonçalves *et al.*, 2015). Another possible factor is that avoidable hospital admissions decrease with better access to primary care. A systematic review by Rosano *et al.* (2013) found a 75% inverse association between primary care access and hospitalisation.

7.4.3 Policy implications

Improving technical efficiency in hospitals is crucial given that hospitals represent a high share of overall health expenditures and provide key services to improve population health. Assessing hospital efficiency is thus fundamental to many decision-making processes related to healthcare. As in primary care facilities, policy makers need to understand the advantages and disadvantages of various methods of assessing hospital efficiency and should integrate efficiency measurement into regular monitoring of the health system.

Better reallocation of healthcare resources is expected to improve technical efficiency. However, public hospitals generally have little autonomy in this regard due to bureaucratic and governmental regulations (Yip & Hsiao, 2014). Public hospitals need more flexibility in purchasing decisions, including hiring and firing, to ensure the presence of competition, meeting demand and thus leading to improvements in efficiency.

Although high-performing hospitals were more frequently found in areas whose populations had lower educational levels and higher poverty levels, policy decisions based on this result should be taken cautiously; this result might reflect poor primary care services in such areas, leading to higher utilisation of hospitals. Therefore, strengthening and improving the quality and quantity of primary care facilities in rural areas, where availability of health services is limited and basic equipment is often poor, is critical (Mahendradhata *et al.*, 2017). Doing so would encourage patients to utilise primary care before accessing hospitals, thus reducing unnecessary hospitalisation. Integration between hospitals and primary care facilities is also important as it increases the overall efficiency of the health system.

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

7.4.4 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; doing so would highlight changes in efficiency due to policy changes or interventions, especially those related to the 2014 implementation of Indonesian national health insurance. In addition, longitudinal data would help address outliers and distinguish between true outliers and measurement errors. Nevertheless, this study demonstrates the feasibility of undertaking national-level assessments of different types of hospitals and including contextual factors. Further research should be performed to investigate hospital efficiency with respect to the expansion of primary healthcare.

7.5 Conclusions

The results of this empirical study indicate a wide variation in efficiency among hospitals. Internal factors (i.e. hospital size and ownership) and external factors (i.e. geographical location, health insurance coverage and educational level) were shown to be important determinants contributing to hospital efficiency. High-performing hospitals were generally located in areas with high levels of insurance coverage for the civil servant and those located on Java and Bali Islands were shown to perform better than those in other parts of the country. Another notable finding is that the efficiency of health facilities cannot be explained by health facility quality. It is therefore important to incorporate routine efficiency measurement into regular health system monitoring.

Having investigated the relative efficiency of hospitals in this chapter, we move to a global discussion of the thesis in Chapter 8.

Chapter 8

Discussion

The previous chapters have measured the efficiency of health care provision in health facilities in Indonesia and explored the determining factors of efficiency levels. This chapter discusses the thesis' findings and limitations; it also offers policy recommendations to improve both efficiency in healthcare delivery and the measurement of efficiency itself.

8.1 Discussion of findings

This thesis has studied the efficiency of health facilities according to Indonesian data employing a wide range of efficiency indicators; it provided robust results which were found similar in terms of the direction of effects across the various methods used. The empirical findings in each chapter involved two elements: the measurement of efficiency levels and the analysis of factors determining efficiency. The measurements in this study covered most types of health facilities, and the facilities sampled were nationally representative of a wide country. To the best of our knowledge, this thesis is the first to use multiple national datasets available in Indonesia to include a wide range of factors determining the efficiency of health facilities.

Chapter 2 provided a description of Indonesia and its health system. This country profile helped contextualise the empirical studies that were undertaken and aided in determining their relevance for country settings with comparable characteristics where similar methods could be used and similar results observed. Indonesia's island geography and health care practices are in some ways similar to remote areas in certain regions of Africa, where distances to health facilities are very large and have a major impact on utilisation rates and health states (Stock, 1983; Titaley *et al.*, 2010a; Erlyana *et al.*, 2011; Yao *et al.*, 2013; Hanson *et al.*, 2015). Chapter 3 provided the framework for the methods used, including theoretical background and a critical discussion of the methods' suitability for this research project.

In Chapter 4, a comprehensive review of efficiency measurement developed a conceptual framework from which to approach the measurement of efficiency performed in Chapters 5, 6 and 7. Chapter 4 also reported methods, including techniques, variables, and efficiency indicators, that have been used frequently in LMICs. It would be beneficial to benchmark empirical results of efficiency between countries by adapting techniques and efficiency indicators that have been used globally and that were mentioned in this literature review. The review in this thesis could also be used in ways that go beyond those proposed previously, for example, to guide policy makers to identify appropriate indicators and frameworks for measuring efficiency within health facilities.

Chapter 5 offered a comprehensive construction of relative efficiency using ratio analysis. It reported multiple efficiency indicators using both a Pabón-Lasso model and costing analysis. Pabón-Lasso models and costing analysis techniques provided evidence on health facility technical and economic efficiency. This thesis shows that simple indicators can be used for comparisons of health facility efficiency in different settings. Simple indicators are easily reproduced in the routine monitoring of efficiency, not only because the data can be quickly obtained, but also because these indicators are easier for policy makers to understand. Combining both techniques also allowed for exploration of the characteristics of high-performing health facilities. One of the main criticisms of ratio analysis is that it does not take into account multiple inputs and outputs or the possible influence of errors (Barnum & Kutzin, 1993; Coelli *et al.*, 2005). As seen in Chapters 6 and 7, frontier analysis offers a more sophisticated method that takes these criticisms into account.

Chapter 6 measured efficiency in primary care facilities using frontier analysis, DEA and SFA. Given that there is currently no consensus as to which technique is best, the use of multiple approaches and the presentation of several efficiency scores offer a way of cross-checking the consistency of the results and perform a form of triangulation. In this empirical analysis, it has been possible to conclude robustly and unambiguously that some health facilities' contextual factors (such as hospital size, geographical location and population health insurance coverage) are significantly associated with estimated efficiency scores. To complement the analysis, a principal component analysis was conducted to consider a wider range of internal and external contextual factors.

In Chapter 7, frontier analyses focusing on hospitals were conducted. To accommodate the complexity of the healthcare services that hospitals provide, the output indicators of hospital efficiency measurements were expanded to consider case mix index and mortality ratio. Case mix index and mortality ratio have both been used widely to evaluate hospital performance and both are needed to adjust service output to avoid bias (Grosskopf & Valdmanis, 1993; Björkgren *et al.*, 2004; Pitocco & Sexton, 2018).

We found SFA failed to identify any inefficiency at hospitals when outpatients were included. The skewness test to check for the validity of the SFA model specification appears no evidence of negative skewness. The statistical errors of the frontier function cannot be distinguished from the inefficiency effect of the model, therefore it is impossible to allow both inefficiency and statistical error in the model. It is difficult to explain this result, but it might be related to the volume and heterogeneity of outpatient services which swamps the total volume of services and mask any inefficiency. This issue needs further investigation. Therefore, in absence of any clear explanation, considering alternative model specifications, we excluded outpatient services from the models.

Generally, the average efficiency score using DEA and SFA at primary care facilities were lower compared to hospitals. Both at primary care facilities and hospitals, DEA output oriented scores were higher than input oriented. DEA efficiency scores were sensitive to the number of inputs and outputs, the more variables applied, the higher efficiency score. Whereas based on the properties that are generally found from the literature review in Chapter 4, SFA generally have higher efficiency scores and are more stable than DEA. The relationships between DEA and SFA efficiency scores were described by the logarithm function form. The findings observed in this study mirror those of the previous study that found the non-linear relationship between DEA and SFA (Jarzebowski, 2013). Outliers were found both in primary care facilities and hospitals, where samples detected efficiency using DEA while inefficient using SFA measurements. Most of the facilities were identified as fully efficient in DEA. These facilities had lower average ratio of output to medical input (e.g.

number of patients to doctors) compared to other health facilities, but higher average ratio of output to other staff. This inconsistency may be due to DEA and SFA emphasising slightly different factors determining efficiency, since SFA seems to calculate a lower efficiency score for health facilities with lower ratio of medical to support and nursing staff. These outliers need further field and methodological investigation.

In Chapter 7, we also demonstrated that the choice of efficiency measurement tools is an important matter. Indeed, the efficiency measurement depends on both the number of categories and the stability of efficiency scores across the techniques. Tables 8.1 and 8.2 illustrate the overall relationship between the ratio analysis results and efficiency scores presented in the previous chapters.

Table 8.1: Efficiency measurement correlation in primary care facilities

	BOR	Throughput	Outpatient unit cost	Bed day unit cost	DEA
BOR					
Throughput	0.88***				
Outpatient unit cost	-0.14	-0.08			
Bed day unit cost	-0.57***	-0.37***	0.33**		
DEA	0.28**	0.22*	-0.60***	-0.24*	
SFA	0.31**	0.25*	-0.67***	-0.25*	0.89***

Significance level: ***0.001, **0.01, *0.05.
BOR: Bed occupancy rate

As shown in Tables 8.1 and 8.2, there are wide and mostly significant variations in the degrees of correlation between the results achieved using all six indicators. In primary care facilities, there is a moderate correlation between ratio analysis, BOR and bed day unit cost (r= -0.57), and strong correlation between outpatient unit cost and both DEA and SFA scores (r= -0.60 and r=-0.67, respectively). The relationship is negative, illustrating that as efficiency increases, unit costs fall. In hospitals, there is a strong and moderate correlation between the SFA and throughput results, and between SFA and BOR (r= 0.74 and r= 0.52, respectively).

Table 8.2: Efficiency measurement correlation in hospitals

	BOR	Throughput	Outpatient unit cost	Bed day unit cost	DEA
BOR					
Throughput	0.65***				
Outpatient unit cost	-0.21**	-0.14*			
Bed day unit cost	-0.38***	-0.14	0.32***		
DEA	0.29***	0.43***	-0.06	-0.21**	
SFA	0.52***	0.74***	-0.14*	-0.21**	0.74***

Significance level: ***0.001, **0.01, *0.05.
BOR Bed occupancy rate

Although the directions of correlation were expected, the variability between efficiency measurements suggests that researchers should not rely on single method. Studies should therefore not produce estimates of efficiency based on a single technique; rather they should consider the estimates of several models together to provide a general picture of efficiency. This is especially relevant because estimated efficiency is influenced by the model specifications, measurement, and error. Measurements based on one specific technique could be inaccurate due to the data indicators and the specifications used. Given the limitations of each available technique, simultaneous analysis using multiple techniques should be performed whenever possible.

The use of frontier analysis in Chapters 6 and 7 enabled us to note that DEA and SFA show wide variations in efficiency scores in both primary care facilities and hospitals. Figures 8.1 and 8.2 show positive efficiency score correlations between primary care facilities and hospitals in 27 of the 30 districts observed. The correlations were moderate in either the DEA (39%) or SFA (40%) results.

There are theoretical reasons for both positive and negative correlations which balance two opposing effects: i) Highly productive primary care facilities treat more patients, which could have a negative impact on patients with less serious illnesses presenting at secondary care facilities (fewer self-referrals) (Silva & Powell-Jackson, 2017; Winpenny *et al.*, 2017), and ii) better primary care may identify more patients to be referred, which could result in higher but also more complex workloads in secondary care facilities. If $i > ii$, then

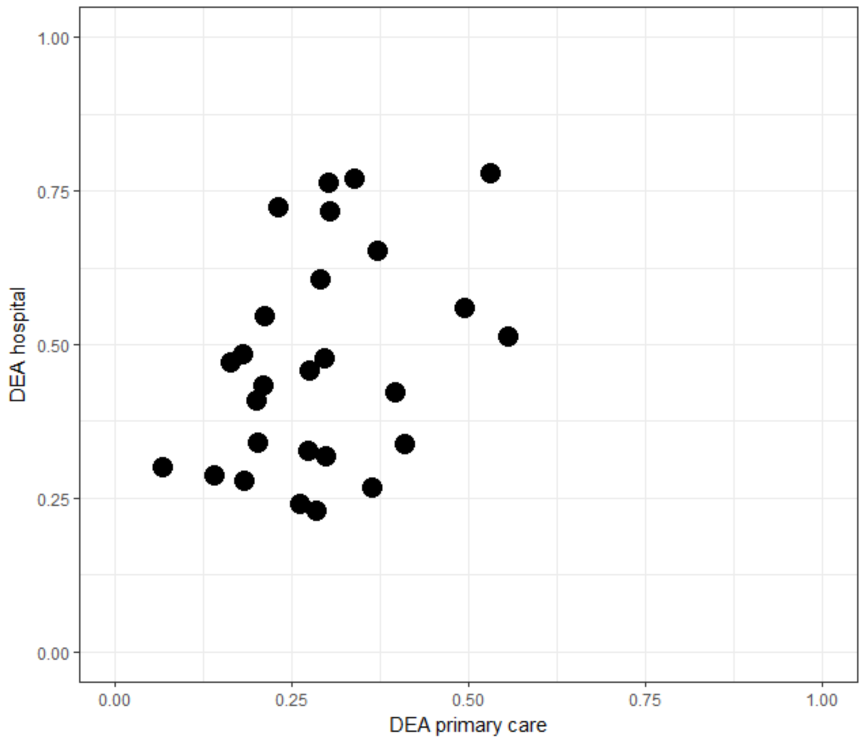


Figure 8.1: Correlation of DEA scores between primary care facilities and hospitals

there may be a negative correlation. If $ii > i$, then there may be a positive correlation. Even there was positive correlations, findings suggests different effects might important in different areas. Further work that examines case mix using patient-level data at each level is required.

Our empirical findings have expanded the knowledge of efficiency in health facilities in Indonesia. In particular, we examined the association between efficiency and contextual factors. We have implemented the internationally recognised techniques of two-stage DEA using truncated regression analysis and one-stage SFA to assess factors determining efficiency.

Using several measurement techniques, we also explored contextual variables with different specifications based on the literature review and data available. Range of potential models produced help policy makers in decision making process based on their priority and have some control over the contextual variables. For example, health facility managers are interested in the quality of health facility, while national health policy makers or non-health stakeholders are interested in regulating national health insurance regulation. However, by looking at the complexity of the model presented, we need to

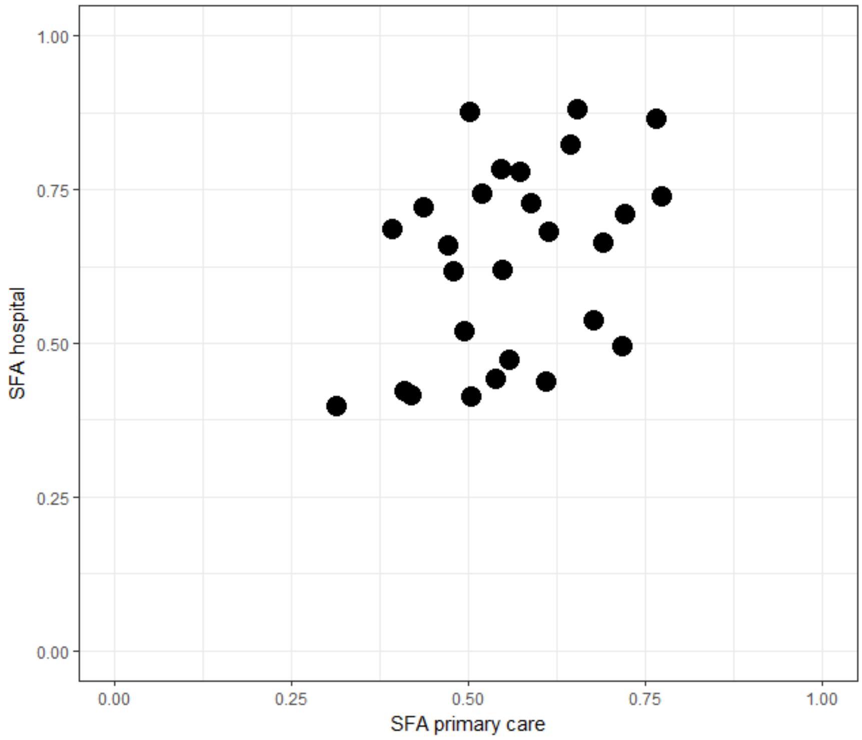


Figure 8.2: Correlation of SFA scores between primary care facilities and hospitals

find the best model to see a more definitive conclusion. Full models are preferable both because they fit better mathematically and can be used to answer a broader range of questions.

The results revealed that the efficiency of primary care facilities can be explained by population health insurance coverage, especially through the insurance scheme for the poor. Geographical factors, such as location on Java or Bali, better access to health facility and location in an urban area, also have a strong impact on efficiency. This results were not surprising. Few studies have been able to establish the impact of an increase in the consumption of healthcare in settings with fewer financial and physical barriers, which was discussed in Chapter 6.

Regression analysis estimating efficiency scores allowed us to distinguish the effects of different health facility characteristics. The results highlighted higher efficiency levels in larger hospitals and privately owned hospitals. However, in practice, policy implications are more than just adding number of beds and privatisation of hospitals. Increasing capacity and better management of health facilities would improve efficiency. Although the quality indicators were inconclusive, further research is needed using more specific indicators, based on the structure, process and output of health care services.

Greater health insurance coverage had a positive and significant influence on efficiency. Such results have never been shown in Indonesia, and they are consistent with the results of the studies of efficiency that have taken place in other low- and middle-income countries (Zeng *et al.*, 2014; Moradi *et al.*, 2017). It would be interesting to replicate the analysis using longitudinal data with larger samples and more detailed health and facility indicators to validate these results and observe the trend; as Audibert *et al.* (2013) found, hospital technical efficiency may decline during the periods of health insurance reform.

8.2 Limitations

Data quality is crucial in secondary data analysis research (Bland & Altman, 1996; Ree & Carretta, 2006). Quality assurance strategies to mitigate measurement error were applied to the data from both the Ministry of Health (MoH) and Central Bureau of Statistics (BPS) (Karsten van der Oord, 2012; BPS, 2014a,b; Kemenkes, 2011a). These strategies reduced data errors such as inconsistency, outliers and missing values. However, the data used in this thesis present several issues. For example, the case mix index and mortality ratio constructed from the INA-CBGs dataset matched only 60% of the hospitals in the current HFCS database. The HFCS database provides no variable reflecting other main functions of primary care, such as health promotion activities and preventive care. The analysis therefore attempted to compensate for the lack of some data, such as data concerning patients' access to health facilities, by using proxy indicators such as the opinions of village leaders regarding access to health facilities and the number of health facilities available to the local population. It would have been particularly advantageous to be able to estimate a model explaining contextual variables more precisely.

Because of the complexity of medical terms, there are potential errors in INA-CBGs coding because of erroneous diagnosis codes in International Classification of Diseases (ICD)-X and procedures in ICD-IX. 'Miscellaneous' is the most prevalent outpatient diagnosis, accounting for more than five trillion rupiah (USD 407 million) in INA-CBGs costs, followed by nephro-urinary diagnoses (Dutta & Fagan, 2017). In addition, only 60% of the total referral diagnoses between primary care facilities and hospitals matched (Thabrany, 2017). Therefore, clinical audits by professional organisations are important to ensure the accuracy of diagnosis.

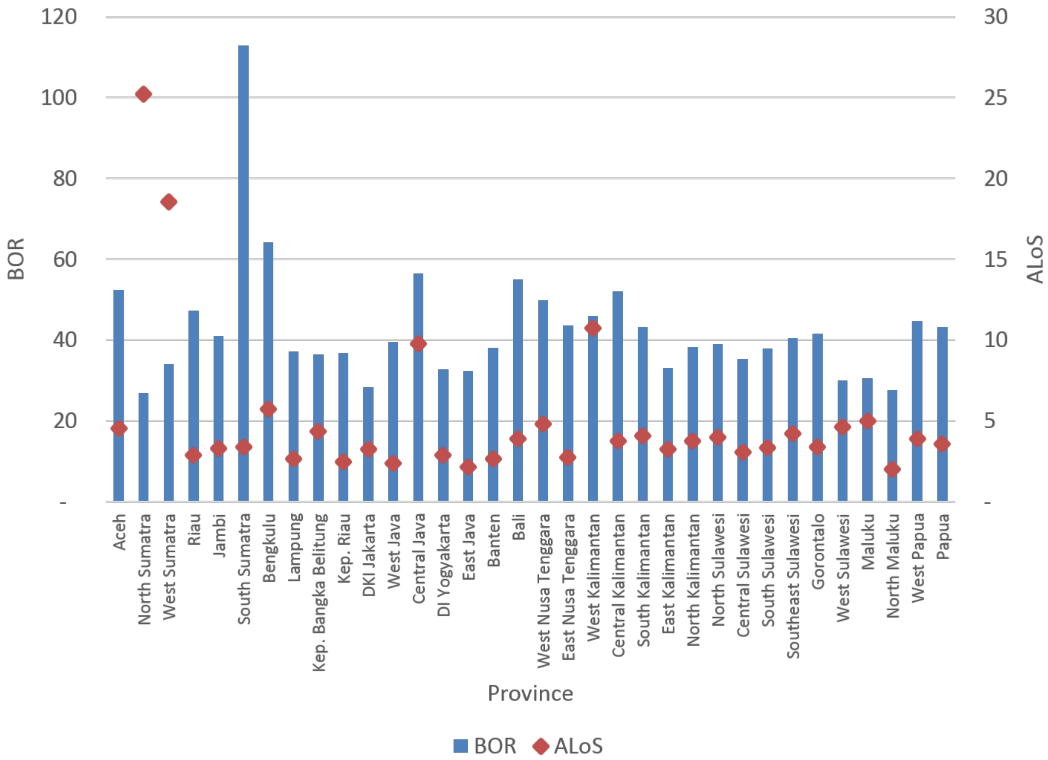


Figure 8.3: Hospital bed occupancy rate and average length of stay. Source: Kemenkes (2017a,b)

The accuracy of data is vital for efficiency measurement. Government monitors utilisation of services using bed occupancy rate (BOR) and length of stay (LOS) indicators; they could therefore direct their limited resources to those areas with the greatest needs. However, BOR and average length of stay (ALOS) (Figure 8.3) data published by the MoH showed great variation and extreme values in certain provinces. The mean BOR in hospitals in South Sumatra was above 110%, while the ALOS in hospitals in North and West Sumatra was over 18 days; these figures were much higher than other provinces, which might be related to epidemiology or may be attributable to errors in measurement. The data were submitted using a self-reporting system; future research would be aided if the Ministry were to develop a stronger monitoring system.

These remarks describe desirable extensions of the performed analyses using a dataset of better quality. This would require a central collection of key data from health facilities to facilitate routine monitoring, as well as the provision of robust data for advanced empirical research (Xu *et al.*, 2015). The use of nationally standardised indicators would ensure both comparability between health facilities and data reliability.

The recent survey conducted by the MoH and BPS should make it possible to merge information between health indicators and socio-economic characteristics to provide a wide range of factors determining health (Kemenkes, 2018). In 2019, Indonesia's entire population is due to be covered under national health insurance; data management in BPJS-K will thus become vital. Data merging between BPJS-K, the MoH and BPS would, for example, require consistent use of unique health facility IDs. It is therefore recommended that government and BPJS-K centralise and unify their platforms to integrate the data. INA-CBGs management (e.g. data structure, documentation, quality control and data output for research purposes) of such data could be undertaken by the research department under BPJS-K. Also, the Director of Health Services of the MoH, who is responsible for public primary care facilities and hospitals, should work together with the research department to improve data quality and data management. Strengthening the current self-reporting system would contribute to the accuracy of future research as well as routine monitoring.

8.3 Policy implications

Policy makers and other stakeholders need clear strategies to guide their decisions in order to achieve better efficiency in policy planning. In closing, we offer more general policy recommendations to improve health facility efficiency. The empirical findings show that, policy makers need to prioritise policy and identify inefficient groups of health facilities on which efforts and resources must be concentrated. Based on the review presented in Chapter 4, two primary supply side strategies are suggested to increase efficiency in health facilities: 1) developing finance strategies through provider payment mechanisms (Ajlouni *et al.*, 2013; Audibert *et al.*, 2013; Bowser *et al.*, 2013); and 2) optimising inputs including human resources (Akazili *et al.*, 2008; Alhassan *et al.*, 2015; Cheng *et al.*, 2015). On the demand side, the strategies suggested are: 1) reducing financial barriers (e.g. introducing health insurance through pooled, pre-paid contributions, subsidising health facilities, or reviewing user fees paid by patients) (Audibert *et al.*, 2013; Kirigia & Asbu, 2013; Jehu-Appiah *et al.*, 2014); 2) increasing quality to gain patients' trust (e.g. adequacy of drugs, medical equipment and presence of staff) (Löfgren *et al.*, 2015; Madinah *et al.*, 2015; Masoompour *et al.*, 2015); and 3) changing health behaviours (e.g. increasing the health knowledge and skills of the general population, promoting health, or implementing disease prevention strategies) (Osei *et al.*, 2005; Kirigia *et al.*, 2008b; Asbu *et al.*, 2012).

8.3.1 Supply side

Provider payment mechanisms

On the supply side, the results of this study indicate that outpatient unit cost has a tendency to fall as facility efficiency score increases (Figure 8.4). Lower outpatient unit cost has been found predominantly with DEA and SFA efficiency scores greater than 0.50 and 0.60, respectively. We also find a tendency of high unit cost of outpatient visits and bed days (adjusted for case mix index) to be associated with low efficiency scores (Figures 8.5 and 8.6). However, the patterns in hospitals appear here to be less straightforward than at primary care facilities. Awareness of an association between low unit costs and high efficiency scores would certainly save healthcare resources and serve as an incentive for health facilities to increase and maintain efficiency.

With regard to the policy context in Indonesia, a strategic purchasing approach through a prospective payment mechanism has been implemented as part of the national health insurance programme. BPJS-K has attempted to improve performance in primary care facilities by using a pay for performance system. For example, contact rates per member per month of less than 15%, more than 5% referrals, and less than 50% chronic disease cases (e.g. diabetes mellitus and hypertension) indicate very poor performance (Thabrany, 2017). Poor performance affects the capitation payment rate and may result in facility's contract being terminated by BPJS-K.

In hospitals, INA-CBGs have been implemented to improve efficiency. INA-CBGs are expected to change health providers' behaviour to be more efficient. However, negative consequences have arisen: the application of INA-CBGs does not satisfy providers because of low reimbursement

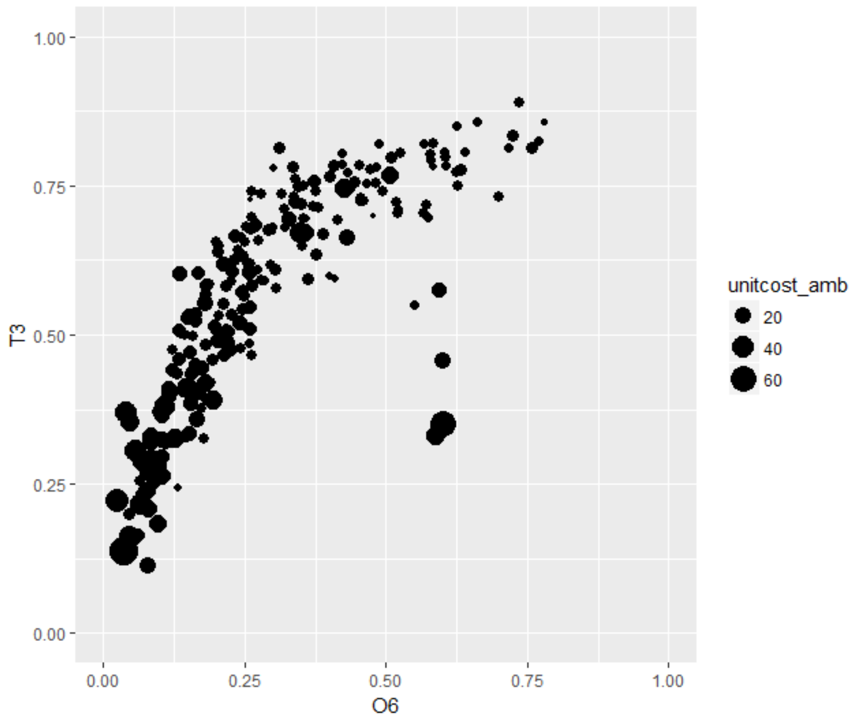


Figure 8.4: Trend between outpatient unit costs and primary care facility efficiency scores
T3 is SFA score, O6 is DEA score,unitcost_amb is unitcost of outpatient visits.

rates, leading to such actions as up-coding, re-admissions and unnecessary admissions. The totals for inpatient services in private hospitals were found to be 25 percentage point higher than in public hospitals. Studies in Europe have also found the use of diagnosis-related groups as a payment mechanism to have many adverse effects. To maximise their revenue, hospitals have been found to assign patients a higher grade of severity than is actually appropriate, reduce the quality of services, and inappropriately treat patients as inpatients rather than outpatients (Sørensen & Burau, 2016).

INA-CBGs tariffs are based on a costing study survey conducted by the MoH. Inefficiency was not taken into account; thus, the unit cost might be higher than the actual cost if taken from inefficient health facilities. Using the costing study results indiscriminately, would give higher, unnecessary incentives to providers and cause inefficiency in the health system. The trend shows an increase in utilisation to be a result of the implementation of the national health insurance programme; the unit cost may therefore also decrease or stagnate. Researchers are responsible to provide transparent, accountable study results to government and providers, resulting in tariff

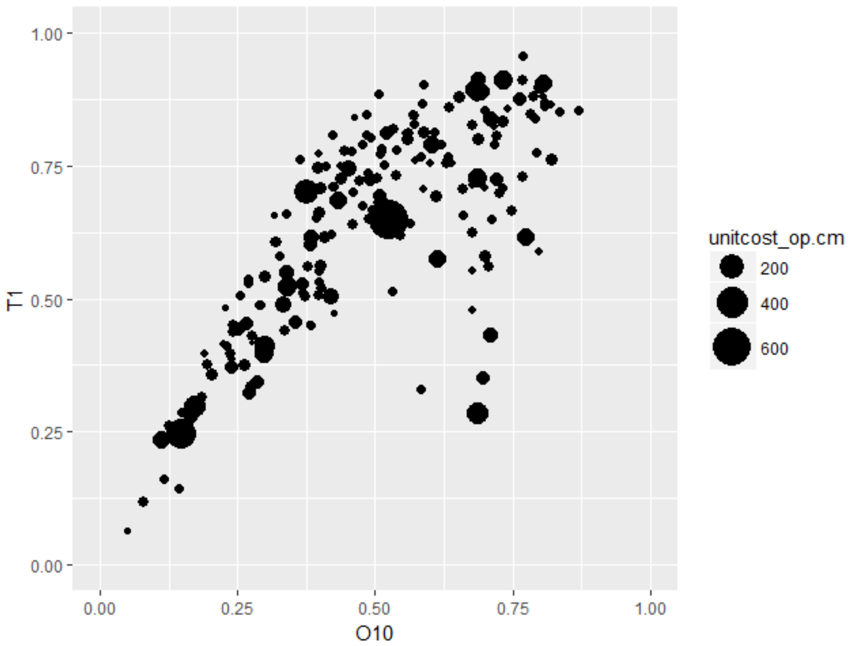


Figure 8.5: Trend between outpatient unit costs and hospital efficiency scores
T1 is SFA score, O10 is DEA score, unitcost_op.cm is unitcost of outpatient visits adjusted by case mix index.

adjustments by government that are acceptable to all stakeholders.

Human resources

Human resource management in health facilities has great potential to improve efficiency. Chapter 5 revealed that staff costs comprise a large proportion of service costs, reaching 60% and 40% in primary care facilities and hospitals, respectively. With the limited availability of health workers in developing countries, it is difficult to reduce the quantity of labour in a health facility to improve efficiency. In addition, political pressure to reduce the unemployment rate may have an effect on hiring and firing practices. To address these issues, flexibility in employment contracts is needed to permit reallocation of staff to work in different institutions, geographical areas and roles.

Remuneration policies have a significant impact on the efficiency of healthcare. Persistent low payment leads to an increase in dual practice, both official and un-official (Socha & Bech, 2011; Johannessen & Hagen, 2014; Koussa *et al.*, 2016). Meliala *et al.* (2013) found doctors in urban areas working at more than three locations, thus spending only a few hours per week in public facilities because of inadequate incentives. When health

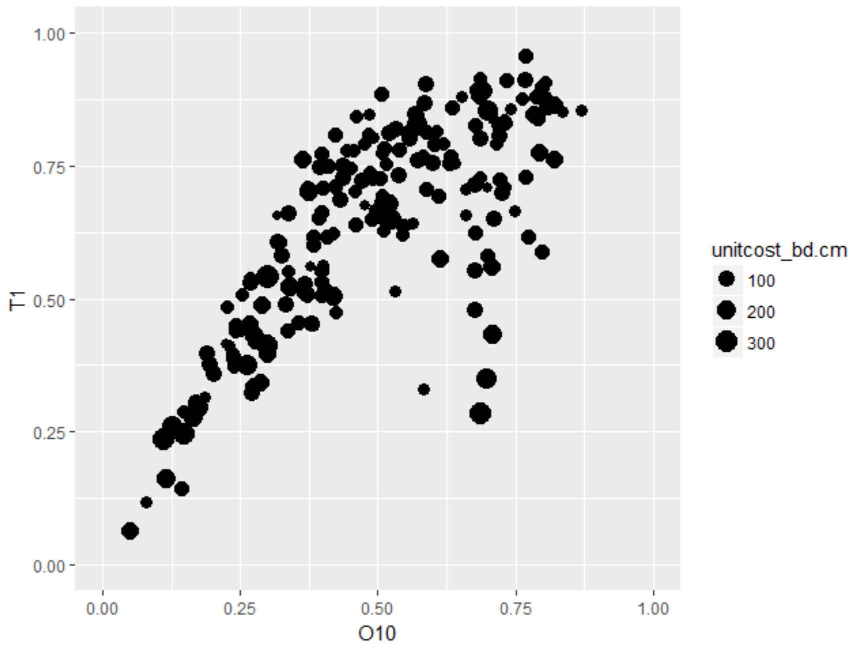


Figure 8.6: Trend between bed day unit costs and hospital efficiency scores
T1 is SFA score, O10 is DEA score, unitcost_op.cm is unitcost of bed days adjusted by case mix index.

workers quit their jobs, vacancies and inefficiency result in the affected health facility cannot provide as many services. Reducing health worker numbers and salaries certainly reduces total cost, but unit costs rise as facilities become less efficient; in addition, it leads to poorer health outcomes (Anderson, 2014). Sufficient take-home pay can increase workers' motivation and improve the quality of services rendered (Fedele, 2018). Thus, local government is attempting to provide more generous allowances to compensate for the low civil servant salary to attract and keep health workers in locations outside Java or in remote areas (Anderson, 2014). In addition, central government introduced programme requiring health graduates particularly doctors to serve in such locations upon beginning their careers (Kemenkes, 2017c; Presiden, 2017).

Extending working hours, especially in public facilities and with adequate incentives, may improve health facilities efficiency. Since most public facilities operate from 8 am to 2 pm, patients may tend to use private facilities (which are open after working hours) to avoid missing work. Nevertheless, the results of the analysis in Chapter 5 show that there is no difference in efficiency between facilities that are open in the afternoon and those that are not. Further research is needed to explore potential methods of maximising the use of public facility services.

8.3.2 Demand side

The analyses in this thesis measure efficiency using output orientation, which answers the question: "How much can output be increased without changing the number of inputs?". Demand-side policies play a key part in achieving output-oriented targets in efficiency measurement. To increase the demand for services, it is crucial to understand the characteristics of health-seeking behaviours, including socio-cultural beliefs, motivations, and levels of health awareness. Health-seeking behaviour is influenced by individual and societal assumptions and decisions, duration of intervention to programmes, health awareness on the part of patients, and healthcare servcies availability (Gopalan *et al.*, 2014). The mechanisms that affect health-seeking behaviour include accountability and consumer confidence in health facilities. For example, Indian mothers who must approach male providers experience physical barriers to accessing health care (Lim *et al.*, 2010). Some Mexican mothers have failed to give nutritional provisions to their children, fearing improved nutritional status would lead to a loss of financial incentives (Fernald *et al.*, 2009). In Indonesia, there are also religious prohibitions limiting the utilisation of vaccinations, thus reducing the number of people using immunisation services (Seale *et al.*, 2015).

Incentive programmes

From the demand side perspective, giving incentives to beneficiaries results in increases in the utilisation of health services. Ensor *et al.* (2017) showed a positive association between a maternity incentive scheme and service delivery in Nepal. In India, many women from villages preferred institutional delivery to professional birth attendance at home as they did not want to lose the incentives offered for delivery in a health facility, even if those incentives did not cover their actual out-of-pocket spending on transportation (Gopalan & Varatharajan, 2012). A distance barrier to care still exists in many countries where services are not available at convenient locations. Inconvenient healthcare service locations force many patients to spend out-of-pocket on transportation. The literature shows that reducing geographical barriers also has an important effect on health facilities' efficiency (Marschall & Flessa, 2009). In this thesis, the effects of health facility density and the ease of accessing health facilities were conclusive. However, the number of satellite *Puskesmas* (primary care facilities), which bring health services closer to the community showed no impact on efficiency. Therefore, further research is needed, with a better sample size and more details on distance variables as well as outreach activities. A study in Benin and Guinea showed that outreach activities increase the utilisation of health services in areas with difficult access to health services (Soucat *et al.*, 1997).

Adequate health service

Incentives can be used to encourage consumers to utilise services, but it is not effective to attempt to gain consumers' trust in providers and thus increase utilisation of health facilities without availability of adequate health services. Inadequate service delivery and quality as well as limited healthcare access, inhibit appropriate health-seeking behaviours, thus affecting health outcomes. Incentives have induced many Indian mothers to access skilled birth attendance, but mothers also chose private facilities for post-partum care because of limited accommodation in public facilities (Gopalan & Varatharajan, 2012). Many elderly people in Honduras attended regular health check-ups more frequently with the availability of health facilities in remote area (Morris *et al.*, 2004a). Vaccine shortages have also been shown to affect immunisation of Brazilian children (Morris *et al.*, 2004b). Informal payments were shown to be an indicator of poor provider accountability in Bangladesh, and over-prescribing is known to increase out-of-pocket expenditures (Schmidt *et al.*, 2010; Ahmed & Khan, 2011).

High health care costs increase financial barriers and reduce patient satisfaction (Fleming *et al.*, 2017). A previous study demonstrated that the choice of providers is associated with increased satisfaction and perception of quality (Hsu *et al.*, 2003). Therefore, involving the community in quality measurement ensures the availability of health care services, promote consumer rights and patient accountability (Gopalan & Varatharajan, 2012). A strategy helping health facilities to meet patients' needs would increase quality and health facility efficiency; however, such a strategy may only be implemented in a competitive environment.

Health knowledge

Providing people with opportunities to gain health knowledge is essential (Gopalan *et al.*, 2014). Regular sensitisation with a focus on appropriate behaviours would improve awareness, which in turn improves health-seeking behaviours. However, our analysis does not allow us to conclude that utilising health care would directly improve health status. Nevertheless, it is expected that it would lead to some form of health status improvements in the long term, as Zhao *et al.* (2014) found an association between high utilisation and better health outcomes.

8.4 Final thoughts

To conclude, there are plentiful opportunities for improving the efficiency of health facilities as suggested by Chan (2010). Given the number of factors that contribute to efficiency, a collaboration among stakeholders is recommended, combining a variety of approaches to improve specific area infrastructures and strengthen disadvantaged health facilities with the aim to reduce the vulnerability of certain populations in terms of healthcare delivery.

References

ABOAGYE, A.Q. & DEGBOE, A.N. (2011). Cost analysis and efficiency of sub-district health facilities in two districts in Ghana. *The International Journal of Health Planning and Management*, **26**, 173–190.

ACEMOGLU, D. & FINKELSTEIN, A. (2008). Input and technology choices in regulated industries: Evidence from the health care sector. *Journal of Political Economy*, **116**, 837–880.

ADAM, T., EVANS, D.B. & MURRAY, C.J.L. (2003). Econometric estimation of country-specific hospital costs. *Cost Effectiveness and Resource Allocation*, **1**, 3–3.

ADAM, T., EVANS, D.B., YING, B. & MURRAY, C.J.L. (2014). Variability in costs across hospital wards. a study of chinese hospitals. *PLOS ONE*, **9**, 1–8.

ADUDA, D.S.O., OUMA, C., ONYANGO, R., ONYANGO, M. & BERTRAND, J. (2015). Voluntary medical male circumcision scale-up in Nyanza, Kenya: Evaluating technical efficiency and productivity of service delivery. *PLoS ONE*, **10**.

AFZALI, H.H., MOSS, J.R. & MAHMOOD, M.A. (2009). A conceptual framework for selecting the most appropriate variables for measuring hospital efficiency with a focus on Iranian public hospitals. *Health Services Management Research*, **22**, 81–91.

AGUS, Y., HORIUCHI, S. & PORTER, S.E. (2012). Rural Indonesia women's traditional beliefs about antenatal care. *BMC Research Notes*, **5**, 1–8.

AHA (2008). *Estimated Useful Lives of Depreciable Hospital Assets Revised 2008 Edition*. Estimated Useful Lives of Depreciable Hospital Assets, American Hospital Association, revised 2008 edition edn.

AHMED, S. & KHAN, M.M. (2011). A maternal health voucher scheme: what have we learned from the demand-side financing scheme in Bangladesh? *Health Policy and Planning*, **26**, 25–32.

AHRQ (2013). 2012 national healthcare quality report. Tech. rep., Agency for Healthcare Research and Quality, Rockville, MD.

AIGNER, D., LOVELL, C. & SCHMIDT, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, **6**, 21 – 37.

AJLOUNI, M.M., ZYOUD, A., JABER, B., SHAHEEN, H., AL-NATOUR, M. & ANSHASI, R.J. (2013). The relative efficiency of Jordanian public hospitals using data envelopment analysis and Pabon Lasso diagram. *Global Journal of Business Research*, **7**, 59–72.

AKAZILI, J., ADJUIK, M., JEHU-APPIAH, C. & ZERE, E. (2008). Using data envelopment analysis to measure the extent of technical efficiency of public health centres in Ghana. *BMC International Health and Human Rights*, **8**, 11.

ALAGHEMANDAN, H., YARMOHAMMADIAN, M.H., KHORASANI, E. & REZAEE, S. (2014). Efficiency improvement of dentistry clinics: Introducing an intervening package for dentistry clinics, Isfahan, Iran. *International Journal of Preventive Medicine*, **5**, 176–84.

ALDULAIMI, S. & MORA, F.E. (2017). A primary care system to improve health care efficiency: Lessons from Ecuador. *The Journal of the American Board of Family Medicine*, **30**, 380–383.

ALHASSAN, R.K., NKETIAH-AMPONSAH, E., AKAZILI, J., SPIEKER, N., ARHINFUL, D.K. & RINKE DE WIT, T.F. (2015). Efficiency of private and public primary health facilities accredited by the national health insurance authority in Ghana. *Cost Effectiveness and Resource Allocation*, **13**.

AMOLE, B.B., OYATOYE, E.O., ALABI-LABAIKA, A.B. & ADEBIYI, S.O. (2016). Data envelopment analysis for estimating health care efficiency in the southwest teaching hospitals in Nigeria. *Journal of Economics & Business Research*, **22**, 143 – 159.

ANDERSON, A.P.P.E., IAN; MELIALA (2014). The production, distribution, and performance of physicians, nurses, and midwives in Indonesia: an update. *The World Bank*, 1–52.

ANSARIADI, A. & MANDERSON, L. (2015). Antenatal care and women's birthing decisions in an Indonesian setting: Does location matter? *Rural and Remote Health*, **15**, 1–17.

APPLANAIDU, S.D., SAMSUDIN, S., ALI, J., DASH, U. & CHIK, A.R. (2014). Technical and scale efficiency of public district hospitals in Kedah, Malaysia: a data envelopment analysis (DEA). *Journal of Health Management*, **16**, 327–335.

ARAÚJO, C., BARROS, C.P. & WANKE, P. (2014). Efficiency determinants and capacity issues in Brazilian for-profit hospitals. *Health Care Management Science*, **17**, 126–138.

ARCHIBALD, G.C. & LIPSEY, R.G. (1982). *An Introduction to A Mathematical Treatment of Economics*. Weidenfeld and Nicolson, London, 3rd edn.

ARFA, C., LELEU, H., GOA&IUML;ED, M. & VAN MOSSEVELD, C. (2017). Measuring the capacity utilization of public district hospitals in Tunisia: Using dual data envelopment analysis approach. *International Journal of Health Policy and Management*, **6**, 9–18.

AROCENA, P. & GARCÍA-PRADO, A. (2007). Accounting for quality in the measurement of hospital performance: evidence from Costa Rica. *Health Economics*, **16**, 667–685.

ASBU, E., WALKER, O., KIRIGIA, J., ZAWAIRA, F., MAGOMBO, F. & ZIMPITA, P. (2012). Assessing the efficiency of hospitals in Malawi: An application of the pabón lasso technique. *African Health Monitor*, **14**, 28–33.

ASMILD, M., HOLLINGSWORTH, B. & BIRCH, S. (2013). The scale of hospital production in different settings: One size does not fit all. *Journal of Productivity Analysis*, **40**, 197–206.

ATILGAN, E. (2016). The technical efficiency of hospital inpatient care services: An application for Turkish public hospitals. *Isletme ve Ekonomi Arastirmalari Dergisi/Business and Economics Research Journal*, **7**, 203–214.

AUDIBERT, M., MATHONNAT, J., PELISSIER, A., HUANG, X.X. & MA, A. (2013). Health insurance reform and efficiency of township hospitals in rural China: An analysis from survey data. *China Economic Review*, **27**, 326 – 338.

BARBER, S.L., GERTLER, P.J. & HARIMURTI, P. (2007). The contribution of human resources for health to the quality of care in Indonesia. *Health AffairsHealth Affairs*, **26**, 367–379.

BARBETTA, G.P., TURATI, G. & ZAGO, A.M. (2007). Behavioral differences between public and private not-for-profit hospitals in the Italian national health service. *Health Economics*, **16**, 75–96.

BARNUM, H.N. (1987). Hospital expenditure in Indonesia (english). techreport no. PHN 8717, Population, Health and Nutrition Department, World Bank, Washington, D.C.

BARNUM, H.N. & KUTZIN, J. (1993). *Public hospitals in developing countries: resource use, cost, financing*. Johns Hopkins University Press, Baltimore; London.

BASTANI, P., VATANKHAH, S. & SALEHI, M. (2013). Performance ratio analysis: A national study on Iranian hospitals affiliated to ministry of health and medical education. *Iranian Journal of Public Health*, **42**, 876–82.

BATTESE, G.E. & COELLI, T.J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, **20**, 325–332.

BELTON, S., MYERS, B. & NGANA, F.R. (2014). Maternal deaths in eastern Indonesia: 20 years and still walking: an ethnographic study. *BMC pregnancy and childbirth*, **14**, 39.

BERMAN, P. (1986). Cost analysis as a management tool for improving the efficiency of primary care: Some examples from java. *International Journal of Health Planning and Management*, **1**, 275–288.

BERMAN, P., BROTOWASISTO, NADJIB, M., SAKAI, S. & GANI, A. (1989). The costs of public primary health care services in rural Indonesia. *Bulletin of the World Health Organization*, **67**, 685–94.

BERNET, P.M., ROSKO, M.D., VALDMANIS, V.G., PILYAVSKY, A. & AARONSON, W.E. (2008). Productivity efficiencies in Ukrainian polyclinics: lessons for health system transitions from differential responses to market changes. *Journal of Productivity Analysis*, **29**, 103–111.

BESSTREMYANNAYA, G. (2013). The impact of Japanese hospital financing reform on hospital efficiency: A difference-in-difference approach. *Japanese Economic Review*, **64**, 337–362.

BITRAN, R. (1992). Technical and economic efficiency in the production of health services. phase 1: Review of concepts and literature and preliminary field work design. *HFS Major Applied Research Paper*.

BJÖRKGREN, M.A., FRIES, B.E., HÄKKINEN, U. & BROMMELS, M. (2004). Case-mix adjustment and efficiency measurement. *Scandinavian Journal of Public Health*, **32**, 464–471, pMID: 15762032.

BLAAKMAN, A.P., SALEHI, A.S. & BOITARD, R. (2014). A cost and technical efficiency analysis of two alternative models for implementing the basic package of health services in Afghanistan. *Global Public Health*, **9**, S110–S123.

BLAND, J.M. & ALTMAN, D.G. (1996). Measurement error and correlation coefficients. *BMJ: British Medical Journal*, **313**, 41–42.

BLANK, J.L.T. & VALDMANIS, V.G. (2010). Environmental factors and productivity on Dutch hospitals: a semi-parametric approach. *Health care management science*, **13**, 27–34.

BOGETOFT, P. & OTTO, L. (2010). *Benchmarking with DEA, SFA, and R*, vol. 157. Springer Science & Business Media.

BOWLIN, W.F. (1998). Measuring performance: An introduction to data envelopment analysis (DEA). *The Journal of Cost Analysis*, **15**, 3–27.

BOWSER, D.M., FIGUEROA, R., NATIQ, L. & OKUNOGBE, A. (2013). A preliminary assessment of financial stability, efficiency, health systems and health outcomes using performance-based contracts in belize. *Global Public Health*, **8**, 1063–1074, pMID: 24028377.

BPS (2011a). Indonesia - pendataan potensi desa 2011. Badan Pusat Statistik, accessed 12 Jun. 2016.

BPS (2011b). Indonesia - survei sosial ekonomi nasional 2011. Badan Pusat Statistik, accessed 18 Des. 2014.

BPS (2014a). Indonesia - survei sosial ekonomi nasional 2011 triwulan 1. Tech. rep., Badan Pusat Statistik, Jakarta.

BPS (2014b). Indonesia-pendataan potensi desa 2011. Tech. rep., Badan Pusat Statistik, Jakarta.

BPS (2014c). Persentase penduduk daerah perkotaan menurut provinsi, 2010-2035. Badan Pusat Statistik, accessed 26 Sep. 2016.

BPS (2014d). Proyeksi penduduk menurut provinsi, 2010-2035 (ribuan). Badan Pusat Statistik, accessed 26 Sep. 2016.

BPS (2015). *Statistical Yearbook of Indonesia 2016*. Badan Pusat Statistik, Jakarta.

BRENZEL, L., YOUNG, D. & WALKER, D.G. (2015). Costs and financing of routine immunization: Approach and selected findings of a multi-country study (epic). *Vaccine*, **33**, A13 – A20.

BUUREN, S. & GROOTHUIS-OUDSHOORN, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of statistical software*, **45**.

BWANA, K.M. (2015). Measuring technical efficiency of faith based hospitals in Tanzania: An application of data envelopment analysis (DEA). *Research in Applied Economics*, **7**, 1.

BWANA, K.M. & RAPHAEL, G. (2015). Technical efficiency of Tanzania teaching hospitals: The case of private not for-profit hospitals. *Business Management and Strategy*, **6**, 97.

CAHYANI, N., AKBAR, M.S. & SUSILANINGRUM, D. (2012). Kajian tentang tingkat efisiensi pelayanan kesehatan rumah sakit umum pemerintah kabupaten/kota di Jawa Timur menggunakan metode PCA-DEA. *Jurnal Sains dan Seni ITS*, **1**, D25–D30.

CASHIN, C.E., BOROWITZ, M. & ZUESS, O. (2002). The gender gap in primary health care resource utilization in Central Asia. *Health Policy and Planning*, **17**, 264–272.

CELLINI, R., PIGNATARO, G. & RIZZO, I. (2000). Competition and efficiency in health care: An analysis of the Italian case. *International Tax and Public Finance*, **7**, 503–519.

CHAABOUNI, S. & ABEDNNADHER, C. (2012). Efficiency of public hospitals in Tunisia: a DEA with bootstrap application. *International Journal of Behavioural and Healthcare Research*, **3**, 198.

CHAABOUNI, S. & ABEDNNADHER, C. (2016). Cost efficiency of Tunisian public hospitals: A bayesian comparison of random and fixed frontier models. *Journal of the Knowldege Economy*, **7**, 771–781.

CHALIDYANTO, D. (2013). *Faktor yang berhubungan dengan efisiensi rumah sakit umum pemerintah di Indonesia*. Disertasi, Universitas Indonesia, Jakarta, Indonesia.

CHARNES, A., COOPER, W. & RHODES, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, **2**, 429 – 444.

CHATTERJEE, S., LEVIN, C. & LAXMINARAYAN, R. (2013). Unit cost of medical services at different hospitals in India. *PloS one*, **8**, e69728.

CHAVENT, M., KUENTZ-SIMONET, V. & SARACCO, J. (2012). Orthogonal rotation in pcamix. *Advances in Data Analysis and Classification*, **6**, 131–146.

CHAVENT, M., KUENTZ-SIMONET, V., LABENNE, A. & SARACCO, J. (2014). Multivariate Analysis of Mixed Data: The R Package PCAmixdata. *ArXiv e-prints*.

CHENG, Z., TAO, H., CAI, M., LIN, H., LIN, X., SHU, Q. & ZHANG, R.N. (2015). Technical efficiency and productivity of Chinese county hospitals: an exploratory study in henan province, China. *BMJ Open*, **5**.

CHENG, Z., CAI, M., TAO, H., HE, Z., LIN, X., LIN, H. & ZUO, Y. (2016). Efficiency and productivity measurement of rural township hospitals in China: a bootstrapping data envelopment analysis. *BMJ Open*, **6**.

CHEPS, PPJK & AIPHSS (2016). Indonesia national health accounts 2014. Tech. rep., Center for Health Financing and Insurance, Ministry of Health, Jakarta.

CHIRIKOS, T.N. & SEAR, A.M. (2000). Measuring hospital efficiency: a comparison of two approaches. *Health services research*, **34**, 1389–1408.

CHISHOLM, D. & EVANS, D.B. (2010). Improving health system efficiency as a means of moving towards universal coverage. World health report, World Health Organization, Geneva, Switzerland.

CHOWDHURY, H., ZELENYUK, V., LAPORTE, A. & WODCHIS, W.P. (2014). Analysis of productivity, efficiency and technological changes in hospital services in Ontario: How does case-mix matter? *International Journal of Production Economics.*, **150**, 74–82.

COELLI, T. & HENNINGSEN, A. (2013). frontier: Stochastic frontier analysis. r package version 1.1-0. CRAN. Retrieved from http://frontier.r-forge.r-project.org.

COELLI, T.J., RAO, D.S.P., O'DONNELL, C.J. & BATTESE, G.E. (2005). *An introduction to efficiency and productivity analysis*. the written permission of the publisher, New York, second edi edn.

COLOMBI, R., MARTINI, G. & VITTADINI, G. (2017). Determinants of transient and persistent hospital efficiency: The case of italy. *Health Economics*, **26**, 5–22, hec.3557.

CONTEH, L. & WALKER, D. (2004). Cost and unit cost calculations using step-down accounting. *Health Policy & Planning*, **19**, 127–35.

CORDERO FERRERA, J.M., CRESPO CEBADA, E. & MURILLO ZAMORANO, L.R. (2014). The effect of quality and socio-demographic variables on efficiency measures in primary health care. *The European journal of health economics : HEPAC : health economics in prevention and care*, **15**, 289–302.

CYLUS, J., PAPANICOLAS, I. & SMITH, P.C. (2016). Health system efficiency: How to make measurement matter for policy and management. European Observatory on Health Systems and Policies.

D'AMBRUOSO, L., ACHADI, E., ADISASMITA, A., IZATI, Y., MAKOWIECKA, K. & HUSSEIN, J. (2009). Assessing quality of care provided by Indonesian village midwives with a confidential enquiry. *Midwifery*, **25**, 528–539.

DANDONA, L., SISODIA, P., PRASAD, T.L., MARSEILLE, E., CHALAPATHI RAO, M., KUMAR, A.A., KUMAR, S.G., RAMESH, Y.K., OVER, M., SOMESHWAR, M. & KAHN, J.G. (2005). Cost and efficiency of public sector sexually transmitted infection clinics in Andhra Pradesh, India. *BMC Health Services Research*, **5**, 69.

DANDONA, L., KUMAR, S.P., RAMESH, Y., RAO, M.C., MARSEILLE, E., KAHN, J.G. & DANDONA, R. (2008). Outputs, cost and efficiency of public sector centres for prevention of mother to child transmission of hiv in Andhra Pradesh, India. *BMC Health Services Research*, **8**, 26.

DASH, U., VAISHNAVI, S., MURALEEDHARAN, V. & ACHARYA, D. (2007). Benchmarking the performance of public hospitals in Tamil Nadu: An application of data envelopment analysis. *Journal of Health Management*, **9**, 59–74.

DASH, U., VAISHNAVI, S. & MURALEEDHARAN, V. (2010). Technical efficiency and scale efficiency of district hospitals: A case study. *Journal of Health Management*, **12**, 231–248.

DE CASTRO LOBO, M.S., OZCAN, Y.A., DA SILVA, A.C.M., LINS, M.P.E. & FISZMAN, R. (2010). Financing reform and productivity change in Brazilian teaching hospitals: Malmquist approach. *Central European Journal of Operations Research*, **18**, 141–152.

DERVAUX, B., LELEU, H., VALDMANIS, V. & WALKER, D. (2003). Parameters of control when facing stochastic demand: A DEA approach applied to Bangladeshi vaccination sites. *International Journal of Health Care Finance and Economics*, **3**, 287–299.

DING, D.X. (2014). The effect of experience, ownership and focus on productive efficiency: A longitudinal study of U.S. hospitals. *Journal of Operations Management*, **32**, 1–14.

DUDLEY, L. & GARNER, P. (2011). Strategies for integrating primary health services in low-and middle-income countries at the point of delivery. *Cochrane Database Syst Rev*, **7**.

DUTTA, A. & FAGAN, T. (2017). Purchasing care with the Indonesia case-based groups (ina-cbgs). In *International Health Economic Association Conference*, Health Policy Plus, Boston.

EDEJER, T.T.T., BALTUSSEN, R., ADAM, T., HUTUBESSY, R., ACHARYA, A., EVANS, D. & MURRAY, C., eds. (2003). *Making choices in health: WHO guide to cost-effectiveness analysis*. World Health Organization, Geneva.

EKIYOR, A. (2015). Evaluating performance of chest diseases departments using hospital efficiency indicators in Turkey. *British Journal of Economics, Management and Trade*, **6**, 145–150, using Smart Source Parsing 17 ref.

EMROUZNEJAD, A., PARKER, B.R. & TAVARES, G. (2008). Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. *Socio-economic planning sciences*, **42**, 151–157.

ENSOR, T. & INDRADJAYA, S. (2012). The costs of delivering health services in Indonesia: report on a prospective survey 2010-2011. Tech. rep., Indonesia Ministry of Health, Jakarta: Indonesia.

ENSOR, T., FIRDAUS, H., DUNLOP, D., MANU, A., MUKTI, A.G., AYU PUSPANDARI, D., VON ROENNE, F., INDRADJAYA, S., SUSENO, U., VAUGHAN, P., MUKTI, G. & PUSPANDARI, D.A. (2012). Budgeting based on need: a model to determine sub-national allocation of resources for health services in Indonesia. *Cost effectiveness and resource allocation : C/E*, **10**, 11.

ENSOR, T., BHATT, H. & TIWARI, S. (2017). Incentivizing universal safe delivery in Nepal: 10 years of experience. *Health Policy and Planning*, **32**, 1185–1192.

ERLYANA, E., DAMRONGPLASIT, K.K. & MELNICK, G. (2011). Expanding health insurance to increase health care utilization: Will it have different effects in rural vs. urban areas? *Health Policy*, **100**, 273–281.

ERUS, B. & HATIPOGLU, O. (2017). Physician payment schemes and physician productivity: Analysis of Turkish healthcare reforms. *Health Policy*, **121**, 553 – 557.

EVERITT, B. & HOTHORN, T. (2011). *An introduction to applied multivariate analysis with R*. Springer Science Business Media, New York;London.

FEDELE, A. (2018). Well-paid nurses are good nurses. *Health Economics*, **27**, 663–674.

FERNALD, L.C., GERTLER, P.J. & NEUFELD, L.M. (2009). 10-year effect of oportunidades, Mexico's conditional cash transfer programme, on child growth, cognition, language, and behaviour: a longitudinal follow-up study. *The Lancet*, **374**, 1997 – 2005.

FIEDLER, J.L., SCHMIDT, R.M. & WIGHT, J.B. (1998). Public hospital resource allocations in El Salvador: Accounting for the case mix of patients. *Health Policy and Planning*, **13**, 296–310.

FLEMING, E., GAINES, J., O'CONNOR, K., OGUTU, J., ATIENO, N., ATIENO, S., KAMB, M.L. & QUICK, R. (2017). Can incentives reduce the barriers to use of antenatal care and delivery services in Kenya?: Results of a qualitative inquiry. *Journal of Health Care for the Poor and Underserved*, **28**, 153–174.

FLESSA, S. (1998). The costs of hospital services: a case study of evangelical lutheran church hospitals in Tanzania. *Health policy and planning*, **13**, 397–407.

FRANKENBERG, E., SURIASTINI, W. & THOMAS, D. (2005). Can expanding access to basic healthcare improve children's health status? lessons from Indonesia's 'midwife in the village' programme. *Population studies*, **59**, 5–19.

GAI, R.Y., ZHOU, C.C., XU, L.Z., ZHU, M., WANG, X.Z., LI, S.X., ZHENG, W.G., SONG, P.P., YANG, X.L., FANG, L.Y., ZHEN, Y.C. & TANG, W. (2010). Health resource allocation and productive efficiency of Chinese county hospitals: data from 1993 to 2005. *Bioscience trends*, **4**, 218–24.

GHOLIPOUR, K., DELGOSHAI, B., MASUDI-ASL, I., HAJINABI, K. & IEZADI, S. (2013). Comparing performance of tabriz obstetrics and gynaecology hospitals managed as autonomous and budgetary units using Pabon Lasso method. *The Australasian Medical Journal*, **6**, 701–707.

GIOKAS, D.I. (2001). Greek hospitals: how well their resources are used. *Omega*, **29**, 73–83.

GIUFFRIDA, A. & GRAVELLE, H. (2001). Measuring performance in primary care: econometric analysis and DEA. *Applied Economics*, **33**.

GKOUNTOURAS, G., LAUER, J.A., ANDERSONSTANCIOLE, STENBERG, K. & EDEJER, T.T.T. (2011). Estimation of unit costs for general health services: Updated who-choice estimates. Tech. rep., World Health Organization, Geneva.

GLIED, S. & SMITH, P. (2011). *The Oxford handbook of health economics*. Oxford University Press, Oxford.

GOK, M.S. & ALTINDAĞ, E. (2015). Analysis of the cost and efficiency relationship: experience in the Turkish pay for performance system. *The European Journal of Health Economics*, **16**, 459–469.

GOK, M.S. & SEZEN, B. (2013). Analyzing the ambiguous relationship between efficiency, quality and patient satisfaction in healthcare services: the case of public hospitals in Turkey. *Health policy (Amsterdam, Netherlands)*, **111**, 290–300.

GOK, S.M. & SEZEN, B. (2012). Capacity inefficiencies of teaching and non-teaching hospitals. *Service Industries Journal*, **32**, 2307–2328.

GONÇALVES, M.R., HAUSER, L., PRESTES, I.V., SCHMIDT, M.I., DUNCAN, B.B. & HARZHEIM, E. (2015). Primary health care quality and hospitalizations for ambulatory care sensitive conditions in the public health system in Porto Alegre, Brazil. *Family Practice*, **33**, 238–242.

GOOLSBEE, A., LEVITT, S. & SYVERSON, C. (2013). *Microeconomics*. Worth Publishers, New York, NY, international edn.

GOPALAN, S.S. & VARATHARAJAN, D. (2012). Addressing maternal healthcare through demand side financial incentives: experience of janani suraksha yojana program in India. *BMC Health Services Research*, **12**, 319.

GOPALAN, S.S., DAS, A. & MUTASA, R. (2014). What makes health demand-side financing schemes work in low- and middle-income countries? a realist review. *Journal of Public Health Research*, **3**.

GOSHTASEBI, A., VAHDANINIA, M., GORGIPOUR, R., SAMANPOUR, A., MAFTOON, F., FARZADI, F. & AHMADI, F. (2009). Assessing hospital performance by the Pabon Lasso model. *Iranian Journal of Public Health*, **38**, 119–124.

GREEN, A., ALI, B., NAEEM, A. & VASSALL, A. (2001). Using costing as a district planning and management tool in Balochistan, Pakistan. *Health policy and planning*, **16**, 180–186.

GROSSKOPF, S. & VALDMANIS, V. (1993). Evaluating hospital performance with case-mix-adjusted outputs. *Medical Care*, **31**, 525–532.

GUERRA, M., DE SOUZA, A.A. & MOREIRA, D.R. (2012). Performance analysis: a study using data envelopment analysis in 26 Brazilian hospitals. *Journal of health care finance*, **38**, 19–35.

GUERRINI, A., ROMANO, G., CAMPEDELLI, B., MOGGI, S. & LEARDINI, C. (2017). Public vs. private in hospital efficiency: Exploring determinants in a competitive environment. *International Journal of Public Administration*, **0**, 1–9.

GUNAWAN, A. (2007). *Perbandingan kepuasan pasien dan persepsi staf puskesmas antara puskesmas yang menerapkan akreditasi dengan sertifikasi ISO 9001: 2000*. Ph.D. thesis, Universitas Gadjah Mada.

HADI, U., DUERINK, D.O., LESTARI, E.S., NAGELKERKE, N.J., WERTER, S., KEUTER, M., SUWANDOJO, E., RAHARDJO, E., VAN DEN BROEK, P. & GYSSENS, I.C. (2008). Survey of antibiotic use of individuals visiting public healthcare facilities in Indonesia. *International Journal of Infectious Diseases*, **12**, 622–629.

HADJI, B., MEYER, R., MELIKECHE, S., ESCALON, S. & DEGOULET, P. (2014). Assessing the relationships between hospital resources and activities: A systematic review. *Journal of Medical Systems*, **38**, 127.

HAFIDZ, F., ENSOR, T. & TUBEUF, S. (2017). Assessing primary care performance in Indonesia: An application of frontier analysis techniques. Working Papers 1703, Academic Unit of Health Economics, Leeds Institute of Health Sciences, University of Leeds.

HAFIDZ, F., ENSOR, T. & TUBEUF, S. (2018a). Assessing health facility performance in Indonesia using the pabón-lasso model and unit cost analysis of health services. *Int J Health Plann Mgmt*.

HAFIDZ, F., ENSOR, T. & TUBEUF, S. (2018b). Assessing Hospital Performance in Indonesia: An Application of Frontier Analysis Techniques. Working Papers 1801, Academic Unit of Health Economics, Leeds Institute of Health Sciences, University of Leeds.

HAFIDZ, F., ENSOR, T. & TUBEUF, S. (2018c). Efficiency measurement in health facilities: A systematic review in low- and middle-income countries. *Applied Health Economics and Health Policy*.

HAJIALIAFZALI, H., MOSS, J.R. & MAHMOOD, M.A. (2007). Efficiency measurement for hospitals owned by the Iranian social security organisation. *Journal of medical systems*, **31**, 166–172.

HAM, C., DIXON, A. & BROOKE, B. (2012). Transforming the delivery of health and social care: the case for fundamental change. *London: King's Fund*.

HAMIDI, S. (2016). Measuring efficiency of governmental hospitals in palestine using stochastic frontier analysis. *Cost Effectiveness and Resource Allocation*, **14**, 3.

HANAM ATAKE, E. (2015). Technical efficiency of public hospitals in Togo: A directional distance function approach. *Economics Bulletin*, **35**, 1752–1764.

HANSON, C., COX, J., MBARUKU, G., MANZI, F., GABRYSCH, S., SCHELLENBERG, D., TANNER, M., RONSMANS, C. & SCHELLENBERG, J. (2015). Maternal mortality and distance to facility-based obstetric care in rural southern Tanzania: a secondary analysis of cross-sectional census data in 226000 households. *The Lancet Global Health*, **3**, e387 – e395.

HATAM, N. (2008). The role of data envelopment analysis (DEA) pattern in the efficiency of social security hospitals in Iran. *Iran Red Crescent Med J*, **10**, 211–217.

HATAM, N., MOSLEHI, S., ASKARIAN, M., SHOKRPOUR, N., KESHTKARAN, A. & ABBASI, M. (2010). The efficiency of general public hospitals in fars province, southern Iran. *Iranian Red Crescent Medical Journal*, **12**, 138–144.

HEIMESHOFF, M., SCHREYOGG, J. & KWIETNIEWSKI, L. (2014). Cost and technical efficiency of physician practices: a stochastic frontier approach using panel data. *Health care management science*, **17**, 150–161.

HELMIG, B. & LAPSLEY, I. (2001). On the efficiency of public, welfare and private hospitals in germany over time: a sectoral data envelopment analysis study. *Health services management research : an official journal of the Association of University Programs in Health Administration / HSMC, AUPHA*, **14**, 263–274.

HENNINGSEN, A. & TOOMET, O. (2011). maxlik: A package for maximum likelihood estimation in r. *Computational Statistics*, **26**, 443–458.

HERR, A. (2008). Cost and technical efficiency of german hospitals: does ownership matter? *Health Economics*, **17**, 1057–1071.

HERRERA, C.A., RADA, G., KUHN-BARRIENTOS, L. & BARRIOS, X. (2014). Does ownership matter? an overview of systematic reviews of the performance of private for-profit, private not-for-profit and public healthcare providers. *PloS one*, **9**.

HEYWOOD, P. & HARAHAP, N.P. (2009). Health facilities at the district level in Indonesia. *Australia and New Zealand Health Policy*, **6**, 13.

HILL, P.S., GOEMAN, L., SOFIARINI, R. & DJARA, M.M. (2014). 'desa siaga', the 'alert village': The evolution of an iconic brand in Indonesian public health strategies. *Health Policy and Planning*, **29**, 409–420.

HOFF, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. *European Journal of Operational Research*, **181**, 425–435.

HOLLINGSWORTH, B. (2003). Non-parametric and parametric applications measuring efficiency in health care. *Health care management science*, **6**, 203–218.

HOLLINGSWORTH, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics.*, **17**, 1107–1128.

HOLLINGSWORTH, B., DAWSON, P.J. & MANIADAKIS, N. (1999). Efficiency measurement of health care: a review of non-parametric methods and applications. *Health care management science*, **2**, 161–172.

HOPKINS, S., IRAVA, W. & KEI, T.Y. (2010). Comparisons of health expenditure in 3 pacific island countries using national health accounts. *Pacific health dialog*, **16**, 41–50.

HORT, K., DJASRI, H. & UTARINI, A. (2013). Regulating the quality of health care: Lessons from hospital accreditation in Australia and Indonesia. *The Nossal Institute for Global Health, Working Paper Series*, **28**.

HOSEN, N. (2005). Religion and the Indonesian constitution: a recent debate. *Journal of Southeast Asian Studies*, **36**, 419–440.

HSIEH, V.C.R., WU, J.C.L., WU, T.N. & CHIANG, T.L. (2013). Universal coverage for primary health care is a wise investment. *Asia Pacific Journal of Public Health*, **27**, NP877–NP886.

HSU, J. (2010). The relative efficiency of public and private service delivery. *World Health Report Background Paper*, **39**, 1–9.

HSU, J., SCHMITTDIEL, J., KRUPAT, E., STEIN, T., THOM, D., FIREMAN, B. & SELBY, J. (2003). Patient choice: A randomized controlled trial of provider selection. *Journal of General Internal Medicine*, **18**, 319–325.

HUANG, Y. & MCLAUGHLIN, C. (1989). Relative efficiency in rural primary health care: an application of data envelopment analysis. *Health services research*, **24**, 143—158.

HUSSEY, P.S., DE VRIES, H., ROMLEY, J., WANG, M.C., CHEN, S.S., SHEKELLE, P.G. & MCGLYNN, E.A. (2009). A systematic review of health care efficiency measures. *Health Services Research*, **44**, 784–805.

HUTUBESSY, R.C.W. & EDEJER, T.T.T. (2002). Diffusion and utilization of magnetic resonance imaging in Asia. *International Journal of Technology Assessment in Health Care*, **18**, 690–704.

IHME (2016). Country profiles: Indonesia - global burden of disease. Institute for Health Metrics and Evaluation (IHME), University of Washington.

IKEGAMI, N. (2016). Achieving universal health coverage by focusing on primary care in Japan: lessons for low-and middle-income countries. *International journal of health policy and management*, **5**, 291.

INEVELD, M.V., OOSTRUM, J.V., VERMEULEN, R., STEENHOEK, A. & KLUNDERT, J.V.D. (2015). Productivity and quality of Dutch hospitals during system reform. *Health Care Management Science*.

ISAI, V. & RADU, R.I. (2016). The cost of medical services per patient and the efficiency of hospital care activity – an insight from the romanian hospitals. *Annals of Dunarea de Jos University. Fascicle I : Economics and Applied Informatics*, **22**, 107–117.

ISWANTO, A.H. (2015). Measuring hospital efficiency through Pabon Lasso analysis: An empirical study in Kemang medical care (KMC). *Social Science Research Network*.

JACOBS, R. (2001). Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis. *Health care management science*, **4**, 103–115.

JACOBS, R., SMITH, P.C. & STREET, A. (2006). *Measuring efficiency in health care: analytic techniques and health policy*, vol. 10. Cambridge University Press, New York.

JARZEBOWSKI, S. (2013). Parametric and non-parametric efficiency measurement – the comparison of results. *Metody Ilościowe w Badaniach Ekonomicznych*, **14**, 170–179.

JAT, T.R. & SEBASTIAN, M.S. (2013). Technical efficiency of public district hospitals in Madhya Pradesh, India: a data envelopment analysis. *Global Health Action*, **6**, 21742, pMID: 28140970.

JEHU-APPIAH, C., SEKIDDE, S., ADJUIK, M., AKAZILI, J., ALMEIDA, S.D., NYONATOR, F., BALTUSSEN, R., ASBU, E.Z. & KIRIGIA, J.M. (2014). Ownership and technical efficiency of hospitals: evidence from Ghana using data envelopment analysis. *Cost Effectiveness and Resource Allocation*, **12**.

JIA, T. & YUAN, H. (2017). The application of DEA (data envelopment analysis) window analysis in the assessment of influence on operational efficiencies after the establishment of branched hospitals. *BMC Health Services Research*, **17**, 265.

JIAN, W., HUANG, Y., HU, M. & ZHANG, X. (2009). Performance evaluation of inpatient service in Beijing: a horizontal comparison with risk adjustment based on diagnosis related groups. *BMC Health Services Research*, **9**, 72.

JOHANNESSEN, K.A. & HAGEN, T.P. (2014). Physicians' engagement in dual practices and the effects on labor supply in public hospitals: results from a register-based study. *BMC Health Services Research*, **14**, 299.

JOHNS, B., MUNTHALI, S., WALKER, D.G., MASANJALA, W. & BISHAI, D. (2013). A cost function analysis of child health services in four districts in Malawi. *Cost Effectiveness and Resource Allocation*, **11**, 10.

JOLLIFFE, I.T. & CADIMA, J. (2016). Principal component analysis: a review and recent developments. *Phil.Trans.R.Soc.A*, **374**.

KARSTEN VAN DER OORD, S.I.L.Z., GERTRUD SCHMIDT-EHRY (2012). Background, strategy, process and lessons learned of the nationwide health facility study in Indonesia. Tech. rep., GIZ, Jakarta.

KATHARAKIS, G., KATHARAKI, M. & KATOSTARAS, T. (2014). An empirical study of comparing DEA and SFA methods to measure hospital units' efficiency. *International Journal of Operational Research*, **21**, 341–364.

KEITH, J. & PRIOR, D. (2014). Scale and scope economies in Mexican private medical units. *Salud Pública de México*, **56**, 348.

KEMENDAGRI (2015). Peraturan menteri dalam negeri republik Indonesia nomor 39 tahun 2015 tentang kode dan data wilayah administrasi pemerintahan. Kementerian Dalam Negeri.

KEMENKES (2006). *Profil kesehatan Indonesia 2004*. Kementerian Kesehatan RI, Jakarta, Indonesia.

KEMENKES (2011a). Peraturan menteri kesehatan republik Indonesia nomor 903/menkes/per/v/2011 tentang pedoman pelaksanaan program jaminan kesehatan masyarakat. Kementerian Kesehatan.

KEMENKES (2011b). *Profil kesehatan Indonesia 2010*. Kementerian Kesehatan RI, Jakarta, Indonesia.

KEMENKES (2011c). Rencana pengembangan tenaga kesehatan tahun 2011-2025. Jakarta.

KEMENKES (2012a). Laporan akhir riset fasilitas kesehatan 2011: Puskesmas. Tech. rep., Badan Penelitian dan Pengembangan Kesehatan, Jakarta.

KEMENKES (2012b). Laporan akhir riset fasilitas kesehatan 2011: Rumah sakit. Tech. rep., Badan Penelitian dan Pengembangan Kesehatan, Jakarta.

KEMENKES (2012c). Pedoman exit strategi dana hibah global fund AIDS, tuberkulosis dan malaria. *Jakarta: Dirjen PP dan PL*.

KEMENKES (2012d). Peraturan menteri kesehatan republik Indonesia nomor 12 tahun 2012 tentang akreditasi rumah sakit. Kementerian Kesehatan Republik Indonesia.

KEMENKES (2012e). *Profil kesehatan Indonesia 2011*. Kementerian Kesehatan RI, Jakarta, Indonesia.

KEMENKES (2014a). Peraturan menteri kesehatan republik Indonesia no 56 tahun 2014 tentang klasifikasi dan perizinan rumah sakit. Kementerian Kesehatan.

KEMENKES (2014b). Peraturan menteri kesehatan republik Indonesia nomor 59 tahun 2014 tentang standar tarif pelayanan kesehatan dalam penyelenggaraan program jaminan kesehatan. Kementerian Kesehatan.

KEMENKES (2014c). Peraturan menteri kesehatan republik Indonesia nomor 75 tahun 2014 tentang pusat kesehatan masyarakat. Kementerian Kesehatan.

KEMENKES (2014d). *Profil Kesehatan Indonesia 2013*. Kementerian Kesehatan RI, Jakarta, Indonesia.

KEMENKES (2015). *Profil Kesehatan Indonesia 2014*. Kementerian Kesehatan RI, Jakarta, Indonesia.

KEMENKES (2016a). Laporan akuntabilitas kinerja 2015 direktorat jenderal bina kefarmasian dan alat kesehatan. Tech. rep., Kementerian Kesehatan, Jakarta.

KEMENKES (2016b). *Profil Kesehatan Indonesia Tahun 2015*. Kementerian Kesehatan Republik Indonesia, Jakarta.

KEMENKES (2017a). Dashboard RS online: BOR. Direktorat Jenderal Pelayanan Kesehatan, Kementerian Kesehatan Republik Indonesia.

KEMENKES (2017b). Dashboard RS online: LoS. Direktorat Jenderal Pelayanan Kesehatan, Kementerian Kesehatan Republik Indonesia.

KEMENKES (2017c). Peraturan menteri kesehatan republik Indonesia nomor 39 tahun 2017 tentang penyelenggaraan program intership dokter dan dokter gigi Indonesia. Kementerian Kesehatan.

KEMENKES (2017d). Profil kesehatan Indonesia 2016. Tech. rep., Kementerian Kesehatan, Jakarta, Indonesia.

KEMENKES (2018). Menkes apresiasi integrasi riskesdas 2018 dengan susenas BPS. Kementerian Kesehatan Republik Indonesia.

KETABI, S. (2011). Efficiency measurement of cardiac care units of Isfahan hospitals in Iran. *Journal of Medical Systems*, **35**, 143–150.

KEYA, K.T., ROB, U., RAHMAN, M.M., BAJRACHARYA, A. & BELLOWS, B. (2014). Distance, transportation cost, and mode of transport in the utilization of facility-based maternity services: Evidence from rural Bangladesh. *International Quarterly of Community Health Education*, **35**, 37–51, pMID: 25416431.

KHAN, M.M. & AHMED, S. (2003). Relative efficiency of government and non-government organisations in implementing a nutrition intervention programme – a case study from Bangladesh. *Public Health Nutrition*, **6**, 19–24.

KHANAL, S. (2017). Use of healthcare services by patients with non-communicable diseases in Nepal: A qualitative study with healthcare providers. *Journal of Clinical and Diagnostic Research*.

KIADALIRI, A.A., HAGHPARAST-BIDGOLI, H. & ZAREI, A. (2011). Measuring efficiency of general hospitals in the south of Iran. *World Applied Sciences Journal*, **13**, 1310–1316.

KIADALIRI, A.A., JAFARI, M. & GERDTHAM, U.G. (2013). Frontier-based techniques in measuring hospital efficiency in Iran: a systematic review and meta-regression analysis. *BMC Health Services Research*, **13**, 312.

KIBAMBE, J.N. & KOCH, S.F. (2007). DEA applied to a gauteng sample of public hospitals. *South African Journal of Economics*, **75**, 351–368.

KIERS, H.A.L. (1991). Simple structure in component analysis techniques for mixtures of qualitative and quantitative variables. *Psychometrika*, **56**, 197–212.

KIRIGIA, J.M. & ASBU, E.Z. (2013). Technical and scale efficiency of public community hospitals in Eritrea: an exploratory study. *Health Economics Review*, **3**, 1–16.

KIRIGIA, J.M., SAMBO, L.G. & SCHEEL, H. (2001). Technical efficiency of public clinics in Kwazulu-Natal Province of South Africa. *East African medical journal*, **78**, S1–13.

KIRIGIA, J.M., EMROUZNEJAD, A. & SAMBO, L.G. (2002). Measurement of technical efficiency of public hospitals in Kenya: using data envelopment analysis. *Journal of medical systems*, **26**, 39–45.

KIRIGIA, J.M., EMROUZNEJAD, A., SAMBO, L.G., MUNGUTI, N. & LIAMBILA, W. (2004). Using data envelopment analysis to measure the technical efficiency of public health centers in Kenya. *Journal of Medical Systems*, **28**, 155–166.

KIRIGIA, J.M., EMROUZNEJAD, A., CASSOMA, B., ASBU, E.Z. & BARRY, S. (2008a). A performance assessment method for hospitals: the case of municipal hospitals in Angola. *Journal of medical systems*, **32**, 509–519.

KIRIGIA, J.M., EMROUZNEJAD, A., VAZ, R.G., BASTIENE, H. & PADAYACHY, J. (2008b). A comparative assessment of performance and productivity of health centres in seychelles. *International Journal of Productivity and Performance Management*, **57**, 72–92.

KIRIGIA, J.M., SAMBO, L.G., RENNER, A., ALEMU, W., SEASA, S. & BAH, Y. (2011). Technical efficiency of primary health units in Kailahun and Kenema districts of Sierra Leone. *International Archives of Medicine*, **4**.

KOSEN, S., TARIGAN, I., USMAN, Y., SURYATI, T., INDRIASIH, E., HARIMAT, MUAS, I., WIDYASTUTI, R., LUCIANA, M., ROSITA, T., HAPSARI, D., TANDON, A., YAP, W.A. & PAMBUDI, E. (2014a). *Supply-side readiness for universal health coverage : assessing the depth of coverage for non-communicable diseases in Indonesia*. World Bank Group, Washington, DC.

KOSEN, S., TARIGAN, I., USMAN, Y., SURYATI, T., INDRIASIH, E., HARIMAT, MUAS, I., WIDYASTUTI, R., LUCIANA, M., ROSITA, T., HAPSARI, D., TANDON, A., YAP, W.A., PAMBUDI, E. & MARZOEKI, P. (2014b). *Universal maternal health coverage? : assessing the readiness of public health facilities to provide maternal health care in Indonesia*. World Bank Group, Washington, DC.

KOUSSA, M.E., ATUN, R., BOWSER, D. & KRUK, M.E. (2016). Factors influencing physicians' choice of workplace: systematic review of drivers of attrition and policy interventions to address them. *Journal of Global Health*, **6**.

KRUK, M.E., PORIGNON, D., ROCKERS, P.C. & VAN LERBERGHE, W. (2010). The contribution of primary care to health and health systems in low- and middle-income countries: A critical review of major primary care initiatives. *Social Science & Medicine*, **70**, 904–911.

KUMBHAKAR, S.C., WANG, H. & HORNCASTLE, A.P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press.

LANGENBRUNNER, J., HIDAYAT, B., MUIRHEAD, D. & NUGROHO, D. (2014). Health sector review: Health financing. Tech. rep., Kementerian PPN/ Bappenas, Jakarta.

LASSO, H.P. (1986). Evaluating hospital performance through simultaneous application of several indicators. *Bulletin of the Pan American Health Organization*, **20**, 341–357.

LEE, K., CHUN, K. & LEE, J. (2008a). Reforming the hospital service structure to improve efficiency: urban hospital specialization. *Health Policy*, **87**, 41–49.

LEE, K.H., YANG, S.B. & CHOI, M. (2008b). The association between hospital ownership and technical efficiency in a managed care environment. *Journal of Medical Systems*, **33**, 307–315.

LEKPRICHAKUL, T. (2001). *Efficiency measurement of 89 public provincial hospitals in Thailand: Parametric and non-parametric estimation methods*. Ph.D., University of Hawai'i, Ann Arbor.

LEVIN, A., AMIN, A., RAHMAN, A., SAIFI, R., KHUDA, B. & MOZUMDER, K. (1999). Cost-effectiveness of family planning and maternal health service delivery strategies in rural Bangladesh. *The International Journal of Health Planning and Management*, **14**, 219–233.

LEVIN, A., DMYTRACZENKO, T., MCEUEN, M., SSENGOOBA, F., MANGANI, R. & VAN DYCK, G. (2003). Costs of maternal health care services in three anglophone African countries. *The International Journal of Health Planning and Management*, **18**, 3–22.

LI, H. & DONG, S. (2015). Measuring and benchmarking technical efficiency of public hospitals in Tianjin, China: A bootstrap–data envelopment analysis approach. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, **52**, 0046958015605487, pMID: 26396090.

LI, H., DONG, S. & LIU, T. (2014). Relative efficiency and productivity: a preliminary exploration of public hospitals in , China. *BMC Health Services Research*, **14**, 158.

LI, N.N., WANG, C.H., NI, H. & WANG, H. (2017). Efficiency and productivity of county-level public hospitals based on the data envelopment analysis model and malmquist index in Anhui, China. *Chinese Medical Journal*, **130**, 2836–43.

LIM, S.S., DANDONA, L., HOISINGTON, J.A., JAMES, S.L., HOGAN, M.C. & GAKIDOU, E. (2010). India's janani suraksha yojana, a conditional cash transfer programme to increase births in health facilities: an impact evaluation. *The Lancet*, **375**, 2009 – 2023.

LINDELOW, M. & WAGSTAFF, A. (2003). *Health Facility Surveys: An Introduction*. The World Bank.

LOBO, M.S.C., SILVA, A.C.M., LINS, M.P.E. & FISZMAN, R. (2009). [impact of the funding reform of teaching hospitals in Brazil]. *Revista de saude publica*, **43**, 437–45.

LOTFI, F., KALHOR, R., BASTANI, P., SHAARBAFCHI ZADEH, N., ESLAMIAN, M., DEHGHANI, M.R. & ZAKARIA KIAEE, M. (2014). Various indicators for the assessment of hospitals' performance status: Differences and similarities. *Iranian Red Crescent Medical Journal*, **16**, e12950.

LÓPEZ-CASASNOVAS, G. & SAEZ, M. (1999). The impact of teaching status on average costs in Spanish hospitals. *Health Economics*, **8**, 641–651.

LÖFGREN, J., MULOWOOZA, J., NORDIN, P., WLADIS, A. & FORSBERG, B.C. (2015). Cost of surgery in a low-income setting in eastern Uganda. *Surgery*, **157**, 983–991.

MACEIRA, D., GOGUADZE, K. & GOTSADZE, G. (2015). The drivers of facility-based immunization performance and costs. an application to moldova. *Vaccine*, **33**, A72 – A78.

MADINAH, N., BOERHANNOEDDIN, A. & ARIFFIN, R.N.B.R. (2015). An evaluation of health centers and hospital efficiency in kampala capital city authority Uganda; using Pabon Lasso technique. *JUMMEC: Journal of Health and Translational Medicine (Formerly known as Journal of the University of Malaya Medical Centre)*, **18**, 12–17.

MAHAPATRA, P. & BERMAN, P. (1994). Using hospital activity indicators to evaluate performance in Andhra Pradesh, India. *The International Journal of Health Planning and Management*, **9**, 199–211.

MAHENDRADHATA, Y., TRISNANTORO, L., LISTYADEWI, S., SOEWONDO, P., MARTHIAS, T., HARIMURTI, P. & PRAWIRA, J. (2017). *The Republic of Indonesia Health System Review*, vol. 7, Number-1. World Health Organization, India.

MAKOWIECKA, K., ACHADI, E., IZATI, Y. & RONSMANS, C. (2008). Midwifery provision in two districts in Indonesia: How well are rural areas served? *Health Policy and Planning*, **23**, 67–75.

MARSCHALL, P. & FLESSA, S. (2009). Assessing the efficiency of rural health centres in Burkina Faso: An application of data envelopment analysis. *Journal of Public Health*, **17**, 87–95.

MARSCHALL, P. & FLESSA, S. (2011). Efficiency of primary care in rural Burkina Faso. a two-stage DEA analysis. *Health Economics Review*, **1**, 1–15.

MARSHALL, A., BILLINGHAM, L.J. & BRYAN, S. (2009). Can we afford to ignore missing data in cost-effectiveness analyses? Springer.

MARTINEAU, T., GONG, Y. & TANG, S. (2004). Changing medical doctor productivity and its affecting factors in rural China. *The International Journal of Health Planning and Management*, **19**, 101–111.

MARZOEKI, P., TANDON, A., BI, X. & PAMBUDI, E.S. (2014). Universal health coverage for inclusive and sustainable development country summary report for Indonesia. Tech. rep., World Bank Group.

MAS-COLELL, A., WHINSTON, M.D. & GREEN, J.R. (1995). *Microeconomic Theory*. Oxford University Press, New York.

MASIYE, F. (2007). Investigating health system performance: an application of data envelopment analysis to Zambian hospitals. *BMC health services research*, **7**, 58–58.

MASIYE, F., KIRIGIA, J.M., EMROUZNEJAD, A., SAMBO, L.G., MOUNKAILA, A., CHIMFWEMBE, D. & OKELLO, D. (2006). Efficient management of health centres human resources in Zambia. *Journal of Medical Systems*, **30**, 473–481.

MASOOMPOUR, S.M., PETRAMFAR, P., FARHADI, P. & MAHDAVIAZAD, H. (2015). Five-year trend analysis of capacity utilization measures in a teaching hospital 2008-2012. *Shiraz E Medical Journal*, **16**.

MATHIYAZHAGAN, M.K. (2007). Determinants of cost efficiency of public and private hospitals of Karnataka state in India. *Journal of Quantitative Economics, New Series*, **5**, 95–115.

MATRANGA, D. & SAPIENZAB, F. (2015). Congestion analysis to evaluate the efficiency and appropriateness of hospitals in Sicily. *Health Policy.*, **119**, 324–332.

MCDONALD, J. (2009). Using least squares and Tobit in second stage DEA efficiency analyses. *European Journal of Operational Research*, **197**, 792–798.

MEDIN, E., ANTHUN, K.S., HÄKKINEN, U., KITTELSEN, S.A., C., LINNA, M., MAGNUSSEN, J., OLSEN, K. & REHNBERG, C. (2011). Cost efficiency of university hospitals in the Nordic countries: a cross-country analysis. *The European Journal of Health Economics : HEPAC*, **12**, 509–19.

MEHRTAK, M., YUSEFZADEH, H. & JAAFARIPOOYAN, E. (2014). Pabon Lasso and data envelopment analysis: a complementary approach to hospital performance measurement. *Global journal of health science*, **6**, 107.

MELIALA, A., HORT, K. & TRISNANTORO, L. (2013). Addressing the unequal geographic distribution of specialist doctors in Indonesia: The role of the private sector and effectiveness of current regulations. *Social Science and Medicine*, **82**, 30–34.

MENKOKESRA (2013). Keputusan menteri koordinator bidang kesejahteraan rakyat republik Indonesia nomor 54 tahun 2013 tentang rencana pengembangan tenaga kesehatan tahun 2011 - 2025. Menteri Koordinator Bidang Kesejahteraan Rakyat.

MILLER, T. (2009). Mapping the global muslim population: A report on the size and distribution of the world's muslim population. *Washington, DC: Pew Research Center*.

MILLS, A. (2014). Health care systems in low-and middle-income countries. *New England Journal of Medicine*, **370**, 552–557.

MILLS, A., HONGORO, C. & BROOMBERG, J. (1997). Improving the efficiency of district hospitals: is contracting an option? *Tropical Medicine & International Health*, **2**, 116–126.

MILLS, A.J., KAPALAMULA, J. & CHISIMBI, S. (1993). The cost of the district hospital: a case study in Malawi. *Bulletin of the World Health Organization*, **71**, 329–339.

MILSUM, J.H., TURBAN, E. & VERTINSKY, I. (1973). Hospital admission systems: Their evaluation and management. *Management Science (pre-1986)*, **19**, 646.

MINH, H.V., GIANG, K.B., HUONG, D.L., HUONG LE, T., HUONG, N.T., GIANG, P.N., HOAT, L.N. & WRIGHT, P. (2010). Costing of clinical services in rural district hospitals in northern Vietnam. *Int J Health Plann Manage*, **25**, 63–73.

MITROPOULOS, P., MITROPOULOS, I. & SISSOURAS, A. (2013). Managing for efficiency in health care: the case of Greek public hospitals. *The European journal of health economics : HEPAC : health economics in prevention and care*, **14**, 929–938.

MOBLEY, L.R. & MAGNUSSEN, J. (1998). An international comparison of hospital efficiency: does institutional environment matter? *Applied Economics.*, **30**, 1089–1100.

MOGYOROSY, Z. & SMITH, P.C. (2005). *The main methodological issues in costing health care services - a literature review*. Centre for Health Economics.

MOHAMMADKARIM, B., JAMIL, S., PEJMAN, H., SEYYED, M.H. & MOSTAFA, N. (2011). Combining multiple indicators to assess hospital performance in Iran using the Pabon Lasso model. *The Australasian medical journal*, **4**, 175.

MORADI, G., PIROOZI, B., SAFARI, H., ESMAIL NASAB, N., MOHAMADI BOLBANABAD, A. & AREZOO, Y.A.R.I. (2017). Assessment of the efficiency of hospitals before and after the implementation of health sector evolution plan in Iran based on Pabon Lasso model. *Iranian Journal of Public Health*, **46**, 389–95.

MORRIS, S., DEVLIN, N. & PARKIN, D. (2007). *Economic analysis in health care*. John Wiley & Sons.

MORRIS, S.S., FLORES, R., OLINTO, P. & MEDINA, J.M. (2004a). Monetary incentives in primary health care and effects on use and coverage of preventive health care interventions in rural honduras: cluster randomised trial. *The Lancet*, **364**, 2030 – 2037.

MORRIS, S.S., OLINTO, P., FLORES, R., NILSON, E.A.F. & FIGUEIRÓ, A.C. (2004b). Conditional cash transfers are associated with a small reduction in the rate of weight gain of preschool children in northeast Brazil. *The Journal of Nutrition*, **134**, 2336–2341.

MUHARROMAH, O. (2011). *Perbandingan antara Metode Pembayaran INA-DRG dengan FFS terhadap Efisiensi dan Mutu Layanan untuk Kasus Sectio Caesaria di RSUD Kota Bandung 2010*. Ph.D. thesis, Universitas Indonesia, Jakarta.

MUJASI, P.N., ASBU, E.Z. & PUIG-JUNOY, J. (2016). How efficient are referral hospitals in Uganda? a data envelopment analysis and Tobit regression approach. *BMC Health Services Research*, **16**, 230.

MUNDIHARNO & THABRANY, H. (2012). *Peta jalan menuju jaminan kesehatan nasional 2012-2019*. Dewan Jaminan Sosial Nasional, Jakarta: Indonesia.

MUTTER, R.L., GREENE, W.H., SPECTOR, W., ROSKO, M.D. & MUKAMEL, D.B. (2013). Investigating the impact of endogeneity on inefficiency estimates in the application of stochastic frontier analysis to nursing homes. *Journal of Productivity Analysis*, **39**, 101–110.

NEDELEA, I.C. & FANNIN, J.M. (2012). Efficiency analysis of rural hospitals: Parametric and semi-parametric approaches. In *2012 Annual Meeting, February 4-7, 2012, Birmingham, Alabama*, Southern Agricultural Economics Association.

NEDELEA, I.C. & FANNIN, J.M. (2013). Technical efficiency of critical access hospitals: An application of the two-stage approach with double bootstrap. *Health Care Management Science*, **16**, 27–36.

NICHOLSON, W. & SNYDER, C. (2007). *Theory and Application of Intermediate Microeconomics*. Thomson/South-Western, Mason, OH, 10th edn.

NORDYKE, R.J. (2002). Determinants of phc productivity and resource utilization: a comparison of public and private physicians in macedonia. *Health Policy*, **60**, 67 – 96.

NOVIGNON, J. & NONVIGNON, J. (2017). Improving primary health care facility performance in Ghana: efficiency analysis and fiscal space implications. *BMC Health Services Research*, **17**, 399.

OANDA (2015). Currency converter foreign exchange rates OANDA.

OBURE, C.D., JACOBS, R., GUINNESS, L., MAYHEW, S. & VASSALL, A. (2016). Does integration of hiv and sexual and reproductive health services improve technical efficiency in Kenya and Swaziland? an application of a two-stage semi parametric approach incorporating quality measures. *Social Science and Medicine*, **151**, 147–156.

OECD (2010). *Health Care Systems: Efficiency and Policy Settings,*. OECD Publishing.

OECD/WHO (2014). *Health at a glance: Asia/Pacific 2014 - Measuring progress towards universal health coverage*. OECD Publishing.

OLUKOGA, A. & HARRIS, G. (2005). Costs of district hospitals in South Africa. *Journal of Interdisciplinary Economics*, **16**, 431–440.

ORACH, C.G. (2009). Health equity: challenges in low income countries. *African health sciences*, **9 Suppl 2**, S49—51.

OSAKI, K., KOSEN, S., INDRIASIH, E., PRITASARI, K. & HATTORI, T. (2015). Factors affecting the utilisation of maternal, newborn, and child health services in Indonesia: the role of the maternal and child health handbook. *Public Health*, **129**, 582–586.

OSEI, D., D'ALMEIDA, S., GEORGE, M.O., KIRIGIA, J.M., MENSAH, A.O. & KAINYU, L.H. (2005). Technical efficiency of public district hospitals and health centres in Ghana: a pilot study. *Cost Effectiveness and Resource Allocation*, **3**, 9.

OZGEN, H. & SAHIN, I. (2010). Measurement of efficiency of the dialysis sector in Turkey using data envelopment analysis. *Health policy (Amsterdam, Netherlands)*, **95**, 185–193.

ÖZGEN NARCI, H., OZCAN, Y.A., ŞAHIN, İ., TARCAN, M. & NARCI, M. (2015). An examination of competition and efficiency for hospital industry in Turkey. *Health Care Management Science*, **18**, 407–418.

O'NEILL, L., RAUNER, M., HEIDENBERGER, K. & KRAUS, M. (2008). A cross-national comparison and taxonomy of DEA-based hospital efficiency studies. *Socio-Economic Planning Sciences*, **42**, 158–189.

PALMER, S. & TORGERSON, D.J. (1999). Definitions of efficiency. *BMJ : British Medical Journal*, **318**, 1136–1136.

PAN, X., DIB, H.H., WANG, X. & ZHANG, H. (2006). Service utilization in community health centers in China: a comparison analysis with local hospitals. *BMC Health Services Research*, **6**, 93.

PARMETER, C.F. & KUMBHAKAR, S.C. (2014). Efficiency analysis: A primer on recent advances. *Foundations and Trends® in Econometrics*, **7**, 191–385.

PAVITRA, P. (2013). Productive efficiency analysis of primary healthcare services in Afghanistan: a DEA study. *International Journal of Behavioural and Healthcare Research*, **4**, 204–217.

PERLOFF, J.M. (2014). *Microeconomics*. Prentice Hall, Upper Saddle River, 7th edn.

PHAM, T.L. (2011). Efficiency and productivity of hospitals in Vietnam. *Journal of Health, Organisation and Management*, **25**, 195–213.

PILYAVSKY, A. & STAAT, M. (2006). Health care in the CIS countries. *The European Journal of Health Economics*, **7**, 185–191.

PILYAVSKY, A. & STAAT, M. (2008). Efficiency and productivity change in Ukrainian health care. *Journal of Productivity Analysis*, **29**, 143–154.

PILYAVSKY, A.I., AARONSON, W.E., BERNET, P.M., ROSKO, M.D., VALDMANIS, V.G. & GOLUBCHIKOV, M.V. (2006). East–west: does it make a difference to hospital efficiencies in Ukraine? *Health Economics*, **15**, 1173–1186.

PINDYCK, R.S. & RUBINFELD, D.L. (2008). *Microeconomics*. Pearson Prentice Hall, Upper Saddle River, 7th edn.

PITOCCO, C. & SEXTON, T.R. (2018). Measuring hospital performance using mortality rates: An alternative to the ramr. *International Journal of Health Policy and Management*, **7**, 308–316.

POPAY, J., ROBERTS, H., SOWDEN, A., PETTICREW, M., ARAI, L., RODGERS, M., BRITTEN, N., ROEN, K. & DUFFY, S. (2006). Guidance on the conduct of narrative synthesis in systematic reviews. *ESRC methods programme*, **15**, 047–71.

PRAKASH, V. & ANNAPOORNI, D. (2015). Performance evaluation of public hospitals in Tamil Nadu: DEA approach. *Journal of Health Management*, **17**, 417–424.

PRESIDEN (2017). Peraturan presiden republik Indonesia nomor 4 tahun 2017 tentang wajib kerja dokter spesialis. Menteri Hukum dan Hak Asasi Manusia Republik Indonesia.

PRINJA, S., JEET, G., KAUR, M., AGGARWAL, A.K., MANCHANDA, N. & KUMAR, R. (2014). Impact of referral transport system on institutional deliveries in Haryana, India. *The Indian Journal of Medical Research*, **139**, 883–91.

PUENPATOM, R.A. & ROSENMAN, R. (2008). Efficiency of thai provincial public hospitals during the introduction of universal health coverage using capitation. *Health Care Management Science*, **11**, 319–338.

PUSPITASARI, H.P., FATURROHMAH, A. & HERMANSYAH, A. (2011). Do Indonesian community pharmacy workers respond to antibiotics requests appropriately? *Tropical Medicine and International Health*, **16**, 840–846.

PUTRA, R.S.P., ARIFIN, M.A., NURHAYANI & AMIR, M.Y. (2013). The unit cost analysis based on the relative value unit (RVU) in obstetric and gynecology unit at ajjapange hospital, soppeng district, 2011. *Jurnal AKK*, **2**, 35–41.

RAEI, B., YOUSEFI, M., RAHMANI, K., AFSHARI, S. & AMERI, H. (2017). Patterns of productivity changes in hospitals by using malmquist-DEA index: A panel data analysis (2011-2016). *Australasian Medical Journal*, **10**, 856–864.

RAHMAN, M.A. & CAPITMAN, J.A. (2012). Factors affecting profit efficiency of private hospitals in Bangladesh: Are urban hospitals more profit-efficient? *Journal of Health Management*, **14**, 83–96.

RAJASULOCHANA, S. & DASH, U. (2012). Technical efficiency of comprehensive emergency obstetric and new-born care centres in Tamil Nadu. *Journal of Health Management*, **14**, 151–160.

RAMANATHAN, T.V., CHANDRA, K.S. & THUPENG, W.M. (2003). A comparison of the technical efficiencies of health districts and hospitals in Botswana. *Development Southern Africa*, **20**, 307–320.

RAMOS, M.C.D.A., CRUZ, L.P.D., KISHIMA, V.C., POLLARA, W.M., LIRA, A.C.O.D. & COUTTOLENC, B.F. (2015). Performance evaluation of hospitals that provide care in the public health system, Brazil. *Revista de saude publica*, **49**, 1–9.

RATKOVIC, B., ANDREJIC, M. & VIDOVIC, M. (2012). Measuring the efficiency of a healthcare waste management system in Serbia with data envelopment analysis. *Waste Management & Research*, **30**, 635–638, pMID: 22081381.

RATTANACHOTPHANIT, T., LIMWATTANANON, C., LIMWATTANANON, S., JOHNS, J.R., SCHOMMER, J.C. & BROWN, L.M. (2008). Assessing the efficiency of hospital pharmacy services in thai public district hospitals. *Southeast Asian Journal of Tropical Medicine and Public Health*, **39**, 753–765.

RAZZAQ, S., CHAUDHARY, A.A. & KHAN, A.R. (2013). Efficiency analysis of basic health units: a comparison of developed and deprived regions in Azad Jammu and Kashmir. *Iranian Journal of Public Health*, **42**, 1223–1231.

REE, M.J. & CARRETTA, T.R. (2006). The role of measurement error in familiar statistics. *Organizational Research Methods*, **9**, 99–112.

RENNER, A., KIRIGIA, J.M., ZERE, E.A., BARRY, S.P., KIRIGIA, D.G., KAMARA, C. & MUTHURI, L.H. (2005). Technical efficiency of peripheral health units in Pujehun district of Sierra Leone: a DEA application. *BMC Health Services Research*, **5**, 77.

ROKX, C. (2009). *Health financing in Indonesia: a reform road map*. World bank publications.

ROKX, C. (2010). *New insights into the provision of health services in Indonesia: a health workforce study*. World Bank Publications.

ROSANO, A., LOHA, C.A., FALVO, R., VAN DER ZEE, J., RICCIARDI, W., GUASTICCHI, G. & DE BELVIS, A.G. (2013). The relationship between avoidable hospitalization and accessibility to primary care: a systematic review. *European Journal of Public Health*, **23**, 356–360.

ROSKO, M.D. (1990). Measuring technical efficiency in health care organizations. *Journal of Medical Systems*, **14**, 307–22.

ROSKO, M.D. & MUTTER, R.L. (2008). Review: Stochastic frontier analysis of hospital inefficiency - a review of empirical issues and an assessment of robustness. *Medical Care Research and Review*, **65**, 131–166.

ROSKO, M.D. & MUTTER, R.L. (2010). Inefficiency differences between critical access hospitals and prospectively paid rural hospitals. *Journal of Health Politics, Policy and Law*, **35**, 95–126.

ROUTH, S., THWIN, A.A., BARB, N. & BEGUM, A. (2004). Cost efficiency in maternal and child health and family planning service delivery in Bangladesh: implications for NGOs. *Health Policy and Planning*, **19**, 11–21.

RUIZ-RODRIGUEZ, M., RODRIGUEZ-VILLAMIZAR, L.A. & HEREDIA-PI, I. (2016). Technical efficiency of women's health prevention programs in Bucaramanga, Colombia: a four-stage analysis. *BMC Health Services Research*, **16**, 576.

SAGRESTANO, L.M., CLAY, J., FINERMAN, R., GOOCH, J. & RAPINO, M. (2014). Transportation vulnerability as a barrier to service utilization for HIV-positive individuals. *AIDS Care*, **26**, 314–319, pMID: 23876086.

SAHIN, I. & OZCAN, Y.A. (2000). Public sector hospital efficiency for provincial markets in Turkey. *Journal of Medical Systems*, **24**, 307–320.

SARI, D.K. (1999). *Efisiensi Biaya Layanan di Instalasi Rawat Jalan Gigi dan Mulut Rumah Sakit dr. Hasan Sadikin Bandung tahun 1998*. Ph.D. thesis, Universitas Indonesia, Jakarta.

SARI, D.P., ARIFA'I, M. & HENDRARTINI, J. (2013). Unit cost of mother and child outpatient care for determining subsidy in a maternal and child hospital. *Jurnal Manajemen Pelayanan Kesehatan*, **16**, 20–23.

SARI, K., SOEWONDO, P., NADJIB, M., YUNITA, PARDEDE, D., KOMARYANI, K., INDAHSARI, L.N. & WULANDHANI, A. (2015). Indonesia NHA update 2013. In *The 47th Asia-Pacific Academic Consortium for Public Health Conference*, Asia-Pacific Academic Consortium, Bandung, Indonesia.

SARMA, S. (2009). Demand for outpatient healthcare. *Applied Health Economics and Health Policy*, **7**, 265–277.

SCHMIDT, J.O., ENSOR, T., HOSSAIN, A. & KHAN, S. (2010). Vouchers as demand side financing instruments for health care: A review of the Bangladesh maternal voucher scheme. *Health Policy*, **96**, 98 – 107.

SCHMIDT, S.S. (2008). *The measurement of productive efficiency and productivity growth*. Oxford University Press.

SCHÜTTE, C., CHANSA, C., MARINDA, E., GUTHRIE, T.A., BANDA, S., NOMBEWU, Z., MOTLOGELWA, K., LERVIK, M., BRENZEL, L. & KINGHORN, A. (2015). Cost analysis of routine immunisation in Zambia. *Vaccine*, **33**, A47 – A52.

SCOTT, S., CHOWDHURY, M.E., PAMBUDI, E.S., QOMARIYAH, S.N. & RONSMANS, C. (2013). Maternal mortality, birth with a health professional and distance to obstetric care in Indonesia and Bangladesh. *Tropical Medicine and International Health*, **18**, 1193–1201.

SEALE, H., MEI, N.S., ATTHOBARI, J., HEYWOOD, A.E., KAUR, R., MACINTYRE, R.C., SOENARTO, Y. & RETNA, S.P. (2015). Knowledge and attitudes towards rotavirus diarrhea and the vaccine amongst healthcare providers in Yogyakarta Indonesia. *BMC Health Services Research*, **15**.

SEPEHRDUST, H. & RAJABI, E. (2013). Technical efficiency measurement of social security hospitals. *Journal of School of Public Health & Institute of Public Health Research*, **10**, Pe91–Pe98.

SHADE, S.B., KEVANY, S., ONONO, M., OCHIENG, G., STEINFELD, R.L., GROSSMAN, D., NEWMANN, S.J., BLAT, C., BUKUSI, E.A. & COHEN, C.R. (2013). Cost, cost-efficiency and cost-effectiveness of integrated family planning and hiv services. *AIDS (London, England)*, **27 Suppl 1**, S87–92.

SHAHHOSEINI, R., TOFIGHI, S., JAAFARIPOOYAN, E. & SAFIARYAN, R. (2011). Efficiency measurement in developing countries: application of data envelopment analysis for Iranian hospitals. *Health Services Management Research*, **24**, 75–80, pMID: 21471577.

SHEPARD, D.S., ANTHONY, Y.E. & HODGKIN, D. (2000). *Analysis of hospital costs: a manual for managers*. World Health Organization, Geneva.

SHETTIAN, M. (2017). *Determinants of Hospital Efficiency and Patient Safety in the United States*. Electronic theses and dissertations, Public Affairs; Health Services Management and Research.

SHONO, A., KONDO, M., OHMAE, H. & OKUBO, I. (2014). Willingness to pay for public health services in rural Central Java, Indonesia: methodological considerations when using the contingent valuation method. *Social science & medicine (1982)*, **110**, 31–40.

SHREAY, S., MA, M., MCCLUSKEY, J., MITTELHAMMER, R.C., GITLIN, M. & STEPHENS, J.M. (2014). Efficiency of U.S. dialysis centers: An updated examination of facility characteristics that influence production of dialysis treatments. *Health Services Research*, **49**, 838–857.

SIDIK, N.A., LAZUARDI, L., AGUNG, F.H., PRITASARI, K., ROESPANDI, H., SETIAWAN, T., PAWITRO, U., NURHAMZAH, W. & WEBER, M.W. (2013). Assessment of the quality of hospital care for children in Indonesia. *Tropical medicine & international health : TM & IH*, **18**, 407–15.

SILVA, E.N.D. & POWELL-JACKSON, T. (2017). Does expanding primary healthcare improve hospital efficiency? evidence from a panel analysis of avoidable hospitalisations in 5506 municipalities in Brazil, 2000–2014. *BMJ Global Health*, **2**.

SIMAR, L. (2007). How to improve the performances of DEA/FDH estimators in the presence of noise? *Journal of Productivity Analysis*, **28**, 183–201.

SIMAR, L. & WILSON, P.W. (2011). Two-stage DEA: caveat emptor. *Journal of Productivity Analysis*, **36**, 205.

SMITH, M.W. & BARNETT, P.G. (2003). Direct measurement of health care costs. *Medical Care Research and Review*, **60**, 74S–91S, pMID: 15095547.

SOCHA, K.Z. & BECH, M. (2011). Physician dual practice: A review of literature. *Health Policy*, **102**, 1 – 7.

SOEWONDO, P., NADJIB, M., SARI, K., YUNITA & AFDHILA, N. (2011). Sha-based health accounts in the asia-pacific region: Indonesia 2005–2009. Tech. rep., OECD-Korea Policy Center, Seoul, Republic of Korea.

SOMANATHAN, A., HANSON, K., DORABAWILA, T. & PERERA, B. (2000). *Operating Efficiency in Public Sector Health Facilities in Sri Lanka: Measurement and Institutional Determinants of Performance*. Partnerships for Health Reform Project, Abt Associates.

SOUCAT, A., LEVY-BRUHL, D., DE BETHUNE, X., GBEDONOU, P., LAMARQUE, J.P., BANGOURA, O., CAMARA, O., GANDAHO, T., ORTIZ, C., KADDAR, M. & KNIPPENBERG, R. (1997). Affordability, cost-effectiveness and efficiency of primary health care: the bamako initiative experience in Benin and Guinea. *International Journal of Health Planning & Management*, **12 Suppl 1**, S81–108.

SPARROW, R. & VOTHKNECHT, M. (2011). Report on infrastructure supply readiness in Indonesia - achievements and remaining gaps. Tech. rep., Coordinating Ministry for People's Welfare in cooperation with TNP2K and PNPM Support Facility, Jakarta.

SPERANDEI, S. (2014). Understanding logistic regression analysis. *Biochemia medica*, **24**, 12–18.

SPINKS, J. & HOLLINGSWORTH, B. (2009). Cross-country comparisons of technical efficiency of health production: a demonstration of pitfalls. *Applied Economics*, **41**, 417–427.

ST-HILAIRE, C. & CREPEAU, P.K. (2000). Hospital and unit cost allocation methods.[erratum appears in healthc manage forum 2000 winter;13(4):31]. *Healthcare Management Forum*, **13**, 12–32.

STARFIELD, B. (1994). Is primary care essential? *The Lancet*, **344**, 1129–1133.

STARFIELD, B., SHI, L. & MACINKO, J. (2005). Contribution of primary care to health systems and health. *The Milbank Quarterly*, **83**, 457–502.

STIGLER, F.L., MACINKO, J., PETTIGREW, L.M., KUMAR, R. & VAN WEEL, C. (2016). No universal health coverage without primary health care. *The Lancet*, **387**, 1811.

STOCK, R. (1983). Distance and the utilization of health facilities in rural Nigeria. *Social Science & Medicine*, **17**, 563 – 570.

SULISTYORINI, N. & MOEDIARSO, B. (2012). Analisis biaya unit pelayanan otopsi dengan metode distribusi ganda. *Jurnal Kedokteran Forensik Indonesia*, **14**, 65–72.

SULKU, S.N. (2012). The health sector reforms and the efficiency of public hospitals in Turkey: provincial markets. *European Journal of Public Health*, **22**, 634–638.

SUPRABA, A. (2014). *Analisis implementasi kebijakan efisiensi terhadap biaya tindan apendiktomi tanpa komplikasi di Rumah Sakit Islam Arafah Jambi tahun 2014*. Ph.D. thesis, Universitas Indonesia, Jakarta.

SUSCA, P., ACHIMAS, A., IANCU, M., URDA-CÎMPEAN, A. & DRUGAN, T.C. (2012). Evaluation of the efficiency of economic and medical activities in romanian hospitals. *Applied Medical Informatics*, **30**, 34–40.

SØRENSEN, M.L.K. & BURAU, V. (2016). Why we need to move beyond diagnosis-related groups and how we might do so. *Journal of Health Services Research & Policy*, **21**, 64–66, pMID: 25972360.

TAGUCHI, N., KAWABATA, M., MAEKAWA, M., MARUO, T., ADITIAWARMAN & DEWATA, L. (2003). Influence of socio-economic background and antenatal care programmes on maternal mortality in Surabaya, Indonesia. *Tropical Medicine and International Health*, **8**, 847–852.

THABRANY, H. (2011). *Asuransi Kesehatan Nasional*. PAMJAKI, Jakarta.

THABRANY, H. (2017). Performance based capitation. In *International Health Economic Association Conference*, Universitas Indonesia, Boston.

THE WORLD BANK (2008). Investing in Indonesia's health: Challenges and opportunities for future public spending. The World Bank Office Jakarta.

THE WORLD BANK (2015a). Country and lending groups. The World Bank, accessed 8 Jun. 2015.

THE WORLD BANK (2015b). GNI per capita (constant 2005 US$). The World Bank, accessed 5 Jul. 2015.

THE WORLD BANK (2015c). Population growth (annual %) data. The World Bank, accessed 5 Jul. 2015.

THE WORLD BANK (2016). GDP per capita (current US$). The World Bank, accessed 29 Feb. 2016.

THE WORLD BANK (2017). Second annual UHC financing forum greater efficiency for better health and financial protection. Background paper, The World Bank, Washington.

THE WORLD BANK (2018). Health expenditure per capita (current US$). The World Bank, accessed 6 Mar. 2018.

THOMASON, J.A. & MITCHELL, M.D. (1991). Cost analysis in health planning and management in Papua New Guinea. *Asia Pacific Journal of Public Health*, **5**, 239–244, pMID: 1823808.

TITALEY, C.R., HUNTER, C.L., DIBLEY, M.J. & HEYWOOD, P. (2010a). Why do some women still prefer traditional birth attendants and home delivery?: a qualitative study on delivery care services in west java province, Indonesia. *BMC pregnancy and childbirth*, **10**, 43.

TITALEY, C.R., HUNTER, C.L., HEYWOOD, P. & DIBLEY, M.J. (2010b). Why don't some women attend antenatal and postnatal care services?: a qualitative study of community members' perspectives in Garut, Sukabumi and Ciamis districts of West Java Province, Indonesia. *BMC pregnancy and childbirth*, **10**, 61.

TJAHJANTO, A. (2016). *Metode lean thinking untuk meningkatkan efisiensi pelayanan rawat jalan di Rumah Sakit Sumber Waras Ciwaringin tahun 2015*. Ph.D. thesis, Universitas Indonesia, Jakarta.

TLOTLEGO, N., NONVIGNON, J., SAMBO, L.G., ASBU, E.Z. & KIRIGIA, J.M. (2010). Assessment of productivity of hospitals in Botswana: a DEA application. *International Archives of Medicine*, **3**, 27.

TNP2K (2015). JKN: Perjalanan menuju kesehatan nasional. Tech. rep., Tim Nasional Percepatan Penanggulangan Kemiskinan, Jakarta, Indonesia.

TORABIPOUR, A., NAJARZADEH, M., MOHAMMAD, A.R.A.B., FARZIANPOUR, F. & GHASEMZADEH, R. (2014). Hospitals productivity measurement using data envelopment analysis technique. *Iranian Journal of Public Health*, **43**, 1576–81.

TSIKRIKTSIS, N. (2005). A review of techniques for treating missing data in om survey research. *Journal of Operations Management*, **24**, 53–62.

VARABYOVA, Y. & SCHREYOGG, J. (2013). International comparisons of the technical efficiency of the hospital sector: panel data analysis of oecd countries using parametric and non-parametric approaches. *Health Policy.*, **112**, 70–79.

VARIAN, H.R. (2010). *Intermediate microeconomics : a modern approach*. W.W. Norton, New York, 8th edn.

VOGEL, J.P., BETRÁN, A.P., WIDMER, M., SOUZA, J.P., GÜLMEZOGLU, A.M., SEUC, A., TORLONI, M.R., MENGESTU, T.K. & MERIALDI, M. (2012). Role of faith-based and nongovernment organizations in the provision of obstetric services in 3 African countries. *American Journal of Obstetrics and Gynecology*, **207**, 495.e1 – 495.e7.

WALKER, D. (2006). Efficiency of primary health care in low and middle-income countries : case studies from Bangladesh, uk.bl.ethos.430775.

WANG, H.J. & SCHMIDT, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, **18**, 129–144.

WANG, M.L., FANG, H.Q., TAO, H.B., CHENG, Z.H., LIN, X.J., CAI, M., XU, C. & JIANG, S. (2017). Bootstrapping data envelopment analysis of efficiency and productivity of county public hospitals in eastern, central, and western China after the public hospital reform. *Journal of Huazhong University of Science and Technology [Medical Sciences]*, **37**, 681–692.

WEAVER, M. & DEOLALIKAR, A. (2004). Economies of scale and scope in Vietnamese hospitals. *Social science & medicine (1982)*, **59**, 199–208.

WEI, Y., YU, H., GENG, J., WU, B., GUO, Z., HE, L. & CHEN, Y. (2018). Hospital efficiency and utilization of high-technology medical equipment: A panel data analysis. *Health Policy and Technology.*.

WHO (2000). *The world health report 2000: health systems: improving performance*. World Health Organization.

WHO (2010). The world health report health systems financing the path to universal coverage. Tech. Rep. 978 92 4 156402 1, World Health Organization, Geneva.

WHO (2014). World health statistics 2014. Tech. rep., World Health Organization, Italy.

WHO (2015a). Achieving the health-related Millennium Development Goals in the South-East Asia Region: measuring indicators 2014. Tech. rep., World Health Organization, India.

WHO (2015b). Diphtheria tetanus toxoid and pertussis (DTP3) data by world bank income group. World Health Organization.

WHO (2015c). Indonesia: Who statistical profile. World Health Organization.

WIBOWO, B. (2014). *Analisis Efisiensi pada Selisih Klaim INA-CBG dengan Pendapatan Rumah Sakit di 4 Rumah Sakit Kelas A Studi Kasus Persalinan Sectio Caesarea*. Ph.D. thesis, Universitas Indonesia, Jakarta.

WIDAYATI, A., SURYAWATI, S., DE CRESPIGNY, C. & HILLER, J.E. (2015). Beliefs about the use of nonprescribed antibiotics among people in yogyakarta city, Indonesia: a qualitative study based on the theory of planned behavior. *Asia-Pacific journal of public health / Asia-Pacific Academic Consortium for Public Health*, **27**, NP402–13.

WIDYAWATI, W., JANS, S., UTOMO, S., VAN, J. & JANSSEN, A.L.M.L. (2015). A qualitative study on barriers in the prevention of anaemia during pregnancy in public health centres: perceptions of Indonesian nurse-midwives. *BMC pregnancy and childbirth*, **15**, 47.

WILSON, P.W. (2008). Fear: A software package for frontier efficiency analysis with r. *Socio-economic planning sciences*, **42**, 247–254.

WINPENNY, E.M., MIANI, C., PITCHFORTH, E., KING, S. & ROLAND, M. (2017). Improving the effectiveness and efficiency of outpatient services: a scoping review of interventions at the primary-secondary care interface. *Journal of Health Services Research & Policy*, **22**, 53–64.

WITTER, S., ENSOR, T., THOMPSON, R. & JOWETT, M. (2000). *Health economics for developing countries. A practical guide*. MacMillan Education, Malaysia.

WONG, R. & BRADLEY, E.H. (2009). Developing patient registration and medical records management system in Ethiopia. *International Journal for Quality in Health Care*, **21**, 253–258.

WORTHINGTON, A.C. (2004). Frontier efficiency measurement in healthcare : A review of empirical techniques and selected applications. *Medical Care Research and Review*, **61**.

WOUTERS, A. (1993). The cost and efficiency of public and private health care facilities in Ogun state, Nigeria. *Health Economics*, **2**, 31–42.

XENOS, P., YFANTOPOULOS, J., NEKTARIOS, M., POLYZOS, N., TINIOS, P. & CONSTANTOPOULOS, A. (2017). Efficiency and productivity assessment of public hospitals in Greece during the crisis period 2009–2012. *Cost Effectiveness and Resource Allocation : C/E*, **15**, 6.

XU, G.C., ZHENG, J., ZHOU, Z.J., ZHOU, C.K. & ZHAO, Y. (2015). Comparative study of three commonly used methods for hospital efficiency analysis in Beijing tertiary public hospitals, China. *Chinese Medical Journal*, **128**, 3185–3190.

YAGUB, A.I.A. & MTSHALI, K. (2015). The role of non-governmental organizations in providing curative health services in North Darfur State, Sudan. *African Health Sciences*, **15**, 1049–55.

YANG, J. & ZENG, W. (2014). The trade-offs between efficiency and quality in the hospital production: Some evidence from Shenzhen, China. *China Economic Review*, **31**, 166–184.

YAO, J., MURRAY, A.T. & AGADJANIAN, V. (2013). A geographical perspective on access to sexual and reproductive health care for women in rural Africa. *Social Science & Medicine*, **96**, 60 – 68.

YAWE, B. (2010). Hospital performance evaluation in Uganda: a super-efficiency data envelope analysis model. *Zambia Social Science Journal*, **1**, 6.

YIP, W. & HSIAO, W. (2014). Harnessing the privatisation of China's fragmented health-care delivery. *The Lancet*, **384**, 805–818.

YUSEFZADEH, H., GHADERI, H., BAGHERZADE, R. & BAROUNI, M. (2013). The efficiency and budgeting of public hospitals: Case study of Iran. *Iranian Red Crescent Medical Journal*, **15**, 393–9.

ZAIM, S., BAYYURT, N., TURKYILMAZ, A., SOLAKOGLU, N. & ZAIM, H. (2008). Measuring and evaluating efficiency of hospitals through total quality management. *Journal of Transnational Management*, **12**, 77–97.

ZENG, W., RWIYEREKA, A.K., AMICO, P.R., ÁVILA FIGUEROA, C. & SHEPARD, D.S. (2014). Efficiency of HIV/AIDS health centers and effect of community-based health insurance and performance-based financing on HIV/AIDS service delivery in Rwanda. *The American Journal of Tropical Medicine and Hygiene*, **90**, 740–6.

ZERE, E., MCINTYRE, D. & ADDISON, T. (2001). Technical efficiency and productivity of public sector hospitals in three South African provinces*. *South African Journal of Economics*, **69**, 336–358.

ZERE, E., MBEELI, T., SHANGULA, K., MANDLHATE, C., MUTIRUA, K., TJIVAMBI, B. & KAPENAMBILI, W. (2006). Technical efficiency of district hospitals: Evidence from Namibia using data envelopment analysis. *Cost Effectiveness and Resource Allocation*, **4**, 5.

ZHAO, Y., THOMAS, S.L., GUTHRIDGE, S.L. & WAKERMAN, J. (2014). Better health outcomes at lower costs: the benefits of primary care utilisation for chronic disease management in remote indigenous communities in Australia's Northern Territory. *BMC health services research*, **14**, 1.

Appendix A

Appendix related to Chapter 3

Table A.1: Input variables from empirical studies

		Input Variable	Measurement
Physical inputs	Capital	Beds	- Number of beds (active) - Staffed-beds - Number of beds in density per 1000 population
		Equipment	Number of technical equipment, e.g. number of haemodialysis machine, MRI, etc.
		Health facility space	Measure is square meters
	Labour/ Material	-Total staff - Physicians - Nurses - Technicians - Mix of medical staff - Specialist - Other/ administrative staff	- Number of staff - Density per 1000 people; - Full time equivalent (FTE)
Financial inputs	All	Total cost	- Annual cost - Cost index
	Labour/ Material	Operational cost	Annual cost
		Price for Labour	Average salary of staff per year
		Drugs and medical supplies	- Number of prescriptions per capita - Expenditure on drugs and medical supplies
	Capital	Price for office space	Price per m2
		Capital/ equipment cost	Average of lease, depreciation, and interest per bed

Source: Besstremyannaya (2013); Chowdhury *et al.* (2014); Ding (2014); Gok & Sezen (2013); Heimeshoff *et al.* (2014); Nedelea & Fannin (2013); Jacobs (2001); Kirigia & Asbu (2013); Matranga & Sapienzab (2015); Mitropoulos *et al.* (2013); Mobley & Magnussen (1998); Mutter *et al.* (2013); Ineveld *et al.* (2015); Varabyova & Schreyogg (2013); Yang & Zeng (2014); Shreay *et al.* (2014)

Table A.2: Output variables from empirical studies

	Output variable	Measurement
Activity output	Outpatient visit	- Total number of visits including emergency, as well as intermediate department such as radiology, laboratory, etc. - Number of visit by department, such as emergency, surgery, etc. - Number of visit / capita
	Discharges	- Number of discharge/ admission - Discharges rates (density per 1000 population) aggregated by case severity - Case mix adjusted admissions
	Inpatient days	- Number of days - Days in different age groups: children, adult, elderly - Case mix adjusted patient days
	Inpatient utilisation	- Bed occupancy rate - Bed turnover rate
	Delivery	- Number of births
	Laboratory	- Number of examination/ test
Quality-output	Undesirable output	- Mortality= 1-average mortality per 100 patients or mortality rate (%)*-1 - Inappropriate discharge rate
	Undesirable admission	- Readmission rate
	Complication	- Percentage of decubitus
	Health target	- Fulfil specific health targets, such as vaccination, initial antibiotic timing

Source: Besstremyannaya (2013); Cordero Ferrera *et al.* (2014); Ding (2014); Gok & Sezen (2013); Heimeshoff *et al.* (2014); Nedelea & Fannin (2013); Kirigia & Asbu (2013); Matranga & Sapienzab (2015); Mobley & Magnussen (1998); Mutter *et al.* (2013); Ineveld *et al.* (2015); Varabyova & Schreyogg (2013); Yang & Zeng (2014)

Table A.3: Contextual variables from empirical studies

Contextual variable	Measurement
External factors	
Health expenditure	- Total health expenditure per capita USD PPP % of GDP - Health facility expenditure per capita USD PPP % of GDP - Private health expenditure % of health expenditure
Economic	- Inequality: Gini coefficient after taxes - Population employed in agriculture - Replacement rate - Median household income - % of population below poverty line
Market competition	- Number of health facilities by density per million population - Herfindahl-Hirschman Index (HHI) - % for profit health facilities in market - % of publicly owned health facilities
Education	- Population with upper secondary education, in density per 1000 population - % of people with education $<$9 years
Demographic	- Ageing population: % of population aged $\geqslant$ 65 of total population - Ageing population ratio - Crude birth rate - Dependency rate - Population density - % of ethnic such as Hispanic, African American
Health status	- Life expectancy at birth in year - Infant mortality rate: deaths per 1000 live births
Geography	- Location: Urban rural - Regional: North, south, west, east - Geopolitics: State - Non profitable area ($<$100 inpatient-day per day; only 1 general hospital in local municipal or within 300 km2)
Health insurance	- Health insurance population coverage
Year	- Year observational
Internal factors	
Utilisation	- ALOS in Days or Difference in length of stay (DLOS)= LOS – mean LOS

Contextual variable	Measurement
	- Bed occupancy rate (BOR) - Outpatient visits as a proportion of inpatient days
Degree of specialisation	- Proportion of non-specialist physician FTE - Proportion of specialists FTE, such as paediatricians, internists, psychologists/ psychiatrists, other
Ownership	- Public, private - Profit status
Size and capacity	- Small ($<$100 beds); medium (up to 500); large ($>$200) - Share of emergency beds (%)
Teaching status	- Teaching health facility, which has affiliated college
Quality	- Received accreditation/ quality certification - Structural quality - Participation in disease management program
System affiliation	- Affiliated with multi health facilities - Solo or group practice
Case mix index	- DRG index - Female patient ratio - Seventy-five years old patient ratio
Experience	- Cumulative patient volume - Age of health facility - Experience of medical staff in days
Funding issue	- Share of patients covered by social health insurance, such as % of Medicare, Medicaid admission - Government subsidy per bed - Drug margin ratio : Reimbursement of the cost prescribed drugs over the cost of prescribed drugs

USD: United States dollar; GDP: Gross domestic product; PPP: Purchasing power parity; DRG: Diagnostic related group; BOR: Bed occupancy rate; FTE: Full time equivalent; ALOS: Average length of stay; LOS: Length of stay; HHI: Herfindahl-Hirschman Index

Source:Besstremyannaya (2013); Cordero Ferrera *et al.* (2014); Ding (2014); Herr (2008); Gok & Sezen (2013); OECD (2010); 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)

Table A.4: Variables used in hospitals

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<. Unique values	Min	Max	Source
Utilisation									
outpatients	Number of outpatient visits	Continuous	4	0	198	195	0.00	708,181.60	HFCS
admissions1	Number of admissions	Continuous	10	0	192	191	293.33	36,735.00	HFCS
bed_days	Number of bed days	Continuous	6	0	196	196	1,581.33	203,273.30	HFCS
bed_occ	Bed occupancy rate	Continuous	6	0	196	196	0.08	3.77	HFCS
throughput	Admission per bed	Continuous	11	0	191	191	5.24	213.58	HFCS
alos	Average length of stay	Continuous	2	0	200	194	1.35	70.88	HFCS
tot_surgery	Number of total surgery	Continuous	4	0	198	176	0.00	18,040.00	HFCS
Size and capacity									
gp_FTE	General practitioners and dentist full time equivalent	Continuous	2	0	200	186	0.00	67.94	HFCS
med_spec_FTE	Medical specialist full time equivalent including internal medicine, paediatrician, neurologist, psychiatrist, dermatologist, dentist specialist, anaesthetist, rehabilitation physicians, other medical specialist.	Continuous	2	0	200	179	0.00	99.31	HFCS
sur_spec_FTE	Surgical specialist full time equivalent including general surgeon, neurosurgeon, obstetrics and gynaecology, ear nose throat specialist, ophthalmologist eye	Continuous	2	0	200	157	0.00	51.85	HFCS
major_spec E	Major specialist full time equivalent including internal medicine, general surgeon, paediatrician, obstetrics and gynaecology.	Continuous	2	0	200	167	0.00	83.99	HFCS
doctor_no	Number of doctor	Continuous	2	0	200	195	2.00	372.30	HFCS
nurse_total	Number of nurse	Continuous	2	0	200	153	0.00	1,101.00	HFCS
other_prof	Number of other staff	Continuous	2	0	200	134	0.00	668.00	HFCS
beds	Number of beds	Continuous	2	0	200	142	23.00	745.00	HFCS
class	Hospital class	Continuous	3	0	199	4	1.00	4.00	HFCS
Ownership									
publichosp l	Hospital publicly owned	Binary	2	0	200	2	0.00	1.00	HFCS
profit	Profit Hospital for-profit	Binary	2	0	200	2	0.00	1.00	HFCS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
Teaching status									
mou_ed_hos l	Hospital has a MoU/partnership with medical education university	Binary	2	0	200	2	0.00	1.00	HFCS
Case mix									
patients_ 65	% of patient over 65 years old	Continuous	4	0	198	196	0.00	0.62	HFCS
prop_r52f_ n	% of patient 1 to 5 years old	Continuous	7	0	195	195	1.71	28.66	HFCS
ncd_disease	% of non-communicable disease treated	Continuous	2	0	200	195	0.00	100.00	HFCS
caseindex_ip	Inpatient case mix index	Continuous	84	0	118	118	0.67	1.74	INA-CBGs
caseindex_op	Outpatient case mix index	Continuous	83	0	119	119	0.72	2.50	INA-CBGs
Year of services									
experience	Year of services	Continuous	12	0	190	82	3.00	183.00	HFCS
Financing									
poor_ins_o p	% of outpatient with poor scheme insurance	Continuous	44	0	158	158	0.00	0.68	HFCS
poor_ins_i p	% of inpatient with poor scheme insurance	Continuous	38	0	164	164	0.00	1.00	HFCS
poor_ins_b p	% of bed days with poor scheme insurance	Continuous	54	0	148	146	0.00	1.00	HFCS
poor_ins_p p	% of payment with poor scheme insurance	Continuous	62	0	140	127	0.00	1.00	HFCS
comp op_prop	% of outpatient with company insurance	Continuous	123	0	79	79	0.00	0.99	HFCS
comp ip_prop	% of inpatient with company insurance	Continuous	120	0	82	82	0.00	0.99	HFCS
compa d_prop	% of bed days with company insurance	Continuous	133	0	69	69	0.00	0.99	HFCS
compa y_prop	% of payment with company insurance	Continuous	116	0	86	79	0.00	0.99	HFCS
no_ins_op_ p	% of outpatient without insurance	Continuous	19	0	183	172	0.01	1.00	HFCS
no_ins_ip_ p	% of inpatient without insurance	Continuous	18	0	184	178	0.01	1.00	HFCS
no_ins_bd_ p	% of bed days without insurance	Continuous	35	0	167	158	0.01	1.00	HFCS
no_ins_pay p	% of payment without insurance	Continuous	46	0	156	143	0.00	1.00	HFCS
aske op_prop	% of outpatient with Askes insurance	Continuous	56	0	146	146	0.00	0.68	HFCS
aske ip_prop	% of inpatient with Askes insurance	Continuous	44	0	158	158	0.01	1.00	HFCS
askes d_prop	% of bed days with Askes insurance	Continuous	64	0	138	138	0.01	0.74	HFCS
askes y_prop	% of payment with Askes insurance	Continuous	69	0	133	129	0.00	0.74	HFCS
othe op_prop	% of outpatient with other insurance	Continuous	118	0	84	84	0.00	0.69	HFCS
othe ip_prop	% of inpatient with other insurance	Continuous	115	0	87	87	0.00	0.69	HFCS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<. Unique values	Min	Max	Source
other d_prop	% of bed days with other insurance	Continuous	128	0	74	74	0.00	0.69	HFCS
other y_prop	% of payment with other insurance	Continuous	139	0	63	63	0.00	0.96	HFCS
Pharmacy									
generic_prop	% of generic drugs prescribed in hospital	Continuous	21	0	181	178	0.00	1.00	HFCS
nongeneric p	% of non-generic drugs prescribed in hospital	Continuous	21	0	181	175	0.00	1.00	HFCS
Quality									
accredit	Hospital accredited by Indonesian hospital accreditation commission	Binary	5	0	197	2	0.00	1.00	HFCS
water	Water disruption in health facility	Binary	5	0	197	6	1.00	6.00	HFCS
electricity	Electricity disruption in health facility in the past year	Binary	5	0	197	6	1.00	6.00	HFCS
medicines_ g	Medicine disruption in health facility in the past year	Binary	6	0	196	7	0.00	6.00	HFCS
salary_late	Employee salary was late on schedule in the past year	Binary	6	0	196	4	1.00	4.00	HFCS
incentive_ e	Employee incentive was late on schedule in the past year	Binary	7	0	195	4	1.00	4.00	HFCS
performanc t	Regular meetings to discuss the performance of services (medical and management) once per week	Binary	7	0	195	8	1.00	8.00	HFCS
death_meet	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	Binary	7	0	195	8	1.00	8.00	HFCS
mentoring	Mentoring with clinical staffs	Binary	6	0	196	2	1.00	2.00	HFCS
workinghou r	Monitoring of working hours of the employee	Binary	8	0	194	2	1.00	2.00	HFCS
death_rate	Number of death per admission	Continuous	19	0	183	183	0.00	0.04	HFCS
mort_ratio	Ratio of actual number of death over expected number of death	Continuous	84	0	118	118	0.00	1.95	INA-CBGs
management c	Difficulty in filling management vacancy	Binary	14	0	188	2	0.00	1.00	HFCS
doc_vac	Difficulty in filling doctor vacancy	Binary	14	0	188	2	0.00	1.00	HFCS
nurse_vac	Difficulty in filling nurse vacancy	Binary	14	0	188	2	0.00	1.00	HFCS
tech_vac	Difficulty in filling technician vacancy	Binary	14	0	188	2	0.00	1.00	HFCS
other_vac	Difficulty in filling other staff vacancy	Binary	14	0	188	2	0.00	1.00	HFCS
Health Expenditure									

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
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	Continuous	2	0	200	129	1.25	48.68	SUSENAS
pharmacy_exp	Preventive household expenditure for the last three months including expenditure on antenatal care, immunisation, medical check-up, family planning, other preventive expenditure	Continuous	2	0	200	129	1.03	12.51	SUSENAS
preventive p	Pharmacy household expenditure for the last three months including prescribed drugs, drugs without prescription, traditional drugs, glasses, protease, wheel chair.	Continuous	2	0	200	129	0.09	10.48	SUSENAS
totalhealt p	Total household health expenditure for the last three months including curative, preventive, and pharmacy expenditure.	Continuous	2	0	200	129	3.98	69.12	SUSENAS
Economic									
fam_agricu e	Proportion of family working in agriculture	Continuous	2	0	200	129	0.00	0.90	PODES
poor	Proportion of poor population in district	Continuous	2	0	200	129	0.00	0.47	SUSENAS
expend	Total household expenditure	Continuous	2	0	200	129	112.82	490.80	SUSENAS
gini	Gini index in district	Continuous	2	0	200	129	0.24	0.46	SUSENAS
Access to health facility									
hospitalpop	Ratio of hospital, including general hospital and maternal hospital over 1000 population	Continuous	2	0	200	129	0.00	0.19	PODES
primarypop	Ratio of primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post over 1000 population	Continuous	2	0	200	129	0.19	2.26	PODES
hospitaleasy	Proportion of very easy and easy to access hospital, including general hospital and maternal hospital	Continuous	0	0	202	126	0.00	4.00	PODES

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
primaryeasy	Proportion of very easy and easy to access primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post	Continuous	0	0	202	125	0.00	12.00	PODES
Education									
primarysch l	Proportion of population with primary school education in the district	Continuous	2	0	200	129	0.20	0.59	SUSENAS
secondarys l	Proportion of population with secondary school education in the district	Continuous	2	0	200	129	0.16	0.52	SUSENAS
highereduc n	Proportion of population with higher education in the district	Continuous	2	0	200	129	0.02	0.29	SUSENAS
Demography									
populat 2011	Number of population in district for hospital, and sub-district for Puskesmas	Continuous	2	0	200	129	42,319.00	4,626,937.00	PODES
female_per	Proportion of female population	Continuous	2	0	200	129	0.47	1.00	PODES
Health status									
under5_mor e	Ratio of mortality under five years old for the last three years over 1000 population	Continuous	2	0	200	129	0.00	0.56	PODES
maternal_m e	Ratio of maternal mortality for the last three years over 1000 population	Continuous	2	0	200	128	0.00	0.10	PODES
Geography									
island	Health facility located in Java or Bali island	Continuous	0	0	202	5	0.00	4.00	HFCS
Insurance coverage									
askesins	Proportion of household covered by Askes insurance (scheme for civil servant)	Continuous	2	0	200	129	0.03	0.31	SUSENAS
jamsostekins	Proportion of household covered by Jamsostek insurance (scheme for employee)	Continuous	2	0	200	127	0.00	0.40	SUSENAS
privateins	Proportion of household covered by private insurance	Continuous	2	0	200	123	0.00	0.11	SUSENAS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
companyins	Proportion of household covered by company insurance (for employee)	Continuous	2	0	200	126	0.00	0.08	SUSENAS
poorins	Proportion of household covered by poor scheme insurance	Continuous	2	0	200	129	0.01	0.67	SUSENAS
healthfund s	Proportion of household covered by health fund insurance (poor scheme)	Continuous	2	0	200	84	0.00	0.08	SUSENAS
otherins	Proportion of household covered by other health insurance scheme	Continuous	2	0	200	113	0.00	0.67	SUSENAS

HFCS: Health facility costing study; SUSENAS: National Socio-economic survey; PODES: Village Potential Statistics; INA-CBGs: Indonesian-Case Base Groups
Obs=. are counts of system missing values; "Obs>." are counts of extended missing values; and Obs<. are counts of nonmissing values.

Table A.5: Variables used in *Puskesmas*

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
Utilisation									
patients_gen	Number of general outpatient visits	Continuous	0	0	234	232	0.00	79556.00	HFCS
patients_mch	Number of maternal and child health visits	Continuous	0	0	234	230	0.00	19706.17	HFCS
bed_days	Number of bed days	Continuous	139	0	95	92	0.00	5166.00	HFCS
occ	Bed occupancy rate	Continuous	139	0	95	92	0.00	1.43	HFCS
alos	Average length of stay	Continuous	158	0	76	75	0.03	4.26	HFCS
throughput	Admission per bed	Continuous	139	0	95	92	0.00	382.67	HFCS
Size and capacity									
doctorstotal	Number of doctor	Continuous	0	0	234	18	0.00	48.00	HFCS
midwife	Number of midwife	Continuous	17	0	217	40	0.00	229.00	HFCS
nurse	Number of nurse	Continuous	17	0	217	45	0.00	157.00	HFCS
otherstaff	Number of other staff	Continuous	0	0	234	51	0.00	191.00	HFCS
poned	Availability of Basic Emergency Obstetric and Newborn Care services in *Puskesmas*	Binary	29	0	205	2	0.00	1.00	HFCS
open_pm	Puskesmas open at afternoon	Binary	32	0	202	2	0.00	1.00	HFCS
emergency_24	Availability of emergency services	Binary	33	0	201	2	0.00	1.00	HFCS
p21a_pustu	Nmber of *Puskesmas* satellite	Continuous	0	0	234	12	0.00	13.00	HFCS
withbeds	Availability of inpatient services	Binary	0	0	234	2	0.00	1.00	HFCS
beds	Number of beds	Continuous	0	0	234	21	0.00	30.00	HFCS
valueofass d	Value of medical asset	Continuous	15	0	219	219	1.48	207167.00	HFCS
Case mix									
patients_0 4	% of patient under 5 years old	Continuous	2	0	232	232	0.00	0.30	HFCS
patients_ 60	% of patient over 60 years old	Continuous	2	0	232	232	0.00	0.41	HFCS
Year of services									
experience	Age of health facility in year	Continuous	42	0	192	47	1.00	79.00	HFCS
Quality									
water	Water disruption in health facility in the past year	Binary	34	0	200	5	1.00	5.00	HFCS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
electricity	Electricity disruption in health facility in the past year	Binary	37	0	197	5	1.00	5.00	HFCS
medicines_ g	Medicine disruption in health facility in the past year	Binary	32	0	202	5	0.00	5.00	HFCS
salary_late	Employee salary was late on schedule in the past year	Binary	33	0	201	4	1.00	4.00	HFCS
incentive_ e	Employee incentive was late on schedule in the past year	Binary	34	0	200	4	1.00	4.00	HFCS
performanc t	Regular meetings to discuss the performance of services (medical and management) once per week	Binary	41	0	193	8	1.00	8.00	HFCS
death_meet	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	Binary	34	0	200	10	0.00	9.00	HFCS
mentoring	No Mentoring with clinical staffs	Binary	34	0	200	2	1.00	2.00	HFCS
workinghou r	No Monitoring of working hours of the employee	Binary	35	0	199	2	1.00	2.00	HFCS
management c	Difficulty in filling management vacancy	Binary	0	0	234	2	0.00	1.00	HFCS
doc_vac	Difficulty in filling doctor vacancy	Binary	0	0	234	2	0.00	1.00	HFCS
nurse_vac	Difficulty in filling nurse vacancy	Binary	0	0	234	2	0.00	1.00	HFCS
tech_vac	Difficulty in filling technician vacancy	Binary	0	0	234	2	0.00	1.00	HFCS
other_vac	Difficulty in filling other staff vacancy	Binary	0	0	234	2	0.00	1.00	HFCS
Health Expenditure									
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	Continuous	0	0	234	30	1.99	38.99	SUSENAS
pharmacy_exp	Preventive household expenditure for the last three months including expenditure on antenatal care, immunisation, medical check-up, family planning, other preventive expenditure	Continuous	0	0	234	30	0.88	10.68	SUSENAS
preventive p	Pharmacy household expenditure for the last three months including prescribed drugs, drugs without prescription, traditional drugs, glasses, protease, wheel chair.	Continuous	0	0	234	30	0.45	5.26	SUSENAS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<.			Source
						Unique values	Min	Max	
totalhealt p	Total household health expenditure for the last three months including curative, preventive, and pharmacy expenditure.	Continuous	0	0	234	30	5.40	48.37	SUSENAS
Economic									
fam_agricu e	Proportion of family working in agriculture	Continuous	0	0	234	189	0.00	0.98	PODES
poor	Proportion of poor population in district	Continuous	0	0	234	30	0.00	0.21	SUSENAS
expend	Total household expenditure	Continuous	0	0	234	30	158.54	433.01	SUSENAS
gini	Gini index in district	Continuous	0	0	234	30	0.24	0.43	SUSENAS
Access to health facility									
hospitalpop	Ratio of hospital, including general hospital and maternal hospital over 1000 population	Continuous	0	0	234	78	0.00	0.33	PODES
primarypop	Ratio of primary care, including clinic, Puskesmas, Puskesmas satellite, general practitioner, village health post, village delivery post over 1000 population	Continuous	0	0	234	195	0.13	2.29	PODES
hospitaleasy	Proportion of very easy and easy to access hospital, including general hospital and maternal hospital	Continuous	0	0	234	90	0.00	4.00	PODES
primaryeasy	Proportion of very easy and easy to access primary care, including clinic, *Puskesmas*, *Puskesmas* satellite, general practitioner, village health post, village delivery post	Continuous	0	0	234	146	0.00	12.00	PODES
Education									
primarysch l	Proportion of population with primary school education in the district	Continuous	0	0	234	30	0.20	0.59	SUSENAS
secondarys l	Proportion of population with secondary school education in the district	Continuous	0	0	234	30	0.23	0.50	SUSENAS
highereduc n	Proportion of population with higher education in the district	Continuous	0	0	234	30	0.03	0.29	SUSENAS
Demography									
population d	Number of population covered by *Puskesmas*	Continuous	35	0	199	198	0.00	145528.00	HFCS

Variable	Description	Type	Obs=.	Obs>.	Obs<.	Obs<. Unique values	Min	Max	Source
density	Density population in sub-district	Continuous	61	0	173	172	0.00	54999.50	HFCS
populat 2011	Number of population in district for hospital, and sub-district for *Puskesmas*	Continuous	0	0	234	194	4374.00	231599.00	PODES
female_per	Proportion of female population	Continuous	0	0	234	195	0.38	1.00	PODES
Health status									
under5_mor e	Ratio of mortality under five years old for the last three years over 1000 population	Continuous	0	0	234	184	0.00	0.83	PODES
maternal_m e	Ratio of maternal mortality for the last three years over 1000 population	Continuous	0	0	234	117	0.00	0.31	PODES
Geography									
island2	Health facility located on Java or Bali island	Binary	0	0	234	2	0.00	1.00	HFCS
ruralurban	*Puskesmas* located in Urban area	Binary	5	0	229	2	0.00	1.00	HFCS
Insurance coverage									
askesins	Proportion of household covered by *Askes* insurance (scheme for civil servant)	Continuous	0	0	234	30	0.04	0.29	SUSENAS
jamsostekins	Proportion of household covered by *Jamsostek* insurance (scheme for employee)	Continuous	0	0	234	30	0.00	0.20	SUSENAS
privateins	Proportion of household covered by private insurance	Continuous	0	0	234	26	0.00	0.04	SUSENAS
companyins	Proportion of household covered by company insurance (for employee)	Continuous	0	0	234	30	0.00	0.05	SUSENAS
poorins	Proportion of household covered by poor scheme insurance	Continuous	0	0	234	30	0.01	0.61	SUSENAS
healthfund s	Proportion of household covered by health fund insurance (poor scheme)	Continuous	0	0	234	21	0.00	0.02	SUSENAS
otherins	Proportion of household covered by other health insurance scheme	Continuous	0	0	234	29	0.00	0.67	SUSENAS

HFCS: Health facility costing study; SUSENAS: National Socio-economic survey; PODES: Village Potential Statistics; PONED: Neonatal obstetrical basic emergency service.
Obs=. are counts of system missing values; "Obs>." are counts of extended missing values; and Obs<. are counts of nonmissing values.

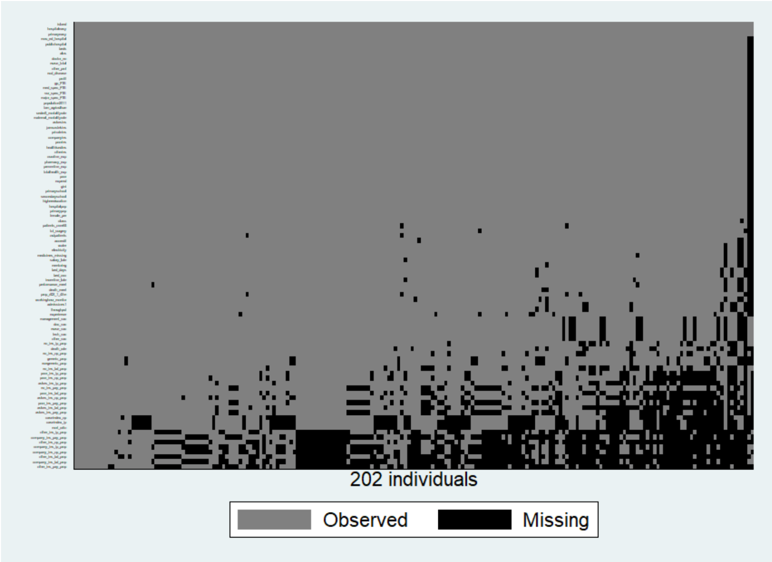


Figure A.1: Pattern of missing hospital variables

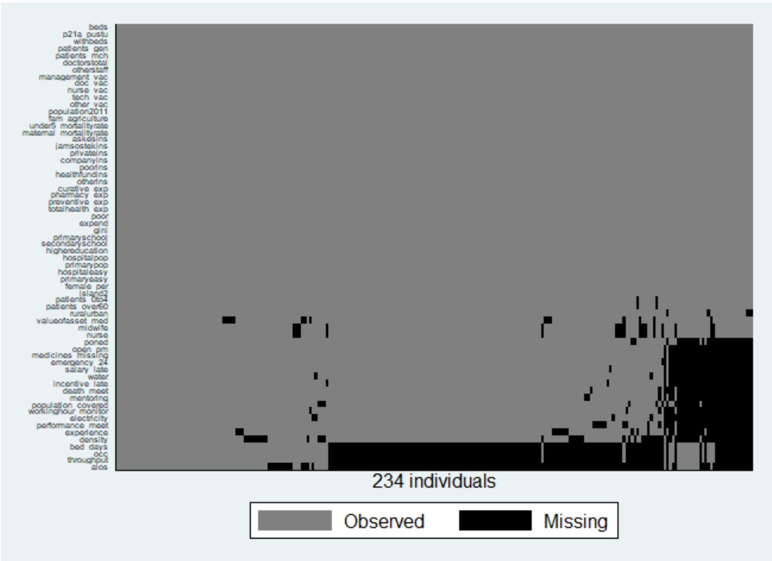


Figure A.2: Pattern of missing *Puskesmas* variables

From: Jennifer Blaikie on behalf of ResearchEthics
Sent: 16 December 2014 15:09
To: Firdaus Shidieq
Subject: RE: Query whether University Faculty Research Ethics Committee approval is required?

Dear Hafidz

Thank you for your email. If the data is anonymised and publically available you don't need to apply for ethical approval to use it.

Best wishes
Jennifer

~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Jennifer Blaikie

Senior Research Ethics Administrator
Performance, Governance and Operations
Research & Innovation Service
University of Leeds
Leeds LS2 9LJ

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Email: j.m.blaikie@leeds.ac.uk
www.leeds.ac.uk/ethics
Follow @UoLResEthics
2014/15 programme of research ethics training courses now available: http://www.sddu.leeds.ac.uk/sddu-research-ethics-courses.html

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From: Firdaus Shidieq [mailto:umfhas@leeds.ac.uk]
Sent: 16 December 2014 12:28
To: ResearchEthics
Subject: Query whether Univeristy Faculty Research Ethics Committee approval is required?

Dear Jennifer Blaikie,

Hope you can help.

I am Firdaus Hafidz As Shidieq, a PhD student in my first year at the Leeds Institute of Health Sciences.
My project uses a quantitative analysis of secondary data. I will be using data from the Health Facility Costing Study in Indonesia, The Village Potential Statistics (PODES) in Indonesia, The National Socioeconomic Survey (SUSENAS) in Indonesia, and Hospital case-mix dataset in Indonesia. This data contains only anonymised data which is held at the Ministry of Health of Indonesia, and Central Bureau of Statistics (BPS) of Indonesia. The data is available once you have applied to use the data.

My question is: Do I still need to apply for University Research Ethics approval before I use this data?

Many thanks,

Hafidz

Figure A.3: Ethical approval
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

KEMENTERIAN KESEHATAN RI

SEKRETARIAT JENDERAL

Jalan H.R. Rasuna Said Blok X-5 Kavling 4 - 9 Jakarta 12950
Telepon: (021) 5201590 (*hunting*)

No	:	TU.01.01.I. 1188.2015	10 April 2015
Lamp	:	1 cd	
Hal	:	Data INA-CBGs Tahun 2011	

Yang terhormat,
Firdaus Hafidz As Shidieq
Mahasiswa Program PhD Jurusan Kesehatan
University Of Leeds
di –
Tempat

Sehubungan dengan surat Saudara, perihal Permohonan Data Penggunaan data INA-CBGs tahun 2011 untuk penelitian dengan topic Tingkat Efisiensi Fasilitas Kesehatan di Indonesia, maka dengan ini kami kirimkan data yang diminta untuk digunakan sebagaimana seharusnya.

Atas perhatian, kami ucapkan terimaskasih.

Kepala Pusat
Pembiayaan dan Jaminan Kesehatan

KEMENTERIAN KESEHATAN
SEKRETARIAT JENDERAL
REPUBLIK INDONESIA

dr. Donald Pardede, MPPM
NIP 195804021986111001

Figure A.4: Indonesia case base group dataset approval

KEMENTERIAN KESEHATAN RI
BADAN PENELITIAN DAN PENGEMBANGAN KESEHATAN

Jalan Percetakan Negara No. 29 Jakarta 10560 Kotak Pos 1226
Telepon : (021) 4261088 Faksimile : (021) 4243933
Surat Elektronik : sesban@litbang.depkes.go.id Laman (*Website*) : http://www.litbang.depkes.go.id

BAKTI HUSADA

SURAT PERNYATAAN

Pada hari ini Senin tanggal 2 bulan 3 tahun 2015 yang bertanda tangan di bawah ini :

Nama	:	Firdaus Hafidz As Shidieq
Alamat E-mail	:	umfhas@leeds.ac.uk
Hp	:	+44 7477 195683
NIP/NPM	:	200796108
Pekerjaan	:	Mahasiswa PhD
Instansi	:	Leeds Institute of Health Sciences
Alamat Kantor	:	101 Clarendon Rd, Leeds, West Yorkshire LS2 9L
Universitas (mahasiswa)	:	University of Leeds
Judul Penelitian	:	Efficiency level of health facilities in Indonesia

Menyatakan dengan sesungguhnya bahwa :

1. Saya sanggup dan bersedia untuk mematuhi ketentuan – ketentuan yang telah ditetapkan dalam melakukan kegiatan penelitian dan pengembangan sesuai dengan Undang – Undang Kesehatan Nomor 36 Tahun 2009 tentang Kesehatan dan Peraturan Pemerintah Nomor 39 Tahun 1995 tentang Penelitian dan Pengembangan Kesehatan.
2. Saya telah menerima subset Data hasil kegiatan penelitian GIZ Studi Rumah Sakit yang direkam dalam media elektronik saat menjadi peneliti GIZ.
3. Data hasil penelitian yang saya peroleh akan saya pergunakan untuk kepentingan Disertasi, Sehingga saya :
   a. Tidak akan membuat salinan dari data tersebut untuk keperluan lain dan pihak lain atau mengalihkan data tersebut kepada pihak lain.
   b. Akan mempergunakan data tersebut hanya untuk 1 (satu) topik judul penelitian, sesuai dengan persetujuan yang diberikan secara formal oleh Badan Litbang Kesehatan.
   c. Apabila saya menggunakan data untuk keperluan lain selain dari ketentuan di atas harus mengajukan kembali secara formal kepada Kepala Badan Litbang Kesehatan.
   d. Akan melakukan komunikasi dengan pihak Laboratorium Manajemen Data untuk pemahaman variable subset data.
   e. Untuk melakukan publikasi hasil analisis, saya sanggup dan bersedia untuk terlebih dahulu memperhatikan etika dan manfaat bagi kepentingan masyarakat.
4. Saya berkewajiban untuk menyerahkan hasil analisis kepada Laboratorium Manajemen Data Badan Penelitian dan Pengembangan kesehatan.

Demikian surat pernyataan ini saya buat dengan sesungguhnya tanpa adanya unsur paksaan dari pihak manapun. Apabila dikemudian hari terjadi penyimpangan dari pernyataan saya tersebut, maka hak penggunaan data dan publikasi dinyatakan batal demi hukum, serta tidak dapat mengajukan kembali permohonan penggunaan data-data Badan Litbangkes untuk kepentingan apapun.

Mengetahui, Ketua/ Wakil Lab. Mandat	Pembuat Set Data	Penerima Data
Ika Dharmayanti	GIZ	METERAI TEMPEL 6000 ENAM RIBU RUPIAH FIRDAUS HAFIDZ AS SHIDIEQ

Figure A.5: Hospital health facility costing study dataset approval

KEMENTERIAN KESEHATAN RI
BADAN PENELITIAN DAN PENGEMBANGAN KESEHATAN

Jalan Percetakan Negara No. 29 Jakarta 10560 Kotak Pos 1226
Telepon : (021) 4261088 Faksimile : (021) 4243933
Surat Elektronik : sesban@litbang.depkes.go.id Laman (*Website*) : http://www.litbang.depkes.go.id

SURAT PERNYATAAN

Pada hari ini Senin tanggal 2 bulan 3 tahun 2015 yang bertanda tangan di bawah ini :

Nama	: Firdaus Hafidz As Shidieq
Alamat E-mail	: umfhas@leeds.ac.uk
Hp	: +44 7477 195683
NIP/NPM	: 200796108
Pekerjaan	: Mahasiswa PhD
Instansi	: Leeds Institute of Health Sciences
Alamat Kantor	: 101 Clarendon Rd, Leeds, West Yorkshire LS2 9L
Universitas (mahasiswa)	: University of Leeds
Judul Penelitian	: Efficiency level of health facilities in Indonesia

Menyatakan dengan sesungguhnya bahwa :

1. Saya sanggup dan bersedia untuk mematuhi ketentuan – ketentuan yang telah ditetapkan dalam melakukan kegiatan penelitian dan pengembangan sesuai dengan Undang – Undang Kesehatan Nomor 36 Tahun 2009 tentang Kesehatan dan Peraturan Pemerintah Nomor 39 Tahun 1995 tentang Penelitian dan Pengembangan Kesehatan.
2. Saya telah menerima subset Data hasil kegiatan penelitian GIZ Studi Puskesmas yang direkam dalam media elektronik yang dibuat oleh Badan Penelitian dan Pengembangan Kesehatan.
3. Data hasil penelitian yang saya peroleh akan saya pergunakan untuk kepentingan Disertasi, Sehingga saya :
   a. Tidak akan membuat salinan dari data tersebut untuk keperluan lain dan pihak lain atau mengalihkan data tersebut kepada pihak lain.
   b. Akan mempergunakan data tersebut hanya untuk 1 (satu) topik judul penelitian, sesuai dengan persetujuan yang diberikan secara formal oleh Badan Litbang Kesehatan.
   c. Apabila saya menggunakan data untuk keperluan lain selain dari ketentuan di atas harus mengajukan kembali secara formal kepada Kepala Badan Litbang Kesehatan.
   d. Akan melakukan komunikasi dengan pihak Laboratorium Manajamen Data untuk pemahaman variable subset data.
   e. Untuk melakukan publikasi hasil analisis, saya sanggup dan bersedia untuk terlebih dahulu memperhatikan etika dan manfaat bagi kepentingan masyarakat.
4. Saya berkewajiban untuk menyerahkan hasil analisis kepada Laboratorium Manajemen Data Badan Penelitian dan Pengembangan kesehatan.

Demikian surat pernyataan ini saya buat dengan sesungguhnya tanpa adanya unsur paksaan dari pihak manapun. Apabila dikemudian hari terjadi penyimpangan dari pernyataan saya tersebut, maka hak penggunaan data dan publikasi dinyatakan batal demi hukum, serta tidak dapat mengajukan kembali permohonan penggunaan data-data Badan Litbangkes untuk kepentingan apapun.

Mengetahui, Ketua/ Wakil Lab. Mandat	Pembuat Set Data	Penerima Data
Ika Dharmayanti	Yudi K	METERAI TEMPEL 6000 ENAM RIBU RUPIAH FIRDAUS HAFIDZ AS SHIDIEQ

Figure A.6: *Puskesmas* health facility costing study dataset approval

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SURAT PERJANJIAN PENGGUNAAN DATA

No : 13/LADU/02/2016
Tanggal : 4 Februari 2016

---

1. Surat Perjanjian Penggunaan Data yang direkam dalam media komputer, dibuat oleh **Badan Pusat Statistik (BPS)**, sebagai penyedia data dan **Firdaus Hafidz As**, sebagai penerima data dalam media komputer. Pada butir-butir selanjutnya, data dalam media komputer disebut rekaman data.
2. BPS, menyetujui untuk menyediakan rekaman data:
   - **Mikro Data Survei Sosial Ekonomi Nasional, KOR dan MODUL Gabungan 2011**
   - **Mikro Data Potensi Desa 2011**

   kepada penerima data dengan syarat-syarat seperti yang dirinci pada butir 3.
3. Penerima data menyetujui bahwa pemakaian rekaman akan mengikuti syarat-syarat yang ditentukan oleh BPS yaitu :
   a. Penerima data tidak akan membuat salinan dari rekaman tersebut untuk keperluan orang lain atau organisasi lain.
   b. Penerima data akan memakai rekaman tersebut hanya untuk keperluan penelitian dan analisis bagi **Firdaus Hafidz As Shidieq** dengan tujuan utama memperdalam pengertian tentang keadaan Indonesia.
   c. Penggunaan rekaman untuk keperluan lain yang menyimpang dari syarat syarat di atas perlu mendapat persetujuan teknis terlebih dahulu dari Kepala BPS.
   d. Penerima data diharapkan menyerahkan hasil penelitiannya kepada BPS.
4. Syarat perjanjian ini ditanda tangani oleh kedua belah pihak sebagai bukti ikatan resmi. Semua data dan keterangan yang ada didalam rekaman tersebut di atas adalah rahasia dan tetap menjadi milik BPS.

Badan Pusat Statistik	Penerima Data
M. Ari Nugraha, M.Sc	Firdaus Hafidz As Shidieq
Direktur Diseminasi Statistik	PhD Student
	Leeds University

Figure A.7: Letter of agreement of BPS-Statistics Indonesia data usage

Appendix B

Appendix related to Chapter 4

Search strategy

Ovid MEDLINE(R) <1946 to February Week 2 2018>

1 exp Health Facilities/ (712330)
2 (health adj1 facilit*).m_titl. (1389)
3 hospital?.m_titl. (215312)
4 nursing home?.m_titl. (13569)
5 Community health cent* .m_titl. (886)
6 (primary adj1 care).m_titl. (32264)
7 Clinic?.m_titl. (58865)
8 General practitioner?.m_titl. (11529)
9 GP.m_titl. (3686)
10 Ambulatory care facilit* .m_titl. (53)
11 Medical cen* .m_titl. (7449)
12 (Secondary adj1 care).m_titl. (621)
13 (Tertiary adj1 care).m_titl. (4542)
14 physician practice* .m_titl. (790)
15 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14 (871004)
16 Efficiency, Organizational/ (20330)
17 ??efficien* .m_titl. (66724)
18 producti* .m_titl. (161640)
19 performance?.m_titl. (133677)
20 benchmark* .tw. (21699)
21 16 or 17 or 18 or 19 or 20 (395146)
22 exp Developing Countries/ (69327)
23 Africa/ (27405)
24 "Africa South of the Sahara"/ (9517)
25 Asia/ (25680)
26 South America/ (9014)
27 Latin America/ (9906)
28 Central America/ (3608)

29 (Afghanistan or Gambia or Niger or Benin or Guinea or Rwanda or "Burkina Faso" or Guinea-Bisau or Sierra Leone or Burundi or Haiti or Somalia or Cambodia or North Korea or South Sudan or Central African Republic or Liberia or Tanzania or Chad or Madagascar or Togo or Comoros or Malawi or Uganda or Congo or Mali or Zimbabwe or Eritrea or Mozambique or Ethiopia or Nepal).tw. (185590)

30 (Armenia or Indonesia or Samoa or Bangladesh or Kenya or "Sao Tome" or Bhutan or Kiribati or Senegal or Bolivia or Kosovo or Solomon Islands or "Cabo Verde" or Kyrgyz or "Sri Lanka" or Cameroon or Lao or Sudan or Congo or Lesotho or Swaziland or "Cote d'Ivoire" or Mauritania or Syrian or Djibouti or Micronesia or Tajikistan or Egypt or Moldova or Timor-Leste or "El Salvador" or Morocco or Ukraine or Georgia or Myanmar or Uzbekistan or Ghana or Nicaragua or Vanuatu or Guatemala or Nigeria or Vietnam or Guyana or Pakistan or "West Bank" or Gaza or Honduras or "Papua New Guinea" or Yemen or India or Philippines or Zambia).tw. (217931)

31 (Albania or Fiji or Namibia or Algeria or Gabon or Palau or "American Samoa" or Grenada or Panama or Angola or Iran or Paraguay or Azerbaijan or Iraq or Peru or Belarus or Jamaica or Romania or Belize or Jordan or Serbia or Bosnia or Herzegovina or Kazakhstan or "South Africa" or Botswana or Lebanon or "Saint Lucia" or "St. Lucia" or Brazil or Libya or "Saint Vincent" or "St. Vincent" or Grenadines or Bulgaria or Macedonia or Suriname or China or Malaysia or Thailand or Colombia or Maldives or Tonga or "Costa Rica" or "Marshall Islands" or Tunisia or Cuba or Mauritius or Turkey or Dominica or Mexico or Turkmenistan or "Dominican Republic" or Mongolia or Tuvalu or Ecuador or Montenegro).tw. (347202)

32 (developing or less$ developed or third world or under developed or poor$).tw. (996620)

33 ((developing or less$ developed or third world or under developed or poor$) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (53306)

34 ((middle income or low income) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (12200)

35 (lmic or lmics).tw. (1492)

36 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 (1703431)

37 15 and 21 and 36 (1855)

Embase Classic+Embase <1947 to 2018 February 16>

1 exp health care facility/ (1483801)
2 (health adj1 facilit*).m_titl. (1961)
3 hospital?.m_titl. (306393)
4 nursing home?.m_titl. (17383)
5 Community health cent* .m_titl. (1194)
6 (primary adj1 care).m_titl. (45162)
7 Clinic?.m_titl. (82916)
8 General practitioner?.m_titl. (15232)
9 GP.m_titl. (5390)
10 Ambulatory care facilit* .m_titl. (56)
11 Medical cen* .m_titl. (10609)

12 (Secondary adj1 care).m_titl. (1290)

13 (Tertiary adj1 care).m_titl. (13050)

14 physician practice* .m_titl. (946)

15 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14 (1727272)

16 exp productivity/ (34925)

17 ??efficien* .m_titl. (106491)

18 producti* .m_titl. (218345)

19 performance?.m_titl. (187922)

20 benchmark* .tw. (34558)

21 16 or 17 or 18 or 19 or 20 (565159)

22 exp developing country/ (89474)

23 Africa/ (58056)

24 ”Africa south of the Sahara”/ (11844)

25 Asia/ (69010)

26 South America/ (13875)

27 ”South and Central America”/ (15917)

28 Central America/ (8813)

29 (Afghanistan or Gambia or Niger or Benin or Guinea or Rwanda or ”Burkina Faso” or Guinea-Bisau or Sierra Leone or Burundi or Haiti or Somalia or Cambodia or North Korea or South Sudan or Central African Republic or Liberia or Tanzania or Chad or Madagascar or Togo or Comoros or Malawi or Uganda or Congo or Mali or Zimbabwe or Eritrea or Mozambique or Ethiopia or Nepal).tw. (262063)

30 (Armenia or Indonesia or Samoa or Bangladesh or Kenya or ”Sao Tome” or Bhutan or Kiribati or Senegal or Bolivia or Kosovo or Solomon Islands or ”Cabo Verde” or Kyrgyz or ”Sri Lanka” or Cameroon or Lao or Sudan or Congo or Lesotho or Swaziland or ”Cote d’Ivoire” or Mauritania or Syrian or Djibouti or Micronesia or Tajikistan or Egypt or Moldova or Timor-Leste or ”El Salvador” or Morocco or Ukraine or Georgia or Myanmar or Uzbekistan or Ghana or Nicaragua or Vanuatu or Guatemala or Nigeria or Vietnam or Guyana or Pakistan or ”West Bank” or Gaza or Honduras or ”Papua New Guinea” or Yemen or India or Philippines or Zambia).tw. (346316)

31 (Albania or Fiji or Namibia or Algeria or Gabon or Palau or ”American Samoa” or Grenada or Panama or Angola or Iran or Paraguay or Azerbaijan or Iraq or Peru or Belarus or Jamaica or Romania or Belize or Jordan or Serbia or Bosnia or Herzegovina or Kazakhstan or ”South Africa” or Botswana or Lebanon or ”Saint Lucia” or ”St. Lucia” or Brazil or Libya or ”Saint Vincent” or ”St. Vincent” or Grenadines or Bulgaria or Macedonia or Suriname or China or Malaysia or Thailand or Colombia or Maldives or Tonga or ”Costa Rica” or ”Marshall Islands” or Tunisia or Cuba or Mauritius or Turkey or Dominica or Mexico or Turkmenistan or ”Dominican Republic” or Mongolia or Tuvalu or Ecuador or Montenegro).tw. (538591)

32 (developing or less$ developed or third world or under developed or poor$).tw. (1581516)

33 ((developing or less$ developed or third world or under developed or poor$) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (79056)

34 ((middle income or low income) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (19164)

35 (lmic or lmics).tw. (2859)

36 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 (2688613)

37 15 and 21 and 36 (4044)

Global Health <1910 to 2018 Week 06>

1 exp health centres/ (12600)
2 (health adj1 facilit∗).m_titl. (802)
3 hospital?.m_titl. (43265)
4 nursing home?.m_titl. (1266)
5 Community health cent∗ .m_titl. (267)
6 (primary adj1 care).m_titl. (4342)
7 Clinic?.m_titl. (8818)
8 General practitioner?.m_titl. (1140)
9 GP.m_titl. (353)
10 Medical cen∗ .m_titl. (1095)
11 (Secondary adj1 care).m_titl. (94)
12 (Tertiary adj1 care).m_titl. (3518)
13 physician practice∗ .m_titl. (47)
14 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 (70936)
15 exp efficiency/ (2160)
16 ??efficien∗ .m_titl. (9471)
17 producti∗ .m_titl. (46840)
18 performance?.m_titl. (25524)
19 benchmark∗ .tw. (2935)
20 15 or 16 or 17 or 18 or 19 (84895)
21 exp developing countries/ (844422)
22 Africa/ (229411)
23 South America/ (130432)
24 Latin America/ (162929)
25 Central America/ (13124)

26 (Afghanistan or Gambia or Niger or Benin or Guinea or Rwanda or "Burkina Faso" or Guinea-Bisau or Sierra Leone or Burundi or Haiti or Somalia or Cambodia or North Korea or South Sudan or Central African Republic or Liberia or Tanzania or Chad or Madagascar or Togo or Comoros or Malawi or Uganda or Congo or Mali or Zimbabwe or Eritrea or Mozambique or Ethiopia or Nepal).tw. (143885)

27 (Armenia or Indonesia or Samoa or Bangladesh or Kenya or "Sao Tome" or Bhutan or Kiribati or Senegal or Bolivia or Kosovo or Solomon Islands or "Cabo Verde" or Kyrgyz or "Sri Lanka" or Cameroon or Lao or Sudan or Congo or Lesotho or Swaziland or "Cote d'Ivoire" or Mauritania or Syrian or Djibouti or Micronesia or Tajikistan or Egypt or Moldova or Timor-Leste or "El Salvador" or Morocco or Ukraine or Georgia or Myanmar or Uzbekistan or Ghana or Nicaragua or Vanuatu or Guatemala or Nigeria or Vietnam or Guyana or Pakistan or "West Bank" or Gaza or Honduras or "Papua New Guinea" or Yemen or India or Philippines or Zambia).tw. (318634)

28 (Albania or Fiji or Namibia or Algeria or Gabon or Palau or "American Samoa" or Grenada or Panama or Angola or Iran or Paraguay or Azerbaijan or Iraq or Peru or Belarus or Jamaica or Romania or Belize or Jordan or Serbia or Bosnia or Herzegovina or Kazakhstan or "South Africa" or Botswana or Lebanon or "Saint Lucia" or "St. Lucia" or Brazil or Libya or "Saint Vincent" or "St. Vincent" or Grenadines or Bulgaria or Macedonia or Suriname or China or Malaysia or Thailand or Colombia or Maldives or Tonga or "Costa Rica" or "Marshall Islands" or Tunisia or Cuba or Mauritius or Turkey or Dominica or Mexico or Turkmenistan or "Dominican Republic" or Mongolia or Tuvalu or Ecuador or Montenegro).tw. (481439)

29 (developing or less$ developed or third world or under developed or poor$).tw. (977851)

30 ((developing or less$ developed or third world or under developed or poor$) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (852065)

31 ((middle income or low income) adj (communit$ or count$ or district? or state? or province? or jurisdiction? or nation? or region? or area? or territor$)).tw. (10178)

32 (lmic or lmics).tw. (1042)

33 "Africa South of Sahara"/ (185427)

34 Asia/ (552902)

35 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 (1174662)

36 14 and 20 and 35 (554)

ProQuest Dissertations and Theses (20 February 2018)

(su.Exact("health facilities") OR ti((health hadj1 facilit∗) OR hospital? OR nursing home? OR (Community health cent∗) OR (primary hadj1 care) OR Clinic? OR (General practitioner?) OR GP OR (Ambulatory care facilit∗) OR (Medical cen∗) OR (Secondary hadj1 care) OR (Tertiary hadj1 care) OR (physician practice∗))) AND (su.Exact("efficiency") OR ti(efficien∗ OR inefficien∗ OR producti∗ OR performance? OR benchmark∗)) AND (su.Exact("developing countries ldcs") OR Africa OR ("Africa South of the Sahara") OR Asia OR ("South America") OR ("Latin America") OR ("Central America") OR (Afghanistan OR Gambia OR Niger OR Benin OR guinean OR Rwanda OR "Burkina Faso" OR guinean-bisque OR Sierra Leone OR Burundi OR Haiti OR Somalia OR Cambodia OR North Korea OR South Sudan OR Central African Republic OR Liberia OR Tanzania OR Chad OR Madagascar OR Togo OR Comoros OR Malawi OR Uganda OR Congo OR Mali OR Zimbabwe OR Eritrea OR Mozambique OR Ethiopia OR Nepal) OR (Armenia OR Indonesia OR Samoa OR Bangladesh OR Kenya OR "sago Tome" OR Bhutan OR Kiribati OR Senegal OR Bolivia OR Kosovo OR Solomon Islands OR "Cabo Verde" OR Kyrgyz OR "Sri Lanka" OR Cameroon OR Lao OR Sudan OR Congo OR Lesotho OR Swaziland OR "Cote d'Ivoire" OR Mauritania OR Syrian OR Djibouti OR Micronesia OR Tajikistan OR Egypt OR Moldova OR Timor-Leste OR "El Salvador" OR Morocco OR Ukraine OR Georgia OR Myanmar OR Uzbekistan OR Ghana OR Nicaragua OR Vanuatu OR Guatemala OR Nigeria OR Vietnam OR Guyana OR Pakistan OR "West Bank" OR Gaza OR Honduras OR "Papua New guinean" OR Yemen OR India OR Philippines OR Zambia) OR (Albania OR Fiji OR Namibia OR Algeria OR Gabon OR Palau OR "American Samoa" OR Grenada OR Panama OR Angola OR Iran OR Paraguay OR Azerbaijan OR Iraq OR Peru OR Belarus OR Jamaica OR Romania OR Belize OR Jordan OR Serbia OR

Bosnia OR Herzegovina OR Kazakhstan OR ”South Africa” OR Botswana OR Lebanon OR ”Saint Lucia” OR ”St. Lucia” OR Brazil OR Libya OR ”Saint Vincent” OR ”St. Vincent” OR Grenadines OR Bulgaria OR Macedonia OR Suriname OR China OR Malaysia OR Thailand OR Colombia OR Maldives OR Tonga OR ”Costa Rica” OR ”Marshall Islands” OR Tunisia OR Cuba OR Mauritius OR Turkey OR Dominica OR Mexico OR Turkmenistan OR ”Dominican Republic” OR Mongolia OR Tuvalu OR Ecuador OR Montenegro) OR (developing OR less developed OR third world OR under developed OR poor) OR ((developing OR less developed OR third world OR under developed OR poor) hadj (communit∗ OR count∗ OR district? OR state? OR province? OR jurisdiction? OR nation? OR region? OR area? OR territory∗)) OR ((middle income OR low income) hadj (communit∗ OR count∗ OR district? OR state? OR province? OR jurisdiction? OR nation? OR region? OR area? OR territory∗)) OR (lmic OR lmics))

Econlit (21 February 2018)

1. Health facilities
2. TI health W1 facilit∗
3. TI hospital?
4. TI nursing home?
5. TI Community health cent∗
6. TI primary W1 care
7. TI Clinic?
8. TI General practitioner?
9. TI GP
10. TI Medical cen∗
11. TI Secondary W1 care
12. TI Tertiary W1 care
13. TI physician practice∗
14. S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13
15. SU efficiency
16. TI ??efficien∗
17. TI producti∗
18. TI performance?
19. AB benchmark∗
20. S15 OR S16 OR S17 OR 18 OR 19
21. Developing countries
22. Africa
23. Africa south of the sahara
24. Asia
25. South America
26. Latin America
27. Central America
28. AB (Afghanistan OR Gambia OR Niger OR Benin OR Guinea OR Rwanda OR ”Burkina Faso” OR Guinea- Bisau OR Sierra Leone OR Burundi OR Haiti OR Somalia OR Cambodia OR North Korea OR South Sudan OR Central African Republic OR Liberia OR

Tanzania OR Chad OR Madagascar OR Togo OR Comoros OR Malawi OR Uganda OR Congo OR Mali OR Zimbabwe OR Eritrea OR Mozambique OR Ethiopia OR Nepal)

29. AB (Armenia OR Indonesia OR Samoa OR Bangladesh OR Kenya OR ”Sao Tome” OR Bhutan OR Kiribati OR Senegal OR Bolivia OR Kosovo OR Solomon Islands OR ”Cabo Verde” OR Kyrgyz OR ”Sri Lanka” OR Cameroon OR Lao OR Sudan OR Congo OR Lesotho OR Swaziland OR ”Cote d’Ivoire” OR Mauritania OR Syrian OR Djibouti OR Micronesia OR Tajikistan OR Egypt OR Moldova OR Timor-Leste OR ”El Salvador” OR Morocco OR Ukraine OR Georgia OR Myanmar OR Uzbekistan OR Ghana OR Nicaragua OR Vanuatu OR Guatemala OR Nigeria OR Vietnam OR Guyana OR Pakistan OR ”West Bank” OR Gaza OR Honduras OR ”Papua New Guinea” OR Yemen OR India OR Philippines OR Zambia)

30. AB (Albania OR Fiji OR Namibia OR Algeria OR Gabon OR Palau OR ”American Samoa” OR Grenada OR Panama OR Angola OR Iran OR Paraguay OR Azerbaijan OR Iraq OR Peru OR Belarus OR Jamaica OR Romania OR Belize OR Jordan OR Serbia OR Bosnia OR Herzegovina OR Kazakhstan OR ”South Africa” OR Botswana OR Lebanon OR ”Saint Lucia” OR ”St. Lucia” OR Brazil OR Libya OR ”Saint Vincent” OR ”St. Vincent” OR Grenadines OR Bulgaria OR Macedonia OR Suriname OR China OR Malaysia OR Thailand OR Colombia OR Maldives OR Tonga OR ”Costa Rica” OR ”Marshall Islands” OR Tunisia OR Cuba OR Mauritius OR Turkey OR Dominica OR Mexico OR Turkmenistan OR ”Dominican Republic” OR Mongolia OR Tuvalu OR Ecuador OR Montenegro)

31. AB (developing OR less∗ developed OR third world OR under developed OR poor∗)

32. AB ((developing OR less∗ developed OR third world OR under developed OR poor∗) W (communit∗ OR count∗ OR district? OR state? OR province? OR jurisdiction? OR nation? OR region? OR area? OR territor∗))

33. AB (lmic OR lmics)

34. AB low and middle income countries

35. AB ((middle income OR low income) N (communit∗ OR count∗ OR district? OR state? OR province? OR jurisdiction? OR nation? OR region? OR area? OR territor∗))

36. S21 OR S22 OR S23 OR S24 OR S25 OR S26 OR S27 OR S28 OR S29 OR S30 OR S31 OR S32 OR S33 OR S34 OR S35

37. S14 AND S20 AND S36

Table B.1: Validity evaluation

Design:	
1. Was the study observational (cross-sectional/ panel)?	Y/N
2. Was the study period defined?	Y/N
Sample:	
1. Was the sample size justified?	Y/N
2. Was the sample drawn from more than one site?	Y/N
3. Did the study include the entire health facility?	Y/N
4. Did the study include more than one type of health facility (public, private, teaching, non-teaching, national, regional)?	Y/N
Indicators:	
1. Were the indicators reliable and valid?	Y/N
2. Were different indicators used to measure the impact on productivity?	Y/N
3. Were explicit numbers given for all indicators?	Y/N
4. Were several inputs and several outputs measured?	Y/N
5. Were different types of health facility staff members assessed?	Y/N
Statistical analysis:	
1. Were multiple statistical methods used?	Y/N
2. Was the statistical method justified?	Y/N

Table B.2: Characteristics of included studies

Reference	Country (Region)	Perspective	Sample size	Time period
Aboagye & Degboe (2011)	Ghana (Sub-Saharan Africa)	Primary care	10	2004 to 2005
Ajlouni *et al.* (2013)	Jordan (Middle East and North Africa)	Hospitals	15	2006 to 2008
Akazili *et al.* (2008)	Ghana (Sub-Saharan Africa)	Primary care	89	2005
Alaghemandan *et al.* (2014)	Iran (Middle East and North Africa)	Other	4	2010
Alhassan *et al.* (2015)	Ghana (Sub-Saharan Africa)	Primary care	64	2012
Amole *et al.* (2016)	Nigeria (Sub-Saharan Africa)	Hospitals	6	2010 to 2014
Araújo *et al.* (2014)	Brazil (Latin America and The Caribbean)	Hospitals	20	2013
Arfa *et al.* (2017)	Tunisia (Middle East and North Africa)	Hospitals	101	2000 and 2010
Arocena & García-Prado (2007)	Costa Rica (Latin America and The Caribbean)	Hospitals	20	1997 to 2001
Asbu *et al.* (2012)	Malawi (Sub-Saharan Africa)	Hospitals	40	2005 to 2006
hanam Atake (2015)	Togo (Sub-Saharan Africa)	Hospitals	139	2011
Atilgan (2016)	Turkey (Middle East and North Africa)	Hospitals	459	2013
Audibert *et al.* (2013)	China (East Asia and Pacific)	Hospitals	24	2000 to 2008
Mohammadkarim *et al.* (2011)	Iran (Middle East and North Africa)	Hospitals	23	2009
BASTANI *et al.* (2013)	Iran (Middle East and North Africa)	Hospitals	139	2008
Berman (1986)	Indonesia (East Asia and Pacific)	Primary care	5	1981 to 1983
Berman *et al.* (1989)	Indonesia (East Asia and Pacific)	Primary care	6	1981
Berman *et al.* (1989)	Indonesia (East Asia and Pacific)	Primary care	173	1986 to 1987
Bernet *et al.* (2008)	Ukraine (Europe and Central Asia)	Primary care	195	1997 to 2001
Blaakman *et al.* (2014)	Afghanistan (South Asia)	Primary care	144	2009
Bowser *et al.* (2013)	Belize (Latin America and The Caribbean)	Other	8	2005 to 2010
Brenzel *et al.* (2015)	Benin, Ghana, Honduras, Moldova, Uganda, and Zambia (Multi region)	Primary care	319	2011/2012
Bwana (2015)	Tanzania (Sub-Saharan Africa)	Hospitals	15	2009 to 2012
Bwana & Raphael (2015)	Tanzania (Sub-Saharan Africa)	Hospitals	16	2009 to 2013
Chaabouni & Abednnadher (2012)	Tunisia (Middle East and North Africa)	Hospitals	10	2000 to 2007
Chaabouni & Abednnadher (2016)	Tunisia (Middle East and North Africa)	Hospitals	10	2000 to 2007
Cheng *et al.* (2016)	China (East Asia and Pacific)	Hospitals	48	2008 to 2014
Cheng *et al.* (2015)	China (East Asia and Pacific)	Hospitals	114	2010 to 2012
Walker (2006)	Bangladesh (South Asia)	Primary care	110	1999

Reference	Country (Region)	Perspective	Sample size	Time period
Dandona *et al.* (2005) (2005)	India (South Asia)	Hospitals	14	2003 to 2004
Dandona *et al.* (2008)	India (South Asia)	Hospitals	16	2005/ 2006
de Castro Lobo *et al.* (2010)	Brazil (Latin America and The Caribbean)	Hospitals	30	2003 to 2006
Dervaux *et al.* (2003)	Bangladesh (South Asia)	Primary care	117	2000
Ekiyor (2015), A (2015)	Turkey (Europe and Central Asia)	Hospitals	8	0
Erus & Hatipoglu (2017)	Turkey (Middle East and North Africa)	Hospitals	81	2002 to 2006
Fiedler *et al.* (1998)	El Salvador (Latin America and The Caribbean)	Hospitals	13	1992
Flessa (1998)	Tanzania (Sub-Saharan Africa)	Hospitals	7	1996
Gai *et al.* (2010)	China (East Asia and Pacific)	Hospitals	31	1993 to 2005
Gholipour *et al.* (2013)	Iran (Middle East and North Africa)	Hospitals	2	2010 to 2012
Gok & Sezen (2013)	Turkey (Europe and Central Asia)	Hospitals	384	2008
Gok & Altındağ (2015)	Turkey (Europe and Central Asia)	Hospitals	566	2001 to 2008
Goshtasebi *et al.* (2009)	Iran (Middle East and North Africa)	Hospitals	6	2006
Guerra *et al.* (2012)	Brazil (Latin America and The Caribbean)	Hospitals	26	2008
Hamidi (2016)	Palestine (Middle East and North Africa)	Hospitals	22	2006, 2007 and 2009 to 2012
Hatam (2008)	Iran (Middle East and North Africa)	Hospitals	18	Not available
Hatam *et al.* (2010)	Iran (Middle East and North Africa)	Hospitals	21	2005 to 2006
ISAI & RADU (2016)	Romania (Europe and Central Asia)	Hospitals	Not available	2011 to 2013
Jat & Sebastian (2013)	India (South Asia)	Hospitals	40	2010
Jehu-Appiah *et al.* (2014)	Ghana (Sub-Saharan Africa)	Hospitals	128	2005
Jia & Yuan (2017)	China (East Asia and Pacific)	Hospitals	5	Not available
Jian *et al.* (2009)	China (East Asia and Pacific)	Hospitals	21	2007
Johns *et al.* (2013)	Malawi (Sub-Saharan Africa)	Primary care	24	2010
Keith & Prior (2014)	Mexico (latin America and The Caribbean)	Hospitals and primary care	2105	2010
Ketabi (2011)	Iran (Middle East and North Africa)	Hospitals	23	2007
Khan & Ahmed (2003)	Bangladesh (South Asia)	Other	35	1999 / 2000
Kiadaliri *et al.* (2011)	Iran (Middle East and North Africa)	Hospitals	19	2006
Kibambe & Koch (2007)	South Africa (Sub-Saharan Africa)	Hospitals	29	2004
Kirigia *et al.* (2001)	South Africa (Sub-Saharan Africa)	Primary care	155	1996
Kirigia *et al.* (2002)	Kenya (Sub-Saharan Africa)	Hospitals	54	Not available
Kirigia *et al.* (2004)	Kenya (Sub-Saharan Africa)	Primary care	32	Not available
Kirigia *et al.* (2008b)	Angola (Sub-Saharan Africa)	Hospitals	28	2000 to 2002
Kirigia & Asbu (2013)	Eritrean (Sub-Saharan Africa)	Hospitals	19	2007

Reference	Country (Region)	Perspective	Sample size	Time period
Kirigia *et al.* (2011)	Sierra Leone (Sub-Saharan Africa)	Primary care	79	2008
Lasso (1986)	Colombia (Latin America and The Caribbean)	Hospitals	79	1977 to 1980
Lekprichakul (2001)	Thailand (East Asia and Pacific)	Hospitals	89	1994
Levin *et al.* (1999)	Bangladesh (South Asia)	Other	6	1996
Levin *et al.* (2003)	Uganda, Malawi, Ghana (Sub-Saharan Africa)	Hospitals and primary care	12	1997
Li *et al.* (2014)	China (East Asia and Pacific)	Hospitals	12	2006 to 2009
Li & Dong (2015)	China (East Asia and Pacific)	Hospitals	14	
Li *et al.* (2017)	China (East Asia and Pacific)	Hospitals	12	2010 to 2015
Lobo *et al.* (2009)	Brazil (Latin America and The Caribbean)	Hospitals	30	2003 and 2006
Löfgren *et al.* (2015)	Uganda (Sub-Saharan Africa)	Hospitals	2	2011
Lotfi *et al.* (2014)	Iran (Middle East and North Africa)	Hospitals	16	2007 to 2011
Maceira *et al.* (2015)	Moldova (Europe and Central Asia)	Primary care	50	2013
Mahapatra & Berman (1994)	India (South Asia)	Hospitals	108	1989 to 1991
Marschall & Flessa (2009)	Burkina Faso (Sub-Saharan Africa)	Primary care	20	2004
Marschall & Flessa (2011)	Burkina Faso (Sub-Saharan Africa)	Primary care	25	2005
Martineau *et al.* (2004)	China (East Asia and Pacific)	Hospitals and primary care	573	1993 and 1998
Masiye *et al.* (2006)	Zambia (Sub-Saharan Africa)	Primary care	40	Not available
Masiye (2007)	Zambia (Sub-Saharan Africa)	Hospitals	30	2003
Masoompour *et al.* (2015)	Iran (Middle East and North Africa)	Hospitals	1	2008 to 2012
Mills *et al.* (1997)	South Africa and Zimbabwe (Sub-Saharan Africa)	Hospitals	6	
Moradi *et al.* (2017)	Iran (Middle East and North Africa)	Hospitals	11	2014/2015
Mujasi *et al.* (2016)	Uganda (Sub-Saharan Africa)	Hospitals	17	2012/2013
Madinah *et al.* (2015)	Uganda (Sub-Saharan Africa)	Hospitals and primary care	11	2012 to 2013
Nordyke (2002))	Macedonia (Europe and Central Asia)	Primary care	273	1997 to 1998
Novignon & Nonvignon (2017)	Ghana (Sub-Saharan Africa)	Primary care	87	2015
Obure *et al.* (2016)	Kenya and Swaziland (Sub-Saharan Africa)	Hospitals and primary care	40	2008 to 2011
Olukoga & Harris (2005)	South Africa (Sub-Saharan Africa)	Hospitals	5	2000
Aduda *et al.* (2015)	Kenya (Sub-Saharan Africa)	Other	21	2011 to 2012

Reference	Country (Region)	Perspective	Sample size	Time period
Osei *et al.* (2005)	Ghana (Sub-Saharan Africa)	Hospitals and primary care	34	2000
Özgen Narcı *et al.* (2015)	Turkey (Europe and Central Asia)	Hospitals	1103	2010
Ozgen & Sahin (2010)	Turkey (Europe and Central Asia)	Other	830	2008
Pan *et al.* (2006)	China (East Asia and Pacific)	Hospitals and primary care	6	
Pavitra (2013)	Afghanistan (South Asia)	Primary care	284	2010/2011
Pham (2011)	Vietnam (East Asia and Pacific)	Hospitals	101	1998 to 2006
Pilyavsky & Staat (2008))	Ukraine (Europe and Central Asia)	Hospitals and primary care	193	1997 to 2001
Pilyavsky *et al.* (2006)	Ukraine (Europe and Central Asia)	Hospitals	61	1997 to 2001
Pilyavsky & Staat (2006)	Ukraine (Europe and Central Asia)	Hospitals	75	1997 to 2001
Prakash & Annapoorni (2015)	India (South Asia)	Hospitals	31	2012 to 2013
Puenpatom & Rosenman (2008)	Thailand (East Asia and Pacific)	Hospitals	92	2000 to 2002
Raei *et al.* (2017)	Iran (Middle East and North Africa)	Hospitals	11	2011 to 2016
Rahman & Capitman (2012))	Bangladesh (South Asia)	Hospitals	185	0
Rajasulochana & Dash (2012)	India (South Asia)	Hospitals	48	2009/2010
Ramanathan *et al.* (2003)	Botswana (Sub-Saharan Africa)	Hospitals and primary care	35	1997
Ramos *et al.* (2015)	Brazil (Latin America and The Caribbean)	Hospitals	533	2012
Ratkovic *et al.* (2012)	Serbia (Europe and Central Asia)	Other	35	2007
Rattanachotphanit *et al.* (2008)	Thailand (East Asia and Pacific)	Hospitals	155	2004
Renner *et al.* (2005)	Sierra Leone (Sub-Saharan Africa)	Primary care	37	2000
Routh *et al.* (2004)	Bangladesh (South Asia)	Other	6	1996 to 1997
Ruiz-Rodriguez *et al.* (2016)	Colombia (Latin America and The Caribbean)	Primary care	21	2013/2014
Razzaq *et al.* (2013)	Pakistan (South Asia)	Primary care	32	2010
Sahin & Ozcan (2000)	Turkey (Europe and Central Asia)	Hospitals	80	1996
Schütte *et al.* (2015)	Zambia (Sub-Saharan Africa)	Primary care	51	2011
Shade *et al.* (2013)	Kenya (Sub-Saharan Africa)	Other	12	2011
Shahhoseini *et al.* (2011)	Iran (Middle East and North Africa)	Hospitals	12	2008
Applanaidu *et al.* (2014)	Malaysia (East Asia and Pacific)	Hospitals	9	2008 to 2010
Somanathan *et al.* (2000) (2000)	Sri Lanka (South Asia)	Hospitals and primary care	218	1998
Soucat *et al.* (1997)	Benin and Guinea (Sub-Saharan Africa)	Primary care	414	1988 to 1993

Reference	Country (Region)	Perspective	Sample size	Time period
Sulku (2012)	Turkey (Europe and Central Asia)	Hospitals	81	2003
Susca *et al.* (2012)	Romania (Europe and Central Asia)	Hospitals	39	2009 to 2010
Thomason & Mitchell (1991)	Papua New Guinea (East Asia and Pacific)	Primary care	76	1987
Tlotlego *et al.* (2010)	Botswana (Sub-Saharan Africa)	Hospitals	21	2006 to 2008
Torabipour *et al.* (2014)	Iran (Middle East and North Africa)	Hospitals	12	2007 to 2010
Dash *et al.* (2007)	India (South Asia)	Hospitals	29	2004
Dash *et al.* (2010)	India (South Asia)	Hospitals	29	2004 to 2005
Wang *et al.* (2017)	China (East Asia and Pacific)	Hospitals	127	2012 to 2015
Wei *et al.* (2018)	China (East Asia and Pacific)	Hospitals	131	2009 to 2013
Wouters (1993)	Nigeria (Sub-Saharan Africa)	Hospitals and primary care	42	1987
Xu *et al.* (2015)	China (East Asia and Pacific)	Hospitals	51	2009 to 2011
Yang & Zeng (2014)	China (East Asia and Pacific)	Hospitals	70	2006 to 2010
Yawe (2010)	Uganda (Sub-Saharan Africa)	Hospitals	23	1999 to 2003
Yusefzadeh *et al.* (2013)	Iran (Middle East and North Africa)	Hospitals	23	2009
Zaim *et al.* (2008)	Turkey (Europe and Central Asia)	Hospitals	12	
Zeng *et al.* (2014)	Rwanda (Sub-Saharan Africa)	Primary care	26	2006 to 2007
Zere *et al.* (2001)	South Africa (Sub-Saharan Africa)	Hospitals	86	1992 to 1997
Zere *et al.* (2006)	Namibia (Sub-Saharan Africa)	Hospitals	26	1997 to 2000

Table B.3: Methodologies of included studies

Reference	Method(s)	Inputs	Outputs
Aboagye & Degboe (2011)	RA: Cost	1. Cost per outpatient 2. Nurse	1. total number of outpatient attendance per annum 2. average number of outpatient attendance per nurse 3. average number of outpatient attendance per employee 4. average amount of funds internally generated per outpatient visit 5. bed turnover ratio 6. Internal genrated fund (IGF)
Ajlouni *et al.* (2013)	DEA and RA: Pabon-Lasso Diagram	1. Bed days 2. Physicans 3. Health personal	1. Patient days 2. Minor operations 3. Major operations
Akazili *et al.* (2008)	DEA	1. Number of non clinical staff including labourers 2. Number of clinical staff 3. Number of beds and cots 4. Expenditure (in local currency call cedi) on drugs and supplies. The inter-bank exchange rate of the cedi to the dollar was 8,500 cedi to 1 US$at the time of the study	1. General outpatient visits 2. Number of antenatal care visits 3. Number of deliveries 4. Number of children immunised 5. Number of family planning visits
Alaghemandan *et al.* (2014)	RA: Production	1. General dentists 2. Dental specialist 3. Working time 4. Receptionist staff 5. Dental equipment	1. Annual patients 2. Annual income
Alhassan *et al.* (2015)	DEA	1. Number of clinical staff 2. Number of support staff 3. Number of observation beds 4. Number of detention wards 5. Number of consulting rooms	1. Number of deliveries 2. Number of out-patients visits 3. Number of antenatal and postnatal visits 4. Number of family planning reproductive and child health visits

Reference	Method(s)	Inputs	Outputs
Amole *et al.* (2016)	DEA	1. Total number of beds (beds) 2. doctors (number of medical doctors including residents and interns) 3. nurses (number of nurses) 4. pharmacists 5. technicians 6. number of administrative staffs 7. engineers 8. other support staff	1. outpatients' visit (total number of outpatients) 2. inpatients' surgeries 3. inpatient visit 4. emergency cases 5. maternal and child health cases
Araújo *et al.* (2014)	DEA	1. Hospital area 2. Number of ICU 3. Number of emergency beds 4. Total number of staff Number of doctors 5. Number of nurses 6. Number of doctor offices 7. Number of surgical rooms	1. Number of ordinary inaptients 2. Number of ICU inpatients 3. Number of emergency inpatients 4. Total number of oupatients (per year) 5. Number of usrgeries
Arfa *et al.* (2017)	DEA	1. Number of physicians; 2. Number of surgical dentists; 3. Number of midwives; 4. Number of nurses and equivalent; 5. Beds, 6. Operating budget	1. Outpatient visits in stomatology ward 2. Outpatient visits in emergency ward 3. Outpatient visits in external wards 4. No. of admissions 5. No. admissions in maternity wards
Arocena & García-Prado (2007)	DEA, Malmquist productivity index	1. FTE phycisians 2. FTE nurses 3. Expenditure in goods and services 4. # of beds	1. Case mix adjusted discharged patients 2. Case mix adjusted outpatient hospital services 3. Case mix adjusted hospital re-admission
Asbu *et al.* (2012)	RA: Pabon Lasso model	Beds	1. Total number of discharges, 2. Total patient days
hanam Atake (2015)	DEA	1. Medical staff 2. Paramedical staff 3. Technical staff 4. Administrative staff 5. Beds	1. Admissions 2. Hospitalisations 3. Number of Surgical activities 4. Child deliveries 5. ANC

Reference	Method(s)	Inputs	Outputs
Atilgan (2016)	SFA	1. total number of physicians 2. total number of ancillary (allied) medical staff 3.total number of the other employees 4. total number of the hospital beds.	1. Total number of discharges, 2. Total patient days
Audibert *et al.* (2013)	DEA	1. Curative medical staff 2. Preventive medical staff 3. Beds 4. Equipments: X-ray, Echograph, Electrocardiogram	1. Outpatient visits 2. Inpatients 3. Vaccinations
Mohammadkarim *et al.* (2011)	RA: Pabon Lasso model	Beds	1. BOR 2. BTO 3. ALOS
BASTANI *et al.* (2013)	RA: Production	Beds	1. Inpatient days 2. Patient admissions
Berman (1986)	RA: Cost	Total cost	Outpatient visit
Berman *et al.* (1989)	RA	Total cost	1. curative care ; 2. MCH/FP contacts
Berman *et al.* (1989)	RA, EE	1. Total cost	1 Curative Care ; 2. Maternal and Child Health ; 3. Family Planning ; 4 Immunization 5. All; 6. Other
Bernet *et al.* (2008)	DEA	1. Physician 2. Nurse	1. Outpatient visits on site 2. Sick visits (house calls)
Blaakman *et al.* (2014)	DEA	1. Number of clinical staff; 2. number of administrative staff; 3. level of available drugs/ medicines; 4. number of beds	1. ANC annual visits 2. DPT 3 annual visits 3. Deliveries annual 4. Family planning annual visits 5. OPD annual visits 6. Nutrition annual visits 7. TB pos annual 8. TT2 annual

Reference	Method(s)	Inputs	Outputs
Bowser *et al.* (2013)	RA: Production	1. GP 2. Perscription 3. Image 4. Lab	1. Productivity per GP team/ day (patients/GP/hours) 2. rational drug use (prescriptions/ patients) 3. rational imaging usage (images/ patients) 4. rational lab usage (labs/ patients)
Brenzel *et al.* (2015) (2015)	RA: Cost	1. Cost	1. Number of immunisation
Bwana (2015)	DEA	1. Licensed hospitals beds ; 2. Full-time equivalent employees (FTE) employees/ staff	1. Total inpatients days ; 2. Total outpatients visits; 3. Surgical operation
Bwana & Raphael (2015)	DEA	1. Licensed hospitals beds ; 2. Number of Doctors ; 3. Number of Nurses ; 4. Number of non-medical	1. Total inpatients discharged ; 2. Total outpatients visits
Chaabouni & Abednnadher (2012)	DEA	1. # beds 2. # physicians 3. # nurses 4. # dentists and pharmacists 5. # of other personnel	1. # of outpatient visits 2. # of admissions 3. Post-admission days
Chaabouni & Abednnadher (2016)	Bayesian frontier model	1. Total cost 2. Prices for the different labor inputs (3), price for capital (4) 6. Physicians 7. Nurses 8. Dentists and pharmacists 9. Beds	1. post-admission days, 2. outpatient visits, 3. admissions
Cheng *et al.* (2016)	Bootstrapping DEA, Bootstrapping Malmquist Productivity Index	1. Total number of medical staff ; 2. total number of other technicians; 3. total number of non-medical staff members; 4. the actual number of open beds	1. The number of outpatient and emergency visits; 2. the number of inpatient; 3. the number of family EHRs under management; 4. the number of chronic diseases patients under management
Cheng *et al.* (2015)	Malmquist productivity index	1. Physicians 2. Nurses 3. Hospital beds	1. Outpatient and emergency visits 2. Inpatient days

Reference	Method(s)	Inputs	Outputs
Walker (2006)	RA:Cost, DEA, SFA	1. labour 2. size of facility dedicated to delivery of EPI services 3. total hours 4. total cost	1. BCG 2. DPT 3. OPV 4. Measles 5. TT 6. Total number of vaccines
Dandona *et al.* (2005)	EE: cost funtction	1. Total economic cost 2. Fixed costs	1. Number of initial visits 2. Number of other visits
Dandona *et al.* (2008)	RA: Cost	Total cost	1. post -HIV test conselled pregnant woman 2. mother-neonate pair who received nevirapine
de Castro Lobo *et al.* (2010)	DEA, Malmquist productivity index	1. Labor force (physicians and full time equivalent non-physicians), 2. Operational expenses (not including payroll) 3. Beds, 4. Service-mix	1. Admissions 2. Inpatient surgeries 3. Outpatient visits all of them adjusted according to the complexity index of the hospital.
Dervaux *et al.* (2003)	DEA	1. Amount of vaccine wastage 2. number of FTE staff 3. size of the facility 4. Number of hours of operation 5. Number of sessions	Number and type of vaccines aimed at children and pregnant women
Ekiyor (2015)	RA: Pabon Lasso model	1. Beds	1. Inpatient days 2. Admission
Erus & Hatipoglu (2017)	DEA Malmquist index	1. Beds 2. Specialists 3. Part-time specialists 4. Practitioners	1. Outpatient visits 2. inpatient visits 3. Inpatietn visits (case mix adjusted) 4. Surgeries
Fiedler *et al.* (1998)	RA: Production	1. Budget - ’000 of colones, colones per bed 2. Beds 3. Staffing - FTE doctors, doctors per 100 beds, Nurses, nurses per 100 beds	1. Total number of discharges, 2. Total patient days 3. Outpatient
Flessa (1998)	RA: Cost	Total cost	1. Outpatient visit 2. Inpatient day

Reference	Method(s)	Inputs	Outputs
Gai *et al.* (2010)	DEA	1. Number of medical staff 2. Number of beds 3. Value of fixed capital 4. Hospital expenditures	1. Outpatient and emergency visits 2. Number of inpatients, 3. Hospital revenue
Gholipour *et al.* (2013)	RA: Pabon Lasso model	Beds	1. Inpatient days 2. Patient admissions
Gok & Sezen (2013)	DEA	1. # Beds 2. # Specialist physicians 3. # non-specialist physicians	1. Bed utilisation rate 2. bed turnover rate 3. total surgical operations 4. number of births 5. total outpatient visits 6. average facility inpatient days 7. number of discharge
Gok & Altındağ (2015)	DEA, Malmquist productivity index	1. Number of specialized physicians 2. Number of non-specialized physicians 3. Total number of hospital beds	1. Surgical operations 2. Number of births 3. Outpatient visits 4. Facility inpatient days 5. Number of discharge
Goshtasebi *et al.* (2009)	RA: Pabon Lasso model	1. Beds	1. Discharges
Guerra *et al.* (2012)	DEA	1. ALOS 2. Days of stay 3. Occupancy rate 4. Occupied beds 5. full time equivalent 6. full-time equivalent per occupied beds	1. The operating margin (OM) 2. The return on assets (ROA) 3. Total asset turnover (TAT)
Hamidi (2016)	SFA	1. Beds 2. Doctors 3. Nurses 4. Non-medical staff	1. Sum of inpatients and outpatients

Reference	Method(s)	Inputs	Outputs
Hatam (2008)	DEA	Technical Efficiency: 1) Fixed hospital beds, 2) the total number of FTE personnel Scale efficiency: 1) number of constant beds Economical efficiency: 1) total expenses; 2) FTE; 3) No of bed	TE: 1) BOR; 2) Patient-day ; 3) occupied bed days; 4) ALOS; 5) Rate of bed turn-over Scale efficiency: 1) ratio of active and constant bed; 2) bed/day Economical efficiency: 1) hoteling expense; 2) bed day expense; 3) personnel expense
Hatam *et al.* (2010)	DEA, Malmquist productivity index	Technical Efficiency: 1) Fixed hospital beds, 2) the total number of FTE physicians, 3) FTE nurses and othe rpersonnel Scale efficiency: 1) number of fixed beds Economical efficiency: 1) total cost	TE: 1) BOR; 2) Patient-day admissions; 3) occupied bed days; 4) ALOS; 5) Rate of bed turn-over Scale efficiency: 1) the number of active to fixed beds Economical efficiency: 1) number of discharged patients
ISAI & RADU (2016)	RA: Cost	1. Total cost	1. Outpatient by department 2. Inpatient-day by department 3. Income
Jat & Sebastian (2013)	DEA	1. # Doctors 2. # nurses 3. # beds	1. # Women with completed three ANC checkup 2. # Deliveries 3. # C-section deliveries 4. # Women receiving post-natal care within 48 hours after delivery 5. # medical terminationof pregnancies 6. # male and female sterilisations 7. # inpatient admissions 8. #outpatient consultation
Jehu-Appiah *et al.* (2014)	DEA	1. Number of beds, 2. clinical staff, 3. nonclinical staff, 4. Recurrent exenditure	1 .outpatients 2. inpatients 3.deliveries 4. lab services
Jia & Yuan (2017)	DEA window analysis	1. The actual number of beds 2. The actual number of staff	1. The number of patients in out-patient and emergency departments, 2. The number of discharged patients, 3. The average days of hospitalization
Jian *et al.* (2009)	RA: Production	1. Medical expenditure 2. Time	1. Charge efficiency index (medical expenditure) 2. Time efficiency index (LOS)

Reference	Method(s)	Inputs	Outputs
Johns *et al.* (2013)	EE: cost function	1. Total cost	1. Outpatient visits 2. Inpatient admission 3. Fully immunised children
Keith & Prior (2014)	DEA	1. Physicians 2. Medical personnel staff 3. Hospital beds 4. Operating rooms	1. Surgical medical procedures 2. Total medical consultations 3. Days to stay
Ketabi (2011)	DEA	1. Number of active beds 2. Medical equipment 3. Personnel 4. Technological capabilities	1. Bed occpancy percenage 2. ALOS 3. Total percentage of survival and performance ratio
Khan & Ahmed (2003)	RA: Cost	Total cost	1. nutrition services: number of individuals enrolled
Kiadaliri *et al.* (2011) (2011)	DEA	1. # Human resources (physicians, specialist, nurses, and other) 2. # beds	1. # of outpatient visits 2. # of inpatient visits 3. # surgeries 4. % occupied beds
Kibambe & Koch (2007)	DEA	1. Active beds 2. Medical doctors & specialists 3. Nurses	1. Outpatient visits 2. Total admission 3. Inpatient days 4. Theater case/ surgeries
Kirigia *et al.* (2001)	DEA	1. # of nursing staff 2. # of general staff	1. # of ANC visits 2. # of births 3. # of child health 4. # of dental care visits 5. # of family planning visits 6. # of psychiatry visits 7. # of STD visits 8. # of tuberculosis visits

Reference	Method(s)	Inputs	Outputs
Kirigia *et al.* (2002)	DEA	1. medical officers/ phamacist/ dentists 2. clinic offciers 3. nurses 4. administrative staff 5. technicians 6. other staff 7. subordinate staff 8. phamaceuticals 9. non phamaceutical supplies 10. maintenance of equipemtn, vehicles, and buildings 11. food and rations	1. OPD casualty visits 2. special clinic visits 3. MCH/ FP visits 4. dental care visits 5. general medical admissions 6. paediatric admissoins 7. maternitiy admissions 8. amenity ward admissions
Kirigia *et al.* (2004)	DEA	1. Clinical officers + nurses, 2. physiotherapists + occupational therapists +public health officers + dental technologists 3. laboratory technologists + laboratory technicians, 4. administrative and general staff 5. beds 6. nonwage recurrent expenditures	1. diarrhoeal visits + malaria visits + STI visits + UTI visits + intestinal worm visits 2. ANC visits +family planning visits 3. Immunisation visits 4. other general outpatient visits
Kirigia *et al.* (2008b)	DEA, Malmquist productivity index	1. Doctornurses 2. Drugother supplies 3. Beds	1. OPDANC Visits 2. Patient admission
Kirigia & Asbu (2013)	DEA	1. Number of physcians (doctors) 2. Number of nurses and midwives. 3. Number of laboratory technicians 4. Number of operational beds and cost	1. Number of outpatient dept visits 2. Number of inpatient dept. discharges
Kirigia *et al.* (2011)	DEA	1. Number of community helath officers + MCH+ State enrolled community health nurses 2. Number of other health staff	1. OMFE: Number of outpatients, maternal, child health and family planning visits, plus immunisation visits 2. number of vector control activities 3. number of helath education sessions
Lasso (1986)	RA: Pabon Lasso model	Beds	1. Total number of discharges, 2. Total patient days

Reference	Method(s)	Inputs	Outputs
Lekprichakul (2001)	DEA, SFA	1. Total variable cost 2. average wage rate of medical employees 3. average wage rate of other non-medical temporary empoyees 4. price of supply 5. number of beds	1. Outpatient visit 2. surgical and orthopedic surgical inpatients 3. obstetric-gynecological inpatients 4. pediatric inpatients 5. medical and other inpatients
Levin *et al.* (1999)	RA: Cost	Total cost	Toal services per activity
Levin *et al.* (2003)	RA: Production	Number of midwives	Number of services volume
Li *et al.* (2014)	Malmquist productivity index	1. Number of open beds; 2. number of employees	1. Number of outpatients and emergency visits 2. Number of discharged patients
Li & Dong (2015)	DEA	1. Number of employees 2. Actual number of open beds	1. Ttoal number of outpatient and emergency visits 2. Number of discharged patietns
Li *et al.* (2017)	DEA and malmquist index	1. number of actual doctors, 2. number of actual nurses, 3. number of beds, 4. total expenditure	1. number of emergency visits, 2. number of discharged, 3.number of hospitalized patients
Lobo *et al.* (2009)	DEA, Malmquist productivity index	1. Operating expenses 2. Labor force (total number of doctors and nondoctors), 3. Number of beds 4. Service mix	1. Admissions 2. Surgical procedures 3. Outpatient consultations
Löfgren *et al.* (2015)	RA: Cost	1. Cost	Number of surgery
Lotfi *et al.* (2014)	Pabon Lasso, DEA, Malmquist	1. Number of active beds 2. Nurses 3. Physicians 4. Other Personnels	1. Inpatient days 2. Outpatient visits 3. Operations

Reference	Method(s)	Inputs	Outputs
Maceira *et al.* (2015)	EE: production and cost function, regression	1. Total working hours 2. Facility square meters 3. Cold chain capital index 4. Total number of infants in the facility 5. Catchment area 6. Facility type 7. Presence of doctor 8. Distance from the facility to the vaccine collection point 9. Overall wasstage rate 10. Total Economic cost (cost function) Indpendent: 1. Ln hourly wage, mid career nruse 2. Ln refrigerator unit price 3. Ln ice pack unit price	1. Number of fully immunised children 2. Total number of doses administrated Cost function 3. Ln Fully immunised children
Mahapatra & Berman (1994)	RA: Pabon Lasso model	Beds	1. BOR 2. BTO
Marschall & Flessa (2009)	DEA	1. Personnel costs (USD) 2. Area (m2) 3. Equipment depreciation (USD) 4. Vaccine (USD)	1. # of general consultations 2.# of deliveries 3. # of other care 4. # of vacccinations
Marschall & Flessa (2011)	DEA	1. Personnel costs in 2005 [US$] 2. CSPS building area [m2] 3. Depreciation of CSPS equipment in 2005 [US$] 4. Vaccination costs in 2005 [US$]	1. general consultation and nursing care, 2. deliveries 3. immunisation 4. special services
Martineau *et al.* (2004)	RA: Production	1. Number of doctor	1. Outpatient visit 2. Inpatient days
Masiye *et al.* (2006)	DEA	1. # of clinical officers 2. # of nurses 3. # other staff	visits
Masiye (2007)	DEA	1. Non-labour cost 2. # medical doctors 3. # nurses + cos + lab techs + radiographers + pharmacists 4. # administrative and other staff	1. # ambulatory care visits 2. # inpatient bed days 3. # of deliveries 4. # lab test + x ray + theatre operations performed

Reference	Method(s)	Inputs	Outputs
Masoompour *et al.* (2015)	RA: Pabon Lasso model	Beds	1. Total number of discharges, 2. Total patient days
Mills *et al.* (1997)	RA: Cost	Total Cost	Admission
Moradi *et al.* (2017)	RA: Pabon Lasso model	1. Beds	1. Inpatient days 2. Admission
Mujasi *et al.* (2016)	DEA	1. total number of medical staff 2. hospital beds	1. outpatient department (OPD) visits 2. in-patient days
Madinah *et al.* (2015)	RA: Pabon Lasso model	Beds	1. Total number of discharges, 2. Total patient days
Nordyke (2002)	Production function	1. Number of nurses/ physician in deparmtent 2. Number of departments in clinic 3. Physician time spent with patient 4. Basic medical equipment inputs	Patient visits per week
Novignon & Nonvignon (2017)	SFA	1. number of personnel, 2. hospital beds	Number of outpatient visits
Obure *et al.* (2016)	DEA	1. Clinical FTE 2. Non clinical FTE 3. Unite size	1. Cervical cancer visits 2. Family Planning visits 3. Post Natal Care visits 4. HIV Counseling test visits 5. Sxually transmitted infections visits 6. HIV visits 7. Other visits 8. Sexual reproductive health visits 9. Total annual aggregated HIV visits 10. Structural qulaity score 11. Process quality score 12. Composite index score for structural and process quality indicators
Olukoga & Harris (2005)	RA: Cost	Total cost	1. Inpatient days 2. Outpatient visits
Aduda *et al.* (2015)	DEA, Malmquist productivity index	1. Clinician 2. Nurse 3. Surgical beds 4. Total operating time	1. MCs performed 2. HTC performed (%) 3. Quality of service

Reference	Method(s)	Inputs	Outputs
Osei *et al.* (2005)	DEA	Hospitals 1. Doctors/ dentist 2. Technical staff (including nurse) 3. Subordinate staff 4. Beds Health centres: 1. Medical assistants/ nurses/ other technical staff 2. Subordinate staff	Hospitals: 1. Maternal and child health care visits 2. Deliveries 3. Inpatient discharges Health centres: 1. Matenral and child health care visits 2. Deliveries 3. Fully-immunized children
Özgen Narcı *et al.* (2015)	DEA	1. Beds 2.Specialists 3. General practitioners 4. Nurses 5. All ohters	1. Discharges 2. Outpatient visits 3. Emergency care 4. Surgeries 5. Daycare
Ozgen & Sahin (2010)	DEA	1. Dialysis machine 2. FTE nurse	1. Dyalisis services
Pan *et al.* (2006)	RA: Production	1. Average professional income per staff 2. Medical income per 100 year fixed assets 3. Level of person-time charge for outpatient service	1. Proportion of administrative to total expenditure 2. Average outpatients per staff
Pavitra (2013)	DEA	2 Settings: 1) Total costs 2) numbers of various labour groups	Outpatient visits
Pham (2011)	DEA, Malmquist productivity index	1. # beds 2. # Personnel	1. # outpatient visits 2. # inpatient days 3. # Surgical operations
Pilyavsky & Staat (2008)	Malmquist productivity index	Hospitals 1. Beds 2. D. Surger 3. Deaths 4. Nurses 5. Physicians Polyclinics 1. Nurses 2. Physicians	Hopitals: 1. Admissions other 2. Admissions surgery 3. Surgerical procedures Polyclinics 1. Admissions sick 2. Admissions home 3. Surgical procedures 4. Laboratory test 5. X-ray

Reference	Method(s)	Inputs	Outputs
Pilyavsky *et al.* (2006)	DEA	1. Number of beds 2. Number of nurses 3. Number of physicians	1. Number of medical admissions 2. Number of surgical admissions
Pilyavsky & Staat (2006)	DEA, Malmquist productivity index	1. Number of beds 2. Physicians 3. Nurses	1. Surgical procedures performed 2. Admissions 3. Patient days
Prakash & Annapoorni (2015)	DEA	1. Beds 2. Nurses 3. Doctors	1. Outpatients treated 2. Major surgeries conducted 3. Deliveries performed
Puenpatom & Rosenman (2008)	DEA	1. Bed 2. Physician 3. Nurse 4. Dentists and pharmacists 5. Others	1. Adjusted number of inpatient visit in surgical 2. Adjusted number of inpatient visits in primary care 3. Adjusted number of inpatient visits in others 4. Surgical outpatient visits 5. Non-surgical outpatient visits
(Raei *et al.*, 2017)	DEA	1 .total number of physician 2. total number of nonphysician staff 3. total number of hospital beds	1. admissions 2. inverse of mortalities proportion
Rahman & Capitman (2012)	DEA	1. Capital expenditure 2. Non-capital expenditure	1. Total revenue 2. Facility service mix
Rajasulochana & Dash (2012)	DEA	1. # of beds for Obstetric and new born 2. # of doctors 3. # of nurses	1. # maternity admissions per year (vol) 2. # neo-natal admissions per year (vol) 3. % complicated maternity cases (insensity) 4. % complicated neo-natal cases (intensity)

Reference	Method(s)	Inputs	Outputs
Ramanathan *et al.* (2003)	DEA and SFA	1. Hospitals in the district 2. Clinics in the district 3. Health posts in the hospitals 4. Beds 5. Doctors 6. Nurses 7. Health staff	1. Outpatients in typhoid 2. Outpatients in malnutrition 3. Outpatients in blood related 4. Outpatients in mental 5. Outpatients in oral 6. Outpatients in pregnancy 7. Outpatients in male genitals 8. Outpatients in muscular 9. Outpatients in eye 10. Outpatients in ears 11. Outpatients in fertility 12. Outpatients (TOTAL) -¿ excluded in DEA approach 13. New birhts discharged alive 14. Patient days
Ramos *et al.* (2015)	RA: Production	Beds	1. Total number of discharges, 2. Total patient days
Ratkovic *et al.* (2012)	DEA	1. Operating hours, 2. fuel costs 3. electricity costs 4. yellow bag costs 5. black bag costs	HCW collected in kg

Reference	Method(s)	Inputs	Outputs
Rattanachotphanit *et al.* (2008)	DEA	1. # FTE Pharmacists 2. # FTE Support personnel	1. drug dispensing: # of otupatient prescriptions 2. drug dispensing: # of inpatient prescriptions 3. drug purchasing and inventory control: value of purchased drugs 4. drug purchasing and inventory control: value of stocked drugs 5. drug purchasing and inventory control: value of drugs supplied 6. patient-oriented activiites: # of patients receiving drug counseling 7. patient-oriented activiites: # of patients receiving drug therapy monitoring 8. patient-oriented activiites: frequency of ADR management, DIS and DUE 9. health consumer protection services: Frequency of conducting helath consumer surveillance 10. health consumer protection services: frequency of conducting education sessions
Renner *et al.* (2005)	DEA	1 # technical staff 2. # sub-odinate staff	1. Antenatal + post natal care 2. babies delivered 3. nutrition/ growth monitoring visits 4. family planning visits 5. under 5's immunised + pregnant women immunised 6. health education nsessions
Routh *et al.* (2004)	RA: Cost	Total cost	1. Family planning 2. Maternal health 3. Curative care 4. Expanded programme on immunisation

Reference	Method(s)	Inputs	Outputs
Ruiz-Rodriguez *et al.* (2016)	DEA	1. Personnel by services (3) 2. Capital by services (3) 3. Consumable resrouces by services (3)	Activity output: 1. ANC: No of consultations 2. DCACU: No. of citologies 3. FP: No of counseling visits Quality output: 1. ANC: Proportion of adherence to guidelines 2. DCACU: Proportion women with 3:1 squme 3. FP: Proportion counseling coverage
Razzaq *et al.* (2013)	DEA	1. Cost to reconstruct BHU; 2. Area; 3. Available staff; 4. Salary	1. Services provided; Patients/ day 2. Patient satisfaction
Sahin & Ozcan (2000)	DEA	1. beds 2. specialists 3. general practitioners 4. nurses 5. other allied professionals 6. revolving funds expenditure	1. outpatient visits 2. discharged patients 3. (1 / hospital mortality rate)
Schütte *et al.* (2015)	RA	Total economic cost	DTP3 vaccinated child
Shade *et al.* (2013)	RA: Cost	Cost	1. marginal cost per HIV-infected female patient (woman), 2. cost per additional use of more effective family planning (costefficiency) 3. cost per pregnancy averted
Shahhoseini *et al.* (2011)	DEA	1. No of active beds 2. No of other professinals 3. No of nurses 4. No of physicians	1. Operations 2. Outpatients visit 3. Bed occupancy rate 4. Average length of stay 5. Inpatient bed days
Applanaidu *et al.* (2014)	DEA	1. number of nurses, 2. physicians, and 3. number of occupied beds	1. Number of outpatients 2. inpatients 3. number of surgeries and 4. deliveries

Reference	Method(s)	Inputs	Outputs
Somanathan *et al.* (2000)	RA, EE	1. Doctors 2. Nurses 3. Paramedic 4. Others 5. Beds	1. Outpatient visits 2. Bed occupancy 3. Admissions
Soucat *et al.* (1997)	RA: Production	1. Specific drugs 2. Outreach cost	number of beneficiaries
Sulku (2012)	DEA, Malmquist productivity index	1. Number beds 2. Number of primary care physicians 3. Number of specialists	1. Inpatient discharges 2. Outpatient visits 3. Surgical operations 4. Death rate
Susca *et al.* (2012)	RA: Cost	Multiple criteria	Economic score
Thomason & Mitchell (1991)	RA: Cost	1. Recurrent and capital expenditure	1. Level of health service outputs
Tlotlego *et al.* (2010)	DEA, Malmquist productivity index	1. # of clinical staff 2. # of hospital beds	1. # of outpatient department visits 2. # inpatient days
Torabipour *et al.* (2014)	DEA, Malmquist productivity index	1. number of nurses, 2. physicians, and 3. number of occupied beds	1. Number of outpatients 2. Admission 3. Inpatient days 4. Major operations
Dash *et al.* (2007)	DEA	1. Numbers of assistant surgeons 2. Civil surgeons 3. Staff nurses 4. Beds	1. In-patient 2. outpatient visits 3. Surgeries 4. Deliveries
Dash *et al.* (2010)	DEA	1. # of Staff 2. # bed	1. outpatient visits 2. # of inpatient 3. # of surgeries undertaken 4. # of deliveries 5. # emergency cases
Wang *et al.* (2017)	DEA, Malmquist productivity index	1. physicians 2. nurses 3. technicians 4. beds	1. outpatient and emergency visits, the 2. inpatient days

Reference	Method(s)	Inputs	Outputs
Wei *et al.* (2018)	SFA	1.Total cost 2.Price of labor 3.Cost of capital	1. Inpatient discharges 2. Number of outpatient visits 3. Quality measures
Wouters (1993)	EE: production and cost function	1. High-level health workers (doctors, nurses, midiwves, pharaciss, community health workers) 2. Low-level health workers (health adids, asistants, cleaners, labourers, clerk) 3. Beds 4. Wage of high level health workers 5. Wage of low level health workers	1. Visits 2. Admission
Xu *et al.* (2015)	RA, DEA, SFA	1. Medical personnel and equipment input 2. Construction input 3. Financial input	1. Bed utilisation output 2. Service output
Yang & Zeng (2014)	DEA (Malmquist productivity index), SFA	1. number of beds (used as a proxy of capital) ; 2. the number of doctors ; 3. the number of nurses ; 4. the number of administrative staff ; 5. the number of other staff (health professionals other than doctors and nurses)	1. number of outpatient visits ; 2. number of inpatients/ days 3 mortality rate 4. ALOS
Yawe (2010)	super effiicency DEA	1. Beds 2. Doctors 3. Nurses 4. Other employees	1. Admissions 2. Outpatient Dept. Attendances 3. Surgical operations 4. Deliveries
Yusefzadeh *et al.* (2013)	DEA	1. Number of active beds; 2. doctors; 3. other personnel	1. Outpatients 2. admision 3. occupied day beds
Zaim *et al.* (2008)	DEA	1. Number of beds 2. number of physicians 3. Critical factors of total quality mangement : Process management, quality data and reporting, employee relations, role o divisional top management and quality policy	1. incorporated financial and non financial performance of hospitals, 2. number of outpatients 3. number of patient days
Zeng *et al.* (2014)	DEA, Malmquist productivity index	1. FTE personnel 2. Non-personnel expenditures	3 HIV services: ART, PMTCT, VCT
Zere *et al.* (2001)	DEA	1. Recurrent expenditure 2. Beds	1. Outpatient visits 2. Inpatient days

Reference	Method(s)	Inputs	Outputs
Zere *et al.* (2006)	DEA	1. Recurrent expenditure (N$) 2. Beds (authorized) 3. Nursing staff	1. Outpatient visits 2. Inpatient days

Appendix C

Appendix related to Chapter 5

Table C.1: Characteristic of hospitals by Pabón-Lasso model sector

Sector	1	2	3	4	*p*
n	74	29	68	20	
Unit costs					
Outpatient unitcost (mean (sd))	42.28 (46.69)	25.70 (49.53)	20.87 (17.68)	28.71 (33.07)	0.009*
Bed day unitcost (mean (sd))	98.38 (70.21)	68.29 (43.94)	65.10 (31.32)	92.40 (39.53)	0.001*
Inpatient unitcost (mean (sd))	357.98 (245.97)	324.68 (186.20)	232.25 (107.23)	218.26 (130.19)	<0.001*
Utilisation					
ALOS (mean (sd))	4.12 (0.69)	4.27 (0.96)	4.45 (1.09)	4.32 (1.38)	0.242
BOR (mean (sd))	0.39 (0.14)	0.69 (0.06)	0.82 (0.38)	0.52 (0.08)	<0.001*
Throughput (mean (sd))	38.59 (13.52)	51.82 (7.44)	80.76 (16.29)	87.56 (33.39)	<0.001*
Ratio of outpatients and bed days (mean (sd))	3.58 (12.06)	3.49 (7.62)	1.85 (1.58)	2.47 (1.66)	0.616
Size and capacity					
Nonspecialist doctors FTE (mean (sd))	12.74 (8.06)	20.47 (15.43)	16.32 (8.79)	12.14 (4.67)	0.001*
Specialist doctors FTE (mean (sd))	9.92 (11.61)	20.79 (23.66)	10.86 (8.06)	7.43 (5.73)	<0.001*
Surgical specialist FTE (mean (sd))	6.29 (6.05)	11.70 (13.29)	6.99 (5.00)	4.64 (3.45)	0.002*
Beds (mean (sd))	133.26 (92.19)	239.45 (207.38)	160.13 (92.82)	111.70 (55.83)	<0.001*
Class A/B (%)	14 (19.2)	11 (37.9)	23 (33.8)	4 (20.0)	0.109
Ownership					
Publicly owned (%)	36 (48.6)	19 (65.5)	48 (70.6)	14 (70.0)	0.040*
For-profit hospital (%)	18 (24.3)	3 (10.3)	9 (13.2)	3 (15.0)	0.222
Teaching status					
Teaching hospital (%)	16 (21.6)	15 (51.7)	24 (35.3)	6 (30.0)	0.026*
Patients case mix					
% of NCD patient treated (mean (sd))	36.53 (14.68)	39.26 (12.04)	39.77 (14.11)	37.14 (13.88)	0.538
Case mix index (mean (sd))	1.02 (0.63)	1.36 (1.11)	1.06 (0.59)	0.94 (0.19)	0.257
% of patient 1 to 5 years old (mean (sd))	9.39 (4.66)	7.31 (4.15)	9.29 (4.55)	10.76 (6.40)	0.081
% of patient over 65 years old (mean (sd))	0.11 (0.08)	0.10 (0.04)	0.13 (0.07)	0.12 (0.05)	0.120
Experience					
Years of service (mean (sd))	42.06 (30.09)	48.69 (29.16)	47.63 (30.53)	34.58 (21.80)	0.270

Sector	1	2	3	4	*p*
Financing					
% of outpatient with *Askes* insurance (mean (sd))	0.26 (0.14)	0.31 (0.17)	0.26 (0.14)	0.23 (0.11)	0.341
% of outpatient with *Jamsotek* insurance (mean (sd))	0.16 (0.21)	0.07 (0.09)	0.10 (0.19)	0.16 (0.28)	0.394
% of outpatient with poor insurance scheme (mean (sd))	0.20 (0.15)	0.22 (0.17)	0.28 (0.18)	0.20 (0.13)	0.054
% of outpatient with other insurance (mean (sd))	0.11 (0.16)	0.06 (0.06)	0.06 (0.09)	0.06 (0.08)	0.411
% of outpatient with without insurance (mean (sd))	0.56 (0.29)	0.48 (0.25)	0.47 (0.27)	0.59 (0.27)	0.163
% of inpatient with *Askes* insurance (mean (sd))	0.15 (0.09)	0.18 (0.07)	0.17 (0.13)	0.14 (0.07)	0.400
% of inpatient with *Jamsotek* insurance (mean (sd))	0.16 (0.17)	0.10 (0.10)	0.09 (0.19)	0.13 (0.28)	0.438
% of inpatient with poor insurance scheme (mean (sd))	0.35 (0.24)	0.37 (0.25)	0.43 (0.23)	0.37 (0.17)	0.275
% of inpatient with other insurance (mean (sd))	0.09 (0.14)	0.08 (0.05)	0.06 (0.10)	0.08 (0.13)	0.739
% of inpatient with without insurance (mean (sd))	0.50 (0.28)	0.42 (0.24)	0.41 (0.24)	0.48 (0.26)	0.223
% of bed days with *Askes* insurance (mean (sd))	0.16 (0.10)	0.23 (0.14)	0.16 (0.08)	0.14 (0.09)	0.040*
% of bed days with *Jamsotek* insurance (mean (sd))	0.17 (0.19)	0.07 (0.08)	0.12 (0.20)	0.01 (0.02)	0.268
% of bed days with poor insurance scheme (mean (sd))	0.41 (0.24)	0.39 (0.25)	0.48 (0.25)	0.40 (0.20)	0.345
% of bed days with other insurance (mean (sd))	0.11 (0.15)	0.08 (0.07)	0.06 (0.10)	0.08 (0.12)	0.664
% of bed days with without insurance (mean (sd))	0.45 (0.29)	0.39 (0.29)	0.39 (0.26)	0.49 (0.28)	0.398
% of payment with *Askes* insurance (mean (sd))	0.15 (0.12)	0.17 (0.14)	0.15 (0.13)	0.13 (0.13)	0.873
% of payment with *Jamsostek* insurance (mean (sd))	0.16 (0.20)	0.04 (0.05)	0.12 (0.22)	0.13 (0.28)	0.343
% of payment with poor insurance scheme (mean (sd))	0.31 (0.28)	0.28 (0.30)	0.30 (0.27)	0.32 (0.28)	0.966
% of payment with other insurance scheme (mean (sd))	0.21 (0.24)	0.28 (0.27)	0.16 (0.19)	0.18 (0.26)	0.556
% of payment with without insurance scheme (mean (sd))	0.47 (0.31)	0.44 (0.30)	0.46 (0.30)	0.55 (0.30)	0.690
Pharmacy					
% of generic drugs prescribed (mean (sd))	0.55 (0.27)	0.55 (0.30)	0.50 (0.28)	0.46 (0.26)	0.546
% of non-generic drugs prescribed (mean (sd))	0.39 (0.26)	0.39 (0.28)	0.40 (0.27)	0.41 (0.23)	0.988
Quality					
Death rate (mean (sd))	0.01 (0.00)	0.01 (0.01)	0.01 (0.01)	0.01 (0.00)	0.013*
Mortality ratio (mean (sd))	0.84 (0.49)	1.10 (0.24)	0.98 (0.32)	0.88 (0.42)	0.097
Accredited (%)	40 (54.8)	18 (62.1)	49 (74.2)	9 (45.0)	0.042*
Without water disruption (%)	31 (42.5)	10 (34.5)	28 (42.4)	5 (25.0)	0.462
Without electricity disruption (%)	17 (23.3)	7 (24.1)	22 (33.3)	4 (20.0)	0.479
Without medicine disruption (%)	39 (53.4)	16 (55.2)	35 (53.8)	8 (40.0)	0.704
Without salary disruption (%)	65 (90.3)	24 (82.8)	61 (92.4)	19 (95.0)	0.433
Without incentive disruption (%)	46 (63.9)	19 (65.5)	41 (63.1)	12 (60.0)	0.983

Sector	1	2	3	4	*p*
Difficulty in filling management vacancy (%)	31 (44.3)	12 (44.4)	23 (37.7)	11 (55.0)	0.586
Difficulty in filling doctor vacancy (%)	45 (64.3)	13 (48.1)	36 (59.0)	15 (75.0)	0.267
Difficulty in filling nurse vacancy (%)	25 (35.7)	7 (25.9)	10 (16.4)	7 (35.0)	0.081
Difficulty in filling technician vacancy (%)	36 (51.4)	12 (44.4)	36 (59.0)	12 (60.0)	0.555
Difficulty in filling other staff vacancy (%)	12 (17.1)	2 (7.4)	10 (16.4)	3 (15.0)	0.671
Performance meeting once per week (%)	25 (34.2)	9 (31.0)	22 (34.4)	1 (5.0)	0.070
Case meeting at least 6 months (%)	36 (49.3)	10 (34.5)	31 (47.7)	6 (30.0)	0.280
Clinical mentoring (%)	72 (98.6)	28 (96.6)	65 (98.5)	19 (95.0)	0.716
Working hours monitoring (%)	69 (100.0)	28 (100.0)	62 (100.0)	19 (100.0)	NA
Economy					
Household expenditure (mean (sd))	292.55 (96.20)	298.15 (91.57)	246.90 (89.37)	269.33 (75.36)	0.012*
Gini index (mean (sd))	0.35 (0.04)	0.35 (0.04)	0.36 (0.04)	0.34 (0.04)	0.488
% of family working in agriculture (mean (sd))	0.39 (0.30)	0.32 (0.33)	0.46 (0.27)	0.50 (0.26)	0.092
% of poor population (mean (sd))	0.06 (0.05)	0.06 (0.07)	0.08 (0.07)	0.06 (0.05)	0.079
Total household health expenditure (mean (sd))	27.89 (15.09)	28.81 (14.27)	25.34 (15.08)	22.69 (10.73)	0.364
Curative household expenditure (mean (sd))	18.96 (11.34)	18.64 (10.11)	17.90 (12.04)	16.13 (8.78)	0.774
Preventive household expenditure (mean (sd))	3.12 (1.76)	3.55 (2.05)	2.84 (1.71)	2.66 (1.25)	0.218
Pharmacy household expenditure (mean (sd))	4.23 (2.09)	4.49 (2.38)	3.33 (2.26)	2.88 (1.44)	0.006*
Access to health facility					
Ratio of hospitals to population (mean (sd))	0.05 (0.05)	0.05 (0.04)	0.03 (0.03)	0.04 (0.04)	0.009*
Ratio of primary care facilities to population (mean (sd))	0.68 (0.33)	0.61 (0.27)	0.55 (0.21)	0.72 (0.48)	0.046*
% of easy access to hospitals (mean (sd))	0.36 (0.14)	0.36 (0.15)	0.37 (0.10)	0.44 (0.21)	0.148
% of easy access to primary care facilities (mean (sd))	0.30 (0.13)	0.31 (0.14)	0.30 (0.06)	0.38 (0.22)	0.082
Education					
% of population with higher education (mean (sd))	0.09 (0.05)	0.12 (0.08)	0.08 (0.06)	0.07 (0.05)	0.009*
% of population with secondary school education (mean (sd))	0.39 (0.08)	0.39 (0.07)	0.35 (0.08)	0.36 (0.08)	0.006*
% of population with primary school education (mean (sd))	0.36 (0.10)	0.34 (0.10)	0.40 (0.11)	0.41 (0.11)	0.009*
Demography					
Population in '000 (mean (sd))	649.15 (631.22)	661.68 (630.61)	788.78 (812.99)	720.18 (837.71)	0.691
% of female population (mean (sd))	0.52 (0.08)	0.52 (0.09)	0.50 (0.01)	0.55 (0.16)	0.187
Health status					
Mortality under five years old over 1000 population (mean (sd))	0.09 (0.07)	0.09 (0.09)	0.08 (0.06)	0.12 (0.13)	0.199

Sector	1	2	3	4	*p*
Maternal mortality over 1000 population (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.02 (0.02)	0.269
Geography					
On Java or Bali island (%)	22 (29.7)	10 (34.5)	36 (52.9)	7 (35.0)	0.035*
Insurance coverage					
Askes insurance coverage (mean (sd))	0.14 (0.06)	0.15 (0.07)	0.12 (0.06)	0.11 (0.06)	0.069
Jamsostek insurance coverage (mean (sd))	0.07 (0.07)	0.08 (0.08)	0.05 (0.05)	0.05 (0.05)	0.140
Private insurance coverage (mean (sd))	0.02 (0.02)	0.03 (0.03)	0.02 (0.02)	0.02 (0.01)	0.019*
Company insurance coverage (mean (sd))	0.02 (0.02)	0.02 (0.02)	0.01 (0.01)	0.02 (0.02)	0.131
Poor insurance coverage (mean (sd))	0.21 (0.15)	0.21 (0.15)	0.24 (0.16)	0.17 (0.10)	0.302
Health fund insurance coverage (mean (sd))	0.01 (0.02)	0.00 (0.01)	0.00 (0.01)	0.00 (0.00)	0.120
Other health insurance coverage (mean (sd))	0.05 (0.15)	0.02 (0.02)	0.07 (0.15)	0.05 (0.15)	0.438

FTE Full-Time Equivalent, *NCD* Non-Communicable Disease

Significance level: *0.05.

Table C.2: Characteristic of *Puskesmas* by Pabón-Lasso model sector

Sector	1	2	3	4	*p*
n	51	6	31	7	
Unit costs					
Outpatient unitcost (mean (sd))	12.76 (10.06)	8.75 (5.02)	9.60 (6.87)	12.18 (10.41)	0.395
Inpatient unitcost (mean (sd))	178.86 (140.47)	138.63 (80.78)	81.98 (42.73)	74.14 (41.52)	0.004*
Bed day unitcost (mean (sd))	116.15 (117.47)	41.75 (23.72)	46.96 (31.73)	62.67 (34.42)	0.012*
Utilisation					
ALOS (mean (sd))	2.08 (0.72)	3.52 (0.39)	2.26 (1.14)	1.37 (0.23)	0.001*
BOR (mean (sd))	0.13 (0.08)	0.41 (0.08)	0.55 (0.25)	0.26 (0.03)	<0.001*
Throughput (mean (sd))	29.08 (15.52)	45.77 (7.58)	116.14 (62.82)	86.62 (14.72)	<0.001*
Ratio of outpatients and bed days (mean (sd))	89.22 (162.83)	14.05 (7.57)	24.63 (31.16)	317.58 (623.72)	0.016*
Size and capacity					
Doctors (mean (sd))	4.06 (7.22)	2.67 (0.82)	2.71 (3.31)	4.57 (4.93)	0.709
Nurses (mean (sd))	20.72 (29.22)	14.50 (7.74)	22.18 (30.05)	16.17 (20.93)	0.915
Midwives (mean (sd))	18.30 (34.47)	11.67 (5.54)	15.71 (20.86)	17.67 (25.36)	0.949
Other staff (mean (sd))	20.37 (26.18)	18.00 (6.32)	16.48 (21.11)	18.00 (25.31)	0.912
Puskesmas satellite (mean (sd))	3.53 (2.48)	3.83 (1.47)	4.45 (2.91)	3.29 (2.43)	0.428
Beds (mean (sd))	10.49 (5.40)	13.17 (8.40)	9.84 (5.17)	8.14 (4.81)	0.399
Emergency services (%)	38 (84.4)	4 (100.0)	21 (87.5)	4 (57.1)	0.197
Open at afternoon = 1 (%)	20 (44.4)	4 (100.0)	11 (45.8)	3 (42.9)	0.197
Availability of BEmONC (%)	27 (58.7)	4 (100.0)	15 (57.7)	3 (42.9)	0.314
Patients case mix					
% of patient under 5 years old (mean (sd))	0.14 (0.06)	0.11 (0.07)	0.13 (0.05)	0.13 (0.03)	0.776
% of patient over 60 years old (mean (sd))	0.17 (0.07)	0.25 (0.07)	0.15 (0.07)	0.14 (0.04)	0.015*
Experience					
Years of service (mean (sd))	30.31 (12.72)	44.75 (23.04)	24.43 (11.47)	30.14 (15.87)	0.044*
Quality					
Without water disruption (%)	18 (40.9)	1 (25.0)	3 (12.5)	0 (0.0)	0.026*
Without electricity disruption (%)	7 (16.3)	0 (0.0)	5 (20.8)	1 (14.3)	0.769
Without medicine disruption (%)	21 (46.7)	2 (50.0)	13 (54.2)	2 (28.6)	0.692

Sector	1	2	3	4	*p*
Without salary disruption (%)	37 (82.2)	4 (100.0)	18 (75.0)	7 (100.0)	0.352
Without incentive disruption (%)	20 (44.4)	1 (25.0)	9 (37.5)	4 (66.7)	0.525
Difficulty in filling management vacancy (%)	39 (76.5)	2 (33.3)	21 (67.7)	5 (71.4)	0.173
Difficulty in filling doctor vacancy (%)	38 (74.5)	2 (33.3)	23 (74.2)	5 (71.4)	0.201
Difficulty in filling nurse vacancy (%)	14 (27.5)	1 (16.7)	7 (22.6)	2 (28.6)	0.914
Difficulty in filling technician vacancy (%)	41 (80.4)	3 (50.0)	23 (74.2)	7 (100.0)	0.163
Difficulty in filling other staff vacancy (%)	34 (66.7)	2 (33.3)	19 (61.3)	3 (42.9)	0.309
Performance meeting once per week (%)	1 (2.3)	0 (0.0)	1 (4.2)	0 (0.0)	0.906
Case meeting at least 6 months (%)	19 (42.2)	3 (75.0)	8 (33.3)	5 (71.4)	0.182
With mentoring (%)	39 (86.7)	4 (100.0)	19 (79.2)	7 (100.0)	0.428
With working monitoring (%)	43 (95.6)	4 (100.0)	22 (95.7)	7 (100.0)	0.918
Economy					
Household expenditure (mean (sd))	246.51 (65.14)	244.89 (100.89)	234.01 (65.04)	235.32 (59.75)	0.863
Gini index (mean (sd))	0.35 (0.05)	0.38 (0.04)	0.34 (0.04)	0.33 (0.06)	0.285
% of family working in agriculture (mean (sd))	0.63 (0.30)	0.63 (0.26)	0.62 (0.25)	0.68 (0.24)	0.956
% of poor population (mean (sd))	0.08 (0.07)	0.11 (0.08)	0.08 (0.06)	0.10 (0.07)	0.758
Total household health expenditure (mean (sd))	22.64 (13.32)	29.04 (6.48)	18.08 (11.80)	12.72 (7.12)	0.043*
Curative household expenditure (mean (sd))	16.50 (11.67)	23.10 (5.70)	12.10 (9.40)	8.45 (6.13)	0.024*
Preventive household expenditure (mean (sd))	2.22 (1.12)	2.26 (0.39)	2.04 (1.23)	1.66 (0.79)	0.600
Pharmacy household expenditure (mean (sd))	2.82 (1.86)	2.01 (0.99)	3.14 (2.29)	2.06 (0.92)	0.402
Access to health facility					
Ratio of hospitals to population (mean (sd))	0.01 (0.03)	0.03 (0.04)	0.02 (0.04)	0.00 (0.00)	0.465
Ratio of primary care facilities to population (mean (sd))	0.80 (0.45)	0.82 (0.49)	0.59 (0.24)	0.85 (0.61)	0.140
% of easy access to hospitals (mean (sd))	0.41 (0.27)	0.56 (0.22)	0.45 (0.27)	0.68 (0.30)	0.065
% of easy access to primary care facilities (mean (sd))	0.35 (0.24)	0.44 (0.28)	0.38 (0.26)	0.63 (0.35)	0.056
Education					
% of population with higher education (mean (sd))	0.07 (0.05)	0.08 (0.03)	0.05 (0.02)	0.04 (0.01)	0.214
% of population with secondary school education (mean (sd))	0.34 (0.06)	0.39 (0.05)	0.32 (0.07)	0.30 (0.04)	0.044*
% of population with primary school education (mean (sd))	0.43 (0.09)	0.38 (0.07)	0.45 (0.08)	0.49 (0.06)	0.065
Demography					
Population (mean (sd))	25812.29 (25228.97)	23946.50 (11234.48)	30329.76 (24729.30)	20744.00 (14143.16)	0.790
Population density (mean (sd))	2555.18 (9537.05)	168.06 (271.49)	421.66 (470.06)	313.08 (427.23)	0.702

Sector	1	2	3	4	*p*
% of female population (mean (sd))	0.56 (0.16)	0.59 (0.20)	0.57 (0.17)	0.71 (0.27)	0.186
Health status					
Mortality under five years old over 1000 population (mean (sd))	0.15 (0.20)	0.06 (0.07)	0.13 (0.13)	0.29 (0.26)	0.121
Maternal mortality over 1000 population (mean (sd))	0.02 (0.04)	0.01 (0.01)	0.01 (0.02)	0.05 (0.08)	0.078
Geography					
On Java or Bali island (%)	20 (39.2)	4 (66.7)	10 (32.3)	1 (14.3)	0.238
In urban area (%)	9 (18.0)	2 (33.3)	7 (22.6)	1 (14.3)	0.789
Insurance coverage					
Askes insurance coverage (mean (sd))	0.12 (0.04)	0.15 (0.06)	0.09 (0.03)	0.09 (0.01)	0.001*
Jamsostek insurance coverage (mean (sd))	0.03 (0.04)	0.02 (0.00)	0.04 (0.06)	0.03 (0.05)	0.710
Private insurance coverage (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.653
Company insurance coverage (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.02)	0.922
Poor insurance coverage (mean (sd))	0.24 (0.16)	0.23 (0.10)	0.21 (0.12)	0.21 (0.09)	0.852
Health fund insurance coverage (mean (sd))	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.575
Other health insurance coverage (mean (sd))	0.10 (0.20)	0.03 (0.03)	0.03 (0.08)	0.01 (0.01)	0.147

BEmONC Basic Emergency Obstetric and Newborn Care

Significance level: *0.05.

Table C.3: Simple linear regression by hospital unit cost

Variable	Unit cost op		Unit cost ip		Unit cost bd	
	coef	pvalue	coef	pvalue	coef	pvalue
alos2	-1.47	0.144	-0.27	0.790	-0.20	0.840
bed_occ	-2.06	0.041	-2.92	0.004	-5.17	0.000
throughput	-3.13	0.002	-5.95	0.000	-3.55	0.000
amb_bedays	-2.17	0.031	0.78	0.439	0.90	0.369
gp_FTE	-3.14	0.002	-0.25	0.804	-0.96	0.340
med_spec_FTE	1.01	0.313	3.74	0.000	2.34	0.020
sur_spec_FTE	-0.01	0.991	2.77	0.006	1.15	0.250
beds	-3.68	0.000	-1.21	0.226	-3.09	0.002
class2	-2.99	0.003	-1.11	0.269	-2.54	0.012
publichospital	-3.63	0.000	-1.93	0.055	-2.44	0.015
profit	2.73	0.007	0.69	0.489	1.53	0.126
mou_ed_hospital	-2.84	0.005	-0.74	0.462	-1.39	0.166
ncd_disease	-0.50	0.618	0.22	0.824	-0.09	0.925
caseindex	-0.40	0.686	1.94	0.055	1.07	0.286
prop_r52f_1_4thn	0.62	0.533	0.20	0.839	1.14	0.257
patients_over65	-1.17	0.244	-1.83	0.069	-1.67	0.096
experience	-2.98	0.003	-2.11	0.036	-2.29	0.023
askes_ins_op_prop	-1.62	0.109	-1.76	0.081	-1.79	0.075
company_ins_op_prop	0.13	0.894	0.87	0.388	0.61	0.547
poor_ins_op_prop	-1.19	0.236	-1.67	0.097	-1.78	0.077
other_ins_op_prop	0.70	0.484	0.39	0.696	0.56	0.579
no_ins_op_prop	4.18	0.000	1.97	0.050	3.46	0.001
askes_ins_ip_prop	-0.76	0.449	-1.16	0.247	-0.94	0.348
company_ins_ip_prop	0.84	0.401	1.42	0.159	0.99	0.324
poor_ins_ip_prop	-2.04	0.043	-1.87	0.063	-1.69	0.094
other_ins_ip_prop	0.72	0.473	1.18	0.243	1.12	0.264
no_ins_ip_prop	3.01	0.003	2.02	0.045	3.53	0.001
askes_ins_bd_prop	-0.83	0.410	-0.44	0.661	-0.78	0.439
company_ins_bd_prop	1.35	0.182	1.46	0.150	1.13	0.263
poor_ins_bd_prop	-1.72	0.088	-1.60	0.111	-1.03	0.304
other_ins_bd_prop	0.46	0.647	1.42	0.159	1.31	0.195
no_ins_bd_prop	2.67	0.008	1.51	0.132	2.84	0.005
askes_ins_pay_prop	-1.54	0.125	-2.01	0.046	-2.33	0.021
company_ins_pay_prop	0.80	0.423	-0.55	0.582	-0.49	0.629
poor_ins_pay_prop	-0.60	0.550	-1.15	0.251	-0.68	0.498
other_ins_pay_prop	0.71	0.481	1.51	0.136	1.58	0.119
no_ins_pay_prop	1.94	0.055	1.07	0.284	1.99	0.048
generic_prop	-2.10	0.037	-0.56	0.578	-1.17	0.245
nongeneric_prop	2.72	0.007	1.55	0.122	2.21	0.029
death_rate	-2.87	0.005	-0.48	0.633	-1.72	0.087
mort_ratio	-1.83	0.070	-0.32	0.753	-1.48	0.141
accredit	-3.14	0.002	-0.35	0.728	-0.90	0.369
water2	-0.26	0.796	-0.28	0.780	-0.08	0.938
electricity2	-1.10	0.274	-1.45	0.147	-1.55	0.123
medicines_missing2	-0.02	0.981	1.21	0.228	0.77	0.440
salary_late2	0.54	0.593	-0.70	0.486	0.25	0.805
incentive_late2	2.24	0.027	0.83	0.405	1.36	0.174
management_vac	1.14	0.254	-0.07	0.943	0.93	0.356
doc_vac	0.25	0.804	-0.61	0.545	0.44	0.660
nurse_vac	2.50	0.013	0.68	0.499	2.26	0.025
tech_vac	0.83	0.406	-0.12	0.902	1.36	0.177

Variable	Unit cost op		Unit cost ip		Unit cost bd	
	coef	pvalue	coef	pvalue	coef	pvalue
other_vac	-1.26	0.210	0.01	0.996	0.77	0.441
performance_meet2	-1.59	0.113	-0.19	0.851	-0.63	0.529
death_meet2	-1.21	0.230	-0.12	0.904	-0.84	0.402
mentoring2	-0.57	0.566	0.80	0.427	0.66	0.511
expend	1.06	0.291	3.59	0.000	2.12	0.035
gini	-0.24	0.814	0.27	0.787	-0.18	0.857
fam_agriculture	-0.77	0.442	-3.15	0.002	-2.18	0.030
poor	-1.57	0.119	-3.48	0.001	-2.96	0.003
totalhealth_exp	-0.44	0.660	2.50	0.013	0.93	0.354
curative_exp	-1.04	0.301	2.01	0.046	0.50	0.616
preventive_exp	1.25	0.214	2.43	0.016	1.83	0.069
pharmacy_exp	1.95	0.053	3.51	0.001	2.11	0.036
hospitalpop	-0.73	0.466	1.53	0.128	0.57	0.567
primarypop	0.44	0.662	0.29	0.776	0.66	0.510
highereducation	-0.57	0.568	2.21	0.029	0.67	0.504
secondaryschool	0.48	0.991	3.07	0.006	2.03	0.250
primaryschool	0.30	0.763	-2.41	0.017	-0.99	0.322
population2011per1000	-0.25	0.806	0.81	0.419	0.38	0.705
female_per	-0.32	0.746	-0.87	0.385	-0.93	0.352
under5_mortalityrate	1.27	0.206	-0.77	0.441	-0.65	0.513
maternal_mortalityrate	1.44	0.152	-0.91	0.364	-1.34	0.183
hospitaleasy	-0.53	0.600	-1.23	0.221	-0.57	0.572
primaryeasy	-1.12	0.266	-1.72	0.087	-1.34	0.182
JavaBali	-2.27	0.024	-1.56	0.120	-1.12	0.266
askesins	-0.62	0.534	0.17	0.868	-0.34	0.738
jamsostekins	0.18	0.858	3.84	0.000	2.56	0.011
privateins	1.06	0.292	4.74	0.000	3.03	0.003
companyins	0.64	0.524	3.31	0.001	3.38	0.001
poorins	-0.34	0.735	-2.91	0.004	-2.56	0.011
healthfundins	0.23	0.816	1.52	0.131	1.68	0.095
otherins	-0.42	0.677	-1.24	0.217	-0.93	0.356

Table C.4: Simple linear regression by *Puskesmas* unit cost

Variable	Unit cost op		Unit cost ip		Unit cost bd	
	coef	pvalue	coef	pvalue	coef	pvalue
alos	-1.91	0.059	-0.69	0.495	-1.87	0.066
bed_occ	-2.06	0.042	-3.84	0.000	-3.76	0.000
throughput	-1.10	0.276	-3.14	0.002	-2.23	0.029
amb_bedays	-1.05	0.299	2.81	0.006	3.65	0.000
doctors	1.67	0.098	4.52	0.000	4.25	0.000
nurses	6.27	0.000	2.46	0.016	2.53	0.014
midwives	2.26	0.027	3.78	0.000	3.71	0.000
other staff	2.57	0.012	3.03	0.003	2.77	0.007
pustu	3.75	0.000	-0.20	0.846	0.14	0.885
beds	-2.59	0.011	-1.23	0.221	-1.61	0.112
emergency	-2.63	0.010	0.03	0.977	-0.31	0.761
open_pm	-1.78	0.080	1.57	0.122	1.44	0.154
poned	-0.49	0.623	1.64	0.105	1.12	0.267
patients_0to4	2.37	0.020	1.06	0.291	0.61	0.544
patients_over60	-3.43	0.001	-0.11	0.912	-0.32	0.750
experience	-2.53	0.013	0.71	0.482	0.33	0.740
water2	-0.47	0.640	0.27	0.787	0.20	0.840
electricity2	0.73	0.469	-0.60	0.553	0.33	0.742
medicines_missing2	0.63	0.532	0.54	0.591	0.96	0.338
salary_late2	-0.27	0.790	-0.35	0.728	-0.14	0.887
incentive_late2	-3.28	0.002	0.16	0.871	0.21	0.832
management_vac	1.97	0.051	-0.53	0.600	-0.26	0.797
doc_vac	3.04	0.003	-0.83	0.410	-0.69	0.491
nurse_vac	-0.17	0.866	-0.38	0.704	-0.91	0.363
tech_vac	2.41	0.018	-0.30	0.768	0.04	0.967
other_vac	2.88	0.005	-0.03	0.977	0.24	0.814
performance_meet2	-1.08	0.282	2.82	0.006	2.82	0.006
death_meet2	0.67	0.507	1.05	0.297	0.50	0.622
mentoring2	-2.34	0.022	1.06	0.291	1.09	0.280
workinghour_monitor2	-0.80	0.426	0.65	0.521	0.54	0.591
expend	2.61	0.011	2.50	0.015	2.50	0.015
gini	-4.39	0.000	0.04	0.967	-0.40	0.687
fam_agriculture	2.46	0.016	-2.29	0.025	-1.77	0.080
poor	-1.27	0.206	-1.25	0.214	-1.67	0.100
totalhealth_exp	-2.84	0.005	0.59	0.555	-0.02	0.983
curative_exp	-3.20	0.002	0.27	0.791	-0.44	0.662
preventive_exp	-0.43	0.665	1.37	0.174	1.17	0.244
pharmacy_exp	0.08	0.938	1.05	0.297	1.18	0.242
hospitalpop	-2.55	0.012	1.49	0.140	0.93	0.356
primarypop	2.72	0.008	0.03	0.978	0.31	0.758
highereducation	-2.38	0.019	1.76	0.083	1.50	0.137
secondaryschool	-3.69	0.000	1.40	0.165	0.63	0.533
primaryschool	4.85	0.000	-1.22	0.228	-0.65	0.516
population covered	-3.52	0.001	2.12	0.038	2.16	0.034
pop density	-1.41	0.164	0.20	0.841	-0.12	0.904
female_per	-1.33	0.187	-1.26	0.211	-0.61	0.541
under5_mortalityrate	2.23	0.028	-0.76	0.451	-0.35	0.724
maternal_mortalityrate	4.79	0.000	0.04	0.966	0.35	0.727
hospitaleasy	-3.25	0.002	-1.64	0.105	-1.25	0.217
primaryeasy	-2.42	0.017	-2.09	0.040	-1.47	0.146
JavaBali	-2.89	0.005	0.21	0.835	-0.30	0.763

Variable	Unit cost op		Unit cost ip		Unit cost bd	
	coef	**pvalue**	**coef**	**pvalue**	**coef**	**pvalue**
urban	-2.19	0.031	1.94	0.056	1.64	0.104
askesins	-0.55	0.584	2.14	0.036	1.21	0.230
jamsostekins	-2.11	0.037	0.34	0.731	0.31	0.755
privateins	-2.86	0.005	1.76	0.083	2.07	0.042
companyins	-2.14	0.035	0.81	0.422	0.65	0.515
poorins	-1.46	0.148	-0.47	0.640	-0.89	0.374
healthfundins	0.90	0.372	1.38	0.171	0.75	0.454
otherins	0.63	0.529	4.35	0.000	4.87	0.000

Table C.5: Comparison of characteristics of high-performing and other hospitals

	Other	High	p
n	152	40	
unitcost_op (mean (sd))	35.25 (42.37)	14.10 (6.85)	0.002
unitcost_bd (mean (sd))	90.94 (57.16)	46.80 (17.86)	<0.001
unitcost_ip (mean (sd))	326.88 (204.87)	170.08 (61.88)	<0.001
alos2 (mean (sd))	4.22 (0.91)	4.52 (1.17)	0.083
bed_occ (mean (sd))	0.55 (0.33)	0.78 (0.12)	<0.001
throughput (mean (sd))	55.75 (26.79)	78.25 (15.04)	<0.001
amb_bedays (mean (sd))	3.09 (9.05)	1.80 (1.55)	0.370
gp_FTE (mean (sd))	14.65 (10.03)	17.75 (9.79)	0.083
med_spec_FTE (mean (sd))	12.07 (14.39)	9.59 (7.32)	0.294
sur_spec_FTE (mean (sd))	7.43 (7.99)	6.29 (4.06)	0.384
beds (mean (sd))	151.59 (124.81)	183.30 (100.13)	0.139
class2 = Class A/B (n(%))	34 (22.5)	18 (45.0)	0.008
publichospital = Public (n(%))	84 (55.3)	35 (87.5)	<0.001
profit = 1 (n(%))	30 (19.7)	2 (5.0)	0.047
mou_ed_hospital = Teaching (n(%))	45 (29.6)	17 (42.5)	0.173
ncd_disease (mean (sd))	37.96 (14.59)	40.37 (14.99)	0.356
caseindex (mean (sd))	1.12 (0.79)	1.04 (0.40)	0.592
prop_r52f_1_4thn (mean (sd))	9.42 (5.12)	8.25 (3.16)	0.174
patients_over65 (mean (sd))	0.11 (0.06)	0.14 (0.08)	0.011
experience (mean (sd))	42.82 (28.23)	51.46 (33.71)	0.112
askes_ins_op_prop (mean (sd))	0.27 (0.16)	0.28 (0.13)	0.955
company_ins_op_prop (mean (sd))	0.14 (0.20)	0.04 (0.06)	0.084
poor_ins_op_prop (mean (sd))	0.21 (0.16)	0.31 (0.16)	0.003
other_ins_op_prop (mean (sd))	0.09 (0.13)	0.05 (0.08)	0.340
no_ins_op_prop (mean (sd))	0.54 (0.28)	0.43 (0.25)	0.034
askes_ins_ip_prop (mean (sd))	0.17 (0.12)	0.16 (0.07)	0.646
company_ins_ip_prop (mean (sd))	0.15 (0.19)	0.04 (0.05)	0.024
poor_ins_ip_prop (mean (sd))	0.36 (0.24)	0.46 (0.19)	0.024
other_ins_ip_prop (mean (sd))	0.08 (0.12)	0.06 (0.10)	0.395
no_ins_ip_prop (mean (sd))	0.47 (0.27)	0.37 (0.22)	0.035
askes_ins_bd_prop (mean (sd))	0.17 (0.11)	0.16 (0.08)	0.480
company_ins_bd_prop (mean (sd))	0.14 (0.19)	0.04 (0.05)	0.069
poor_ins_bd_prop (mean (sd))	0.41 (0.26)	0.51 (0.17)	0.045
other_ins_bd_prop (mean (sd))	0.09 (0.13)	0.04 (0.10)	0.235
no_ins_bd_prop (mean (sd))	0.45 (0.29)	0.34 (0.22)	0.035
askes_ins_pay_prop (mean (sd))	0.15 (0.12)	0.17 (0.15)	0.419
company_ins_pay_prop (mean (sd))	0.13 (0.20)	0.10 (0.18)	0.620
poor_ins_pay_prop (mean (sd))	0.29 (0.28)	0.34 (0.28)	0.306
other_ins_pay_prop (mean (sd))	0.21 (0.24)	0.15 (0.20)	0.381
no_ins_pay_prop (mean (sd))	0.49 (0.31)	0.38 (0.27)	0.054
generic_prop (mean (sd))	0.51 (0.28)	0.57 (0.25)	0.297
nongeneric_prop (mean (sd))	0.41 (0.26)	0.33 (0.23)	0.071
death_rate (mean (sd))	0.01 (0.00)	0.01 (0.01)	0.040
mort_ratio (mean (sd))	0.91 (0.40)	1.05 (0.29)	0.077
accredit = 1 (n(%))	87 (57.6)	30 (78.9)	0.026
water2 = Without water disruption (n(%))	59 (39.1)	15 (39.5)	1.000
electricity2 = Without electricity disruption (n(%))	38 (25.2)	13 (34.2)	0.358
medicines_missing2 = Without medicine disruption (n(%))	81 (53.6)	18 (48.6)	0.718
salary_late2 = Without salary disruption (n(%))	137 (91.3)	33 (86.8)	0.595
incentive_late2 = Without incentive disruption (n(%))	95 (63.3)	23 (62.2)	1.000
management_vac = 1 (n(%))	63 (43.8)	13 (37.1)	0.604

	Other	High	p
doc_vac = 1 (n(%))	86 (59.7)	23 (65.7)	0.647
nurse_vac = 1 (n(%))	44 (30.6)	5 (14.3)	0.085
tech_vac = 1 (n(%))	76 (52.8)	20 (57.1)	0.783
other_vac = 1 (n(%))	18 (12.5)	9 (25.7)	0.090
performance_meet2 = Performance meeting once per week (n(%))	44 (29.1)	14 (38.9)	0.349
death_meet2 = Death meeting at least 6 months (n(%))	62 (41.3)	21 (55.3)	0.173
mentoring2 = With mentoring (n(%))	146 (96.7)	38 (100.0)	0.568
workinghour_monitor2 = With working monitoring (n(%))	142 (100.0)	36 (100.0)	NA
expend (mean (sd))	285.83 (92.39)	230.66 (83.01)	0.001
gini (mean (sd))	0.35 (0.04)	0.35 (0.04)	0.763
fam_agriculture (mean (sd))	0.39 (0.30)	0.51 (0.27)	0.018
poor (mean (sd))	0.06 (0.05)	0.10 (0.09)	0.001
totalhealth_exp (mean (sd))	27.23 (14.36)	22.74 (14.91)	0.082
curative_exp (mean (sd))	18.57 (10.87)	15.86 (11.82)	0.171
preventive_exp (mean (sd))	3.13 (1.70)	2.56 (1.87)	0.063
pharmacy_exp (mean (sd))	3.95 (2.10)	3.23 (2.50)	0.067
hospitalpop (mean (sd))	0.05 (0.04)	0.03 (0.03)	0.006
primarypop (mean (sd))	0.65 (0.32)	0.56 (0.22)	0.083
highereducation (mean (sd))	0.09 (0.06)	0.07 (0.05)	0.011
secondaryschool (mean (sd))	0.38 (0.08)	0.33 (0.08)	0.001
primaryschool (mean (sd))	0.37 (0.10)	0.43 (0.10)	0.001
population2011per1000 (mean (sd))	676.92 (664.33)	789.91 (905.85)	0.379
female_per (mean (sd))	0.52 (0.10)	0.50 (0.01)	0.241
under5_mortalityrate (mean (sd))	0.09 (0.08)	0.09 (0.07)	0.888
maternal_mortalityrate (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.766
hospitaleasy (mean (sd))	0.38 (0.16)	0.36 (0.11)	0.482
primaryeasy (mean (sd))	0.32 (0.15)	0.30 (0.05)	0.372
JavaBali = Jawa and Bali (n(%))	53 (34.9)	21 (52.5)	0.063
askesins (mean (sd))	0.14 (0.06)	0.11 (0.06)	0.022
jamsostekins (mean (sd))	0.07 (0.07)	0.04 (0.05)	0.017
privateins (mean (sd))	0.02 (0.02)	0.01 (0.01)	0.004
companyins (mean (sd))	0.02 (0.02)	0.01 (0.01)	0.010
poorins (mean (sd))	0.21 (0.14)	0.27 (0.17)	0.022
healthfundins (mean (sd))	0.01 (0.01)	0.00 (0.01)	0.210
otherins (mean (sd))	0.05 (0.13)	0.07 (0.15)	0.440

Table C.6: Comparison of characteristics of high-performing and other *Puskesmas*

	Other	High	p
n	76	17	
unitcost_amb (mean (sd))	12.85 (9.35)	5.75 (2.90)	0.003
unitcost_ip (mean (sd))	155.76 (121.69)	61.51 (30.63)	0.002
unitcost_bd (mean (sd))	96.93 (99.75)	32.12 (18.82)	0.010
alos (mean (sd))	2.12 (0.92)	2.56 (1.00)	0.098
occ (mean (sd))	0.23 (0.19)	0.59 (0.28)	<0.001
throughput (mean (sd))	51.29 (51.17)	103.10 (41.56)	<0.001
amb_bedays (mean (sd))	90.80 (222.28)	21.68 (15.21)	0.206
doctorstotal (mean (sd))	3.89 (6.36)	2.47 (1.70)	0.364
nurse (mean (sd))	21.59 (30.60)	15.80 (5.75)	0.469
midwife (mean (sd))	17.92 (31.28)	13.27 (9.12)	0.572
otherstaff (mean (sd))	20.25 (25.72)	13.94 (9.09)	0.323
p21a_pustu (mean (sd))	3.87 (2.61)	3.88 (2.57)	0.984
beds (mean (sd))	10.11 (5.73)	11.35 (4.33)	0.401
emergency_24 = 1 (n(%))	54 (81.8)	13 (100.0)	0.213
open_pm = 1 (n(%))	33 (50.0)	5 (38.5)	0.647
poned = 1 (n(%))	40 (58.0)	8 (61.5)	1.000
patients_0to4 (mean (sd))	0.13 (0.06)	0.12 (0.05)	0.319
patients_over60 (mean (sd))	0.17 (0.07)	0.17 (0.08)	0.829
experience (mean (sd))	29.58 (14.36)	28.73 (10.75)	0.851
water2 = Without water disruption (n(%))	19 (29.2)	3 (23.1)	0.910
electricity2 = Without electricity disruption (n(%))	8 (12.5)	5 (38.5)	0.061
medicines_missing2 = Without medicine disruption (n(%))	29 (43.9)	9 (69.2)	0.172
salary_late2 = Without salary disruption (n(%))	55 (83.3)	10 (76.9)	0.876
incentive_late2 = Without incentive disruption (n(%))	27 (41.5)	6 (46.2)	1.000
management_vac = 1 (n(%))	54 (71.1)	12 (70.6)	1.000
doc_vac = 1 (n(%))	55 (72.4)	12 (70.6)	1.000
nurse_vac = With nurse vacancy (n(%))	20 (26.3)	4 (23.5)	1.000
tech_vac = 1 (n(%))	61 (80.3)	12 (70.6)	0.582
other_vac = 1 (n(%))	47 (61.8)	10 (58.8)	1.000
performance_meet2 = Performance meeting/week (n(%))	1 (1.5)	1 (7.7)	0.749
death_meet2 = Death meeting at least 6 months (n(%))	30 (45.5)	4 (30.8)	0.502
mentoring2 = With mentoring (n(%))	58 (87.9)	10 (76.9)	0.545
workinghour_monitor2 = With working monitoring (n(%))	62 (95.4)	13 (100.0)	1.000
expend (mean (sd))	246.03 (66.84)	217.28 (54.89)	0.102
gini (mean (sd))	0.34 (0.05)	0.36 (0.02)	0.300
fam_agriculture (mean (sd))	0.64 (0.28)	0.60 (0.25)	0.623
poor (mean (sd))	0.09 (0.07)	0.08 (0.05)	0.846
totalhealth_exp (mean (sd))	20.71 (12.72)	21.59 (12.68)	0.797
curative_exp (mean (sd))	14.90 (11.02)	15.22 (10.46)	0.915
preventive_exp (mean (sd))	2.09 (1.03)	2.28 (1.41)	0.518
pharmacy_exp (mean (sd))	2.71 (1.88)	3.12 (2.08)	0.430
hospitalpop (mean (sd))	0.01 (0.03)	0.03 (0.05)	0.130
primarypop (mean (sd))	0.79 (0.44)	0.53 (0.17)	0.018
highereducation (mean (sd))	0.06 (0.05)	0.05 (0.02)	0.605
secondaryschool (mean (sd))	0.33 (0.06)	0.35 (0.07)	0.341
primaryschool (mean (sd))	0.44 (0.09)	0.42 (0.06)	0.317
population_covered (mean (sd))	24179.92 (22093.35)	40336.00 (28951.51)	0.025
density (mean (sd))	1874.97 (8073.57)	551.06 (522.81)	0.591
female_per (mean (sd))	0.59 (0.19)	0.54 (0.12)	0.338
under5_mortalityrate (mean (sd))	0.16 (0.20)	0.11 (0.11)	0.271
maternal_mortalityrate (mean (sd))	0.02 (0.04)	0.01 (0.01)	0.178

	Other	High	p
hospitaleasy (mean (sd))	0.45 (0.29)	0.44 (0.19)	0.862
primaryeasy (mean (sd))	0.39 (0.28)	0.35 (0.19)	0.536
JavaBali = Java and Bali (n(%))	26 (34.2)	9 (52.9)	0.244
ruralurban = 1 (n(%))	13 (17.3)	5 (29.4)	0.427
askesins (mean (sd))	0.11 (0.04)	0.09 (0.02)	0.083
jamsostekins (mean (sd))	0.03 (0.04)	0.05 (0.07)	0.212
privateins (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.441
companyins (mean (sd))	0.01 (0.01)	0.01 (0.01)	0.207
poorins (mean (sd))	0.23 (0.14)	0.23 (0.14)	0.945
healthfundins (mean (sd))	0.00 (0.00)	0.00 (0.00)	0.573
otherins (mean (sd))	0.08 (0.17)	0.02 (0.04)	0.196

Appendix D

Appendix related to Chapter 6

Table D.1: Statistics of *Puskesmas*, complete and imputed

	n missing	complete	imputed	p
n		234	234	
Doctors (mean (sd))	38	3.49 (4.53)	3.51 (4.42)	0.967
Nurses (mean (sd))	29	16.45 (21.63)	16.63 (21.89)	0.931
Midwives (mean (sd))	29	14.34 (21.45)	14.80 (21.72)	0.823
Other staff (mean (sd))	17	18.82 (21.40)	19.28 (21.36)	0.819
Value of medical asset_med (mean (sd))	15	23557.45 (24280.55)	23445.89 (23872.23)	0.961
General outpatient (mean (sd))	3	17542.35 (12527.04)	17556.66 (12530.18)	0.990
MCH outpatient (mean (sd))	4	3717.87 (3763.27)	3732.96 (3772.85)	0.966
% of patient under 5 years old (mean (sd))	2	0.14 (0.06)	0.14 (0.06)	0.974
Jamsostek insurance coverage (mean (sd))	0	0.04 (0.05)	0.04 (0.05)	1.000
Askes insurance coverage (mean (sd))	0	0.12 (0.05)	0.12 (0.05)	1.000
Poor insurance coverage (mean (sd))	0	0.24 (0.14)	0.24 (0.14)	1.000
Population in ’000 (mean (sd))	0	43.45 (40.10)	43.45 (40.10)	1.000
Ratio of hospitals to population (mean (sd))	0	0.03 (0.05)	0.03 (0.05)	1.000
Ratio of primary care facilities to population (mean (sd))	0	0.70 (0.37)	0.70 (0.37)	1.000
% of easy access to hospitals (mean (sd))	1	0.42 (0.22)	0.42 (0.22)	0.998
% of easy access to primary care facilities (mean (sd))	1	0.35 (0.21)	0.35 (0.21)	0.988
% of family working in agriculture (mean (sd))	0	0.55 (0.30)	0.55 (0.30)	1.000
% of poor population (mean (sd))	0	0.08 (0.06)	0.08 (0.06)	1.000
% of population with secondary school education (mean (sd))	0	0.34 (0.07)	0.34 (0.07)	1.000
% of population with higher education (mean (sd))	0	0.07 (0.05)	0.07 (0.05)	1.000
% of population with primary school education (mean (sd))	0	0.43 (0.09)	0.43 (0.09)	1.000
Without water disruption (n(%))	34	71 (35.5)	88 (37.6)	0.723
Without electricity disruption (n(%))	37	38 (19.3)	58 (24.8)	0.211
Without medicine disruption (n(%))	32	104 (51.5)	121 (51.7)	1.000
Without salary disruption (n(%))	33	168 (83.6)	191 (81.6)	0.682
Without incentive disruption (n(%))	34	96 (48.0)	118 (50.4)	0.683
Case meeting at least 6 months (n(%))	34	93 (46.5)	107 (45.7)	0.949
With clinical mentoring (n(%))	34	180 (90.0)	202 (86.3)	0.304
With working monitoring (n(%))	35	191 (96.0)	213 (91.0)	0.063
With bed (n(%))	0	95 (40.6)	95 (40.6)	1.000
In Urban (n(%))	5	64 (27.9)	64 (27.4)	0.968
On Java and Bali (n(%))	0	94 (40.2)	94 (40.2)	1.000

Appendix E

Appendix related to Chapter 7

Table E.1: Statistics of hospitals, complete and imputed

	n missing	complete	imputed	p
n		200	200	
Number of doctors (mean (sd))	0	42.30 (40.28)	42.30 (40.28)	1.000
Nonspecialist doctors FTE (mean (sd))	1	15.37 (9.96)	15.35 (9.94)	0.986
Specialist doctors FTE (mean (sd))	4	19.61 (20.56)	19.75 (20.46)	0.943
Number of nurses (mean (sd))	25	177.70 (143.99)	177.62 (141.86)	0.996
Number of other staff (mean (sd))	36	139.41 (123.95)	139.26 (130.83)	0.991
Beds (mean (sd))	0	158.71 (123.14)	158.71 (123.14)	1.000
Outpatients (mean (sd))	6	70919.81 (109237.43)	70586.07 (108423.62)	0.976
Bed days (mean (sd))	4	35748.55 (33379.70)	35563.32 (33075.01)	0.956
Admissions (mean (sd))	8	8984.44 (6941.03)	8943.55 (6891.41)	0.953
Total surgery (mean (sd))	19	2078.68 (2297.34)	2016.55 (2248.73)	0.790
Deat rate (mean (sd))	17	0.01 (0.01)	0.01 (0.00)	0.858
Mortality ratio (mean (sd))	83	0.96 (0.37)	0.81 (0.45)	0.002
Inpatient case mix index (mean (sd))	82	0.98 (0.22)	1.03 (0.25)	0.051
Outpatient case mix index (mean (sd))	81	0.96 (0.29)	1.00 (0.32)	0.390
% of NCD patient treated (mean (sd))	0	38.14 (14.92)	38.14 (14.92)	1.000
% of patient 1 to 5 years old (mean (sd))	5	9.16 (4.72)	9.12 (4.69)	0.934
Jamsostek insurance coverage (mean (sd))	0	0.07 (0.06)	0.07 (0.06)	1.000
Askes insurance coverage (mean (sd))	0	0.13 (0.06)	0.13 (0.06)	1.000
Poor insurance coverage (mean (sd))	0	0.21 (0.15)	0.21 (0.15)	1.000
Population in ’000 (mean (sd))	0	724.85 (729.24)	724.85 (729.24)	1.000
Ratio of hospitals to population (mean (sd))	0	0.04 (0.04)	0.04 (0.04)	1.000
Ratio of primary care facilities to population (mean (sd))	0	0.63 (0.30)	0.63 (0.30)	1.000
% of easy access to hospitals (mean (sd))	0	0.37 (0.15)	0.37 (0.15)	1.000
% of easy access to primary care facilities (mean (sd))	0	0.31 (0.13)	0.31 (0.13)	1.000
% of family working in agriculture (mean (sd))	0	0.41 (0.30)	0.41 (0.30)	1.000
% of poor population (mean (sd))	0	0.07 (0.06)	0.07 (0.06)	1.000
% of population with secondary school education (mean (sd))	0	0.37 (0.08)	0.37 (0.08)	1.000
% of population with higher education (mean (sd))	0	0.09 (0.06)	0.09 (0.06)	1.000
% of population with primary school education (mean (sd))	0	0.38 (0.11)	0.38 (0.11)	1.000
Without water disruption (n(%))	3	78 (39.6)	78 (39.0)	0.985
Without electricity disruption (n(%))	3	53 (26.9)	53 (26.5)	1.000
Without medicine disruption (n(%))	4	102 (52.0)	104 (52.0)	1.000
Without salary disruption (n(%))	4	177 (90.3)	181 (90.5)	1.000
Without incentive disruption (n(%))	5	123 (63.1)	124 (62.0)	0.907
Performance meeting once per week (n(%))	5	62 (31.8)	65 (32.5)	0.966
With clinical mentoring (n(%))	4	191 (97.4)	192 (96.0)	0.598
With working monitoring (n(%))	15	185 (100.0)	185 (100.0)	NA
Class A/B (n(%))	1	54 (27.1)	54 (27.0)	1.000
Teaching hospital (n(%))	0	64 (32.0)	64 (32.0)	1.000
Publicly owne (n(%))	0	122 (61.0)	122 (61.0)	1.000
On Java or Bali island (n(%))	0	79 (39.5)	79 (39.5)	1.000