Inter-Regional Child Mortality, Programme Efficiency, and Throughput: An Evaluation of the Ethiopian Health Extension Programme

By:

Yibrah Hagos Gebresilassie

(Student No. 214584997)

A Thesis submitted to the University of KwaZulu-Natal for Examination of the Degree of Doctor of Philosophy (Ph.D.) in Economics

Supervisor: Dr. Phocenah Nyatanga

School of Accounting, Economics, and Finance

College of Law and Management Studies

University of KwaZulu-Natal (UKZN)

South Africa

September 2018

Supervisor's Permission to Submit for Examination

Student Name: **Yibrah Hagos Gebresilassie**

Student ID No.: **214584997**

Doctoral thesis title: Inter-Regional Child Mortality, Programme Efficiency, and Throughput: An Evaluation of the Ethiopian Health Extension Programme.

As the candidate's supervisor, I agree to the submission of this thesis.

Supervisor's signature: ______________________________ Date: ___________________

(Dr. Phocenah Nyatanga)

Declaration I: Plagiarism

The research work described in this thesis was carried out in the school of accounting, economics, and finance, college of law and management studies, University of KwaZulu-Natal, Pietermaritzburg campus, South Africa, under the guidance and supervision of Dr. Phocenah Nyatanga.

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Declaration II: Publications

Publication 1:

Title of the article: Efficiency of the Ethiopian Health Extension Program: An Application of Data Envelopment Analysis.

This publication emanated from chapter five of this thesis and was published by Yibrah Hagos GEBRESILASSIE (the Ph.D. candidate) and Phocenah NYATANGA.

The paper can be accessed using the following link: http://doi:10.17015/ejbe.2017.019.06 or http://www.ejbe.org/EJBE-2017-May-10-19.html

The paper was also presented at the Ethiopian Economic Association (EEA) on 25, 07, 2017 in Addis Ababa, Ethiopia.

Publication 2:

Title of the article: Explaining inter-regional differentials in under-five child mortality in rural Ethiopia: An extension of the Oaxaca-Blinder decomposition Analysis.

The article emanated from this thesis and is still under review for publication in the Journal of Biosocial Science (ISSN: 0021-9320), with a manuscript ID of JBS-4335.

Publication 3:

Title of the article: The performance of the community-based health worker programmes: A systematic review evidence from less developing countries. The article is ready for publication in the upcoming issue (November 2018) in Eurasian Journal of Business and Economics (ISSN Electronic: 1694-5972), with Manuscript ID EJBE-18-231016-01

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Acknowledgments

Firstly, I ascribe all glory to the almighty God for the successful completion of my thesis. Secondly, I wish to acknowledge my supervisor Dr. Phocenah Nyatanga for her valuable and constructive criticisms. I could not have reached this point of completion without her devotion and input throughout the writing of this thesis. I am therefore indebted to her for her kind and tireless efforts that have enabled me to reach the finalisation of my thesis.

I would like to thank the federal ministry of health and regional health bureaus of Ethiopia for providing me with the data for my study purpose. I am also indebted to all my friends and colleagues at Adigrat University, Ethiopia. Finally, I owe special appreciation and thanks to my beloved wife, Mrs. Hiwet Beyene Gebreyesus, for her endurance, care, notable support and love which cannot be quantified. Her prayers and words of encouragement meant a lot to the success of my study. Special thanks to my son, Nathran Yibrah Hagos, who endured my long absence from home during my doctoral study. Their endurance and sacrifice are much appreciated.

ABSTRACT

Background: Despite the remarkable improvement Ethiopia had made in the overall health outcomes, such as reducing under-five child mortality rate, there were substantial variations in the rate of progress across its administrative regions over different periods of time. Moreover, compared to many other developing countries, the progress that Ethiopia made in child mortality reduction remained low, and accounted for three percent of the share of global under-five child deaths in 2015. While the community-based health extension programme contributed to improving health outcomes of the population, such as reducing child mortality, access to and use of basic healthcare services are limited, with significant variations across regions of the country. Much less is known about the factors affecting the inter-regional variations in under-five child mortality: how efficient the health extension programme is in delivering basic healthcare services to its rural societies across regions and the determinant factors affecting the health extension programme beneficiary households' graduation in rural settings of Ethiopia. This study is therefore the first attempt to explore determinants of inter-regional differentials in under-five child mortality, and to evaluate the efficiency and productivity changes of the community-based health extension programme in rural areas of Ethiopia at the national level. This study addresses three specific objectives. These are: i) to examine the determinant factors affecting the inter-regional differentials in under-five child mortality. ii) to evaluate the efficiency and productivity growth (changes) of the community-based health extension programme. iii) to identify the determinant factors influencing the health extension programme beneficiary households' graduation.

Methodology: This study employed cross-sectional secondary data from the Ethiopian demographic and health survey, 2016, for a total of 4,200 deaths of under-five children. It also utilised data from the regional health bureaus of Ethiopia, constituting a sample of 1,552 health posts and 4,244 rural households for the years 2013 and 2014. The statistical methods employed include the extended Oaxaca-Blinder decomposition to count data model, Data Envelopment Analysis, Tobit, ordinary least square, and the multiple logistic regressions.

Results: The main findings, which addressed the first objective of the study, revealed that the regional differentials in under-five child mortality were due to socio-economic factors (such as mother's age at first birth, antenatal healthcare services, parental education, households' wealth status, and household size), proximate factors (such as child's birth spacing, child's birth order, and size of the child at birth), and environmental factors (such as place of delivery). However, their relative contributions in explaining the regional differences varied significantly within and across groups in the regional comparisons. The main findings, which addressed the second objective of the study, indicated that there was a substantial variation in technical and scale efficiency estimates among health posts, both across the regions and over periods of time. The results indicated that about 5.67 percent of health posts were a variable return to scale (VRS) technical efficient, with an average technical efficiency estimate of 79.6 percent in 2014. Moreover, most of the health posts (91.24 percent) were operating below their optimal scale size, indicating a potential for improving the efficiency of the health extension programme by improving the scale size, the efficiency of the scale as well as technically inefficient health posts. Furthermore, the overall productivity change increased by about 6.7 percent due to the technological progress. In a subsequent study, results of the regression analysis indicated that households' travel distance to the nearest health posts, provision of supportive supervision to the health extension workers, religion, and region of residence of the health extension workers affected the disparities in technical efficiency estimates among the health posts. The main findings addressing the third objective of the study explained the reason behind the rate of graduating households as model households. The results indicated that family size, head of the household head, parental level of education, households' access to the agricultural extension programme, mothers' age, and the professional level of the health extension workers were the major determinant factors affecting the health extension programme beneficiary households' graduation.

Conclusion: The explained part of the regional differentials in under-five child mortality was due to differences in socio-economic, proximate, and environmental factors among the regions, with significant differences in the magnitude of the effect. Most of the health posts were operating below their optimal scale size, with substantial variations in technical and scale efficiency estimates, suggesting potential room for improving the efficiency of the health extension programme. Therefore, this study suggests the need for sustained efforts with a due focus on improving households' economic status, maternal education, sustained in-service training and supportive supervision provision to the health extension workers across regions of the country.

Keywords: Child mortality, Efficiency, Ethiopia, Data Envelopment Analysis, Decomposition, Graduation, Health hosts, Health extension programme, Health extension worker, Productivity

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List of Abbreviations

ADU	Adigrat University
AIDS	Acquired Immunodeficiency Syndrome
ANC	Antenatal Healthcare
ANM	Auxiliary Nurse Midwife
BG	Benshangul-Gumuz
BMI	Body Mass Index
CHEWs	Community Health Extension Workers
CHWs	Community Health Workers
CNHDE	Center for National Health Development in Ethiopia
CRS	Constant returns to scale
CSA	Central Statistics Authority
CSPS	Centre de Recherche en Sante de de Nouna
DEA	Data Envelopment Analysis
DFA	Distribution-Free Approach
DHS	Demographic and Health Survey
DLHS	District Level Household and Facility Survey
DMU	Decision-Making Units
EAG	Empowered Action Group
EDHS	Ethiopian Demographic and Health Survey
EPRDF	Ethiopian People's Revolutionary Democratic Front
FDHS	Free-Disposable Hull Analysis
FHS	Family Health Strategy programme
FMoH	Federal Ministry of Health
GOE	Government of Ethiopia
HDI	Human Development Index
HEP	Health Extension Programme
HEWs	Health Extension Workers
HIV	Human Immunodeficiency Virus
HP	Health Post
HSDP	Health Sector Development Programme
IMR	Infant Mortality Rate
LPP	Linear Programming Problem

MDGs	Millennium Development Goals
MoFED	The Ministry of Finance and Economic Development (Ethiopia)
NRHM	National Rural Health Mission
PPP	Purchasing Power Parity
PSNP	Productive Safety Net Programme
RHB	Regional Health Bureaus
SCRCSSP	Steering Committee for the Review of Commonwealth/State Service Provision
SE	Scale Efficiency
SE	Standard Error
SFA	Stochastic Frontier Analysis
TE	Technical efficiency
TGE	Transitional Government of Ethiopia
U5MR	Under-five child mortality rate
UN	United Nations
UNDP	United Nations Development Programme
UNICEF	United Nations Children's Fund
USAID	United States Agency for International Development
VRS	Variable returns to scale
WB	World Bank
WDI	World Development Indicators
WHO	World Health Organisation

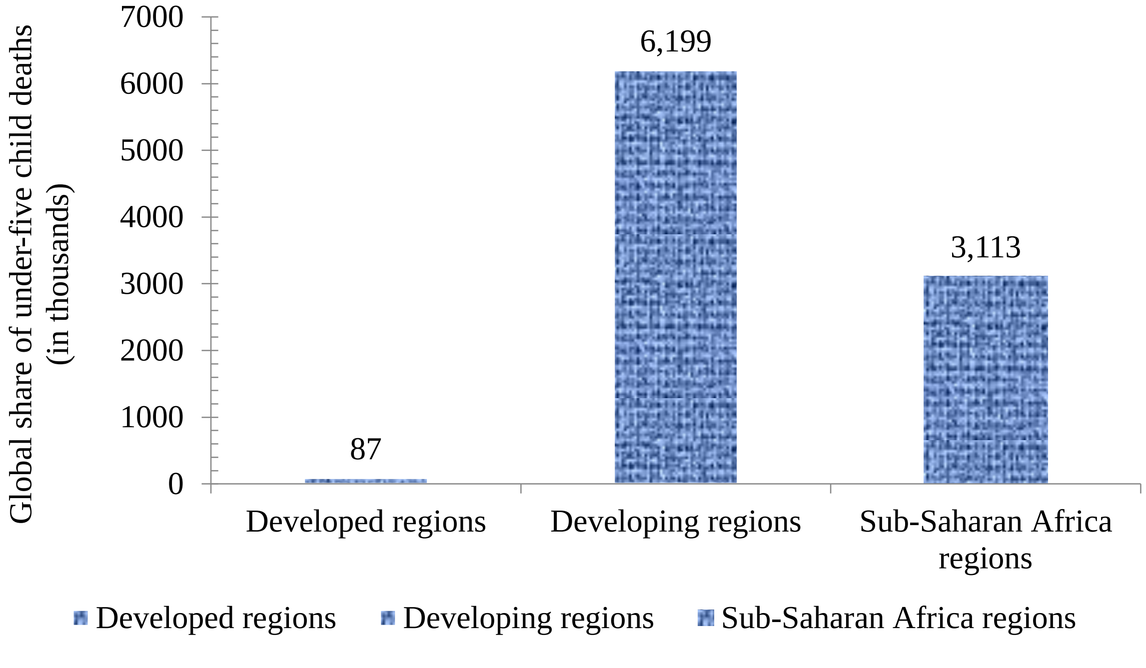
CHAPTER ONE

INTRODUCTION

1.1. Background and outline of the research problem

Health is an issue of serious concern and healthy societies are believed to play an important role in poverty reduction, economic growth, and development (Sachs, 2002). Of the World Health Organisation (WHO) eight-millennium development goals (MDGs), health takes centre stage as reflected in goals IV, V, and VI and is considered to be supportive in the attainment of the other five MDGs (Bhutta et al., 2010; WHO, 2005). Globally, disparities in child health outcomes, both among and within countries, is a significant challenge with the death of children under five years of age having been reduced from 12.7 million in 1990 to 5.9 million in 2015 (UNIGME, 2015).

However, the infant mortality rates (IMR) and the under-five child mortality rates (U5MR) for developing countries remain significantly higher than that of developed countries[1]. For instance; in 2012, the infant and the under-five child mortality rates between developing and developed countries were 63 and 95, and 12 and 10 deaths per thousand births, respectively (UNIGME, 2013).



Source: Own computation using data from UNIGME (2014)

Figure 1. 1: Global share of under-five child's deaths (in thousand), 2013

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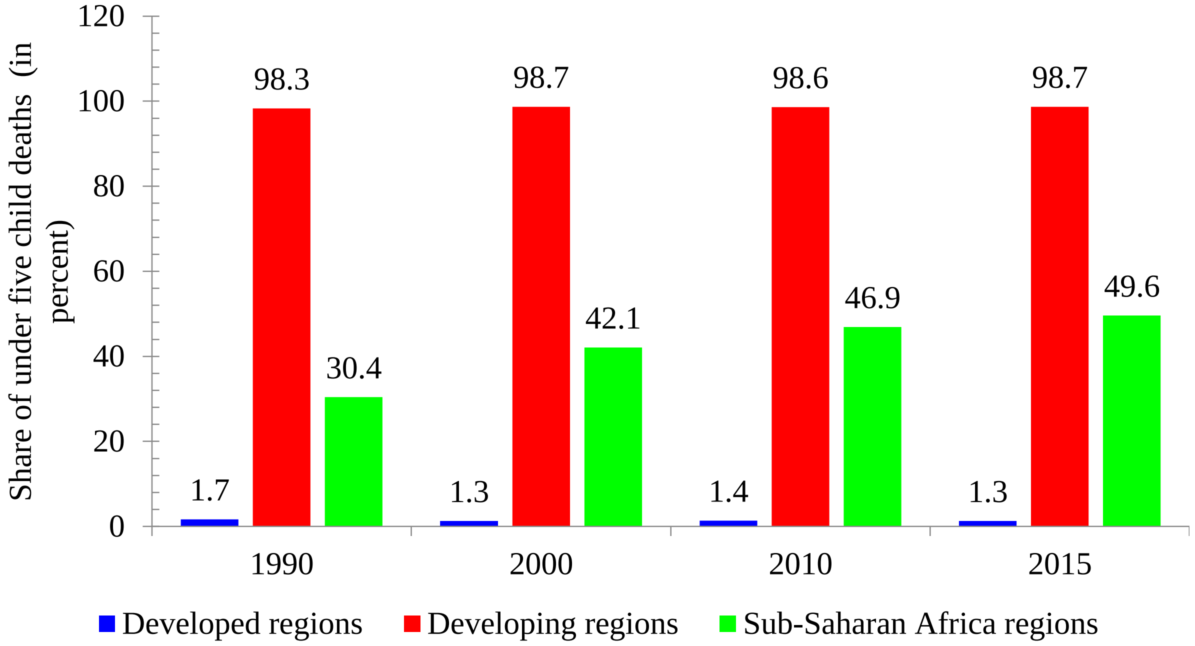
[1] Infant mortality rate is defined as the probability of child dying before celebrating his or her firth birthday while U5MR is defined as the probability of a child dying before celebrating his or her fifth birthday (both are expressed per thousand births (CSA & ICF International, 2012).

According to a 2014 report by UNIGME, the under-five child mortality rate is significantly higher in developing regions (66 percent) than it is in developed regions (1 percent). About 33 percent of the global under-five child deaths occur in Sub-Saharan Africa, as shown in Figure 1.1. While the global reduction in under-five child mortality was more than 54 percent between 1990 and 2015, Sub-Saharan Africa remains with the highest under-five child mortality rate in the world, where the under-five child mortality rate in this region increased from 30.4 percent in 1990 to 49.6 percent in 2015 (UNIGME, 2015). The under-five child mortality rate for developing regions also remain high, increasing slightly from 98.3 percent in 1990 to 98.7 percent in 2015 (see Figure 1.2) relative to developed countries, where the under-five child mortality rate declined from 1.7 percent in 1990 to 1.3 percent in 2015 (UNIGME, 2015).



Sources: Own elaboration and presentation using data from UNIGME (2015)

Figure 1. 2: Share of global under-five child mortality rate between 1990 and 2015

Most under-five child deaths still occur in Sub-Saharan Africa, the region with the highest burden of under-five child deaths, where on the average, one child in every twelve dies before reaching five years of age. This is high compared to the average death of one under-five child in every 147 in developed countries (UNIGME, 2015). A child born in the highest under-five child mortality country (Sub-Saharan African countries) is about 80 times more likely to die before the age of five compared to his or her counterpart in the lowest under-five child mortality countries (such as Canada, Finland, Estonia, Luxembourg, Norway, Spain, Sweden, and United Kingdom) (UNIGME, 2015). In the Sub-Saharan Africa region, there are significant variations in under-five child mortality rate. For example, the under-five child mortality rate in Nigeria was 750 deaths per thousand births; in Angola, it was 169 deaths; in Democratic Republic of the Congo, it was 161 deaths, in Mali, it was 115 deaths; and in Benin, it was 100 deaths per thousand births (UNIGME, 2015). On the other hand, the under-five child mortality rate in Seychelles was 14 deaths per thousand births; in Botswana, it was two deaths; in Swaziland, it was two deaths; and in Cabo Verde, it was one death per thousand births (UNICEF, 2015). Thus, these figures indicate how increasingly wide the disparities are in the under-five child mortality rates between developed and developing countries, such as those in Sub-Saharan African countries.

Ethiopia's health problems are one of the major challenges affecting the country's overall development. The country is characterised by primary healthcare facilities that are inaccessible due to inadequate public health expenditure, poor provision of services, underdeveloped infrastructure, and a lack of trained healthcare service providers in the country's rural areas (Bilal et al., 2011; FMoH, 2015; USAID, 2008). In addition, the Ethiopian healthcare system is characterised by irregular distribution of access to and utilisation of healthcare services (FMoH, 2015). It is also highly centralised in urban areas, and poorly coordinated with the existing major health problems (UNDP, 2012). As a result, the healthcare system of the country is unable to reach the majority of the population at the grassroots level (FMoH, 2010; UNDP, 2012). In response to these problems, and in realising the widening gap between the need for healthcare services and poor basic healthcare services provision, the Ethiopian government launched, in 2004, a community-based health intervention programme known as Health Extension Programme (HEP) (CNHDE, 2011; HEPCAPS1, 2012).

The health extension programme is a government led community-based healthcare service programme, which targets households in rural communities (Bilal et al., 2011). The programme focuses on prevention, health promotion, and selected curative healthcare, with the primary objective being to improve the rural population's overall health status and most importantly to significantly reduce child and maternal mortality rates. The Health Extension Workers (HEWs) administer the programme at village health posts where they undertake basic healthcare service provisions to the rural community. Since the inception of the programme in 2004, the Ethiopian government increased the national health budget from

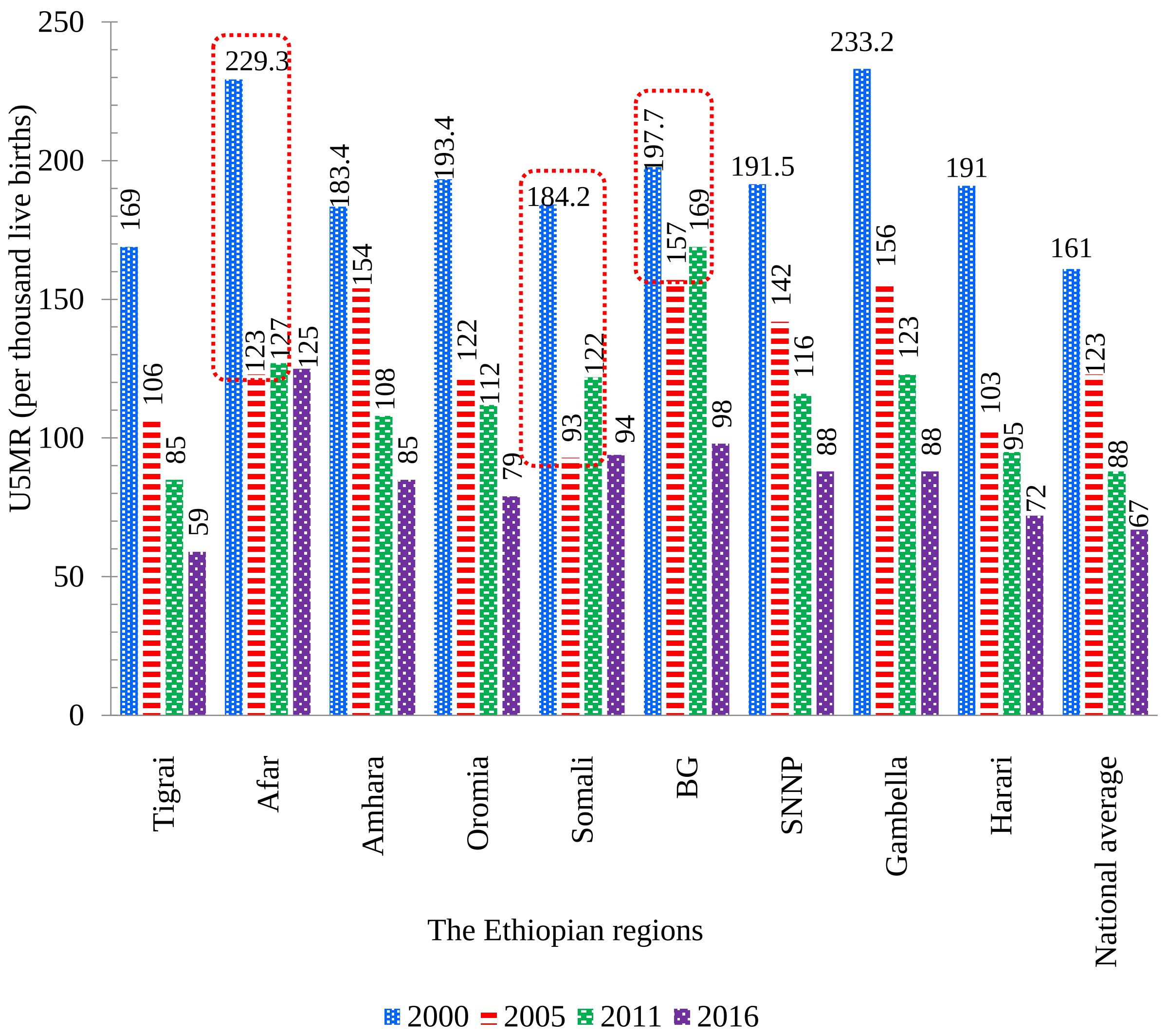
$522 million in 2004/05 to $1.2 billion in 2007/08 (FMoH, 2010) and further in 2012/13 to $1.6 billion (Dibaba et al., 2014; FMoH, 2014d) so as to accelerate access to and utilisation of basic healthcare services for the rural communities across all regions of the country (USAID, 2008)[2].

In Ethiopia, evidence shows that the number of under-five child deaths in rural areas is 29 percent higher than for urban areas (CSA & ICF International, 2012; 2016; CSA & ORCMacro., 2000, 2006). Despite the remarkable progress that Ethiopia has made in reducing the overall under-five child mortality rate from 123 deaths per thousand births in 2005 to 67 deaths in 2016 at the national level, evidence indicated that the magnitude of variations in under-five child mortality rate widened over time and varied considerably across regions of the country (Abebaw, 2013; CSA & ICF International, 2012; 2016; CSA & ORCMacro., 2006; Heins et al., 2001; UNDP, 2012). Although all regions reduced their under-five child mortality between 2011 and 2016 as indicated in Figure 1.3, their rates of reduction were below the national average except the Tigrai region (CSA & IFC International, 2012; & 2016). In 2016, the highest number of 125 deaths per thousand births was found in the Afar region, while the lowest number of 59 deaths per thousand births was also found in the Tigrai region. Moreover, the magnitude of variations in under-five child mortality rate remained considerably high across regions of the country (CSA & IFC International, 2012; 2016). Most importantly, between 2000 and 2016, compared to the national average rate of reduction, there were wide disparities in under-five child mortality rates among the Ethiopian regions, as indicated in Figure 1.3 (CSA & IFC International, 2012; 2016; CSA & ORCMacro., 2000; & 2006). Moreover, although the magnitude of the difference is significantly higher for under-five child mortality rate, pronounced differences in the infant mortality rate among regions were also noted (CSA & IFC International, 2012; & 2016).

The child mortality rate is considered a socio-economic development indicator, and thus, understanding of the regional differences in the levels of under-five child mortality and identifying the factors affected the regional gaps is imperative in terms of economic, social, allocation of resources, and health planning (Gayawan et al., 2016; Jhamba, 1999). This

[2] Health posts are healthcare satellite units in rural villages (kebelles) of Ethiopia in which the community health extension workers provide basic healthcare services of the health extension program targeting households in communities between 3,000 to 5,000 people in order to improve their overall health status (CNHDE, 2011). Thus, in the present study, the health posts are employed as decision-making units and are used to evaluate the technical efficiency and productivity changes of the Ethiopian rural health extension programme.

needs to be addressed in order to speed up the rate of reduction in under-five child mortality and promote inclusive, broad-based, and equitable basic healthcare services provision across regions of the country (UNDP, 2012).



Sources: Own computation with data from CSA and ICF International (2012; 2016); CSA and ORCMacro. (2000; 2006)

Figure 1. 3: Trend of under-five child mortality rates among the Ethiopian regions

Considering the evidence presented above, one can see that the substantial variations as well as rate of reduction in under-five child mortality rate among the Ethiopian regions were masked by the average decline in under-five child mortality at the national level. The wide disparities in under-five child mortality rates among Ethiopia's regions might be indicative of the differentials in access to and utilisation of basic healthcare service provision. Most of the available studies on the domain of child mortality focused on factors affecting the infant and the under-five child mortality in Ethiopia (Amouzou et al., 2014; Dejene & Girma, 2013; Deribew et al., 2007; Gizaw, 2015; Regassa, 2012, among others). Most importantly, these studies did not pay sufficient attention to identifying the factors responsible for the inter-regional differentials in infant and under-five child mortality in rural areas of Ethiopia. Concurrently, improvements in child mortality rates are considered to be the outcome of a combination of various healthcare services outputs, such as the use of immunisation, mother's level of health knowledge, accessibility of healthcare service, use of improved latrines, and safe drinking water (UNICEF, 2014). In Ethiopia, as in many other countries, these healthcare services are delivered by the health extension programme in rural communities (CNHDE, 2011; FMoH, 2005b). Evidence indicated that a properly implemented community-based health intervention programme, which has optimal coverage such as health extension programme, can save thousands of children's lives (Perry & Zulliger, 2012).

While Ethiopia's health extension programme, along with Pakistan, Nepal, Iran, India, Bangladesh, and Brazil, is one of the biggest community-based health worker programmes in the world, much less is known about how efficient and productive the programme is in delivering its packages of basic healthcare services to its population at the national level. Most previous studies in Ethiopia (Admassie et al., 2009; Amare, 2013; Gebrehiwot et al., 2015; Fetene et al., 2016; Kelbessa et.al., 2014; Medhanyie et al., 2016; Negusse et.al., 2007; Tesfa & Jibat 2014; Workie & Ramana, 2013, among others) did not give due attention to the efficiency of the health extension programme as well as factors explaining the health extension programme beneficiary households' graduation at the national level. In 2007, a local study by San Sebastián & Lemma (2010) evaluated the technical efficiency of the health posts in rural districts of the Tigrai region, Ethiopia. The study employed two input variables (number of health extension workers and voluntary health workers) and eight output variables (number of health education sessions, child deliveries, antenatal healthcare visits, under-five children treated diarrheal cases, family planning visits, visits made to households by the health extension workers, new patients treated, and malaria cases treated). The study indicated that only 25 percent of the health posts were technically efficient. Findings of analysis revealed that there were variations in technical and scale efficiency estimates among the sample health posts. None of the regressed variables had a significant effect on the disparities in the technical efficiency among the health posts. This study was however carried out at a micro-regional level at an infant stage of the programme, which might not indicate the real impact of the programme. An extensive evaluation of changes in health posts' efficiency level (productivity growth) was overlooked because a one-year data sample was used. Most importantly, the number of health extension programme's beneficiary graduates was overlooked as an important output variable, while evaluating the efficiency of the health posts.

Bilal et al. (2011) evaluated the performance of the Ethiopian health extension workers in terms of enhancing access to and utilization of healthcare services coverage for the poor section of the rural households. Bilal's findings revealed that the health extension workers contributed to improving the universal healthcare coverage of the rural society of the country. Furthermore, Admassie et al. (2009) also examined the impact of the Ethiopian health extension programme and found heterogeneity results in child immunization coverage across regions of the country. They indicated that the proportion of fully immunised children was higher for the health extension programme beneficiary households than the non-programme beneficiary households.

Most importantly, although the provision of training and graduation of the health extension programme beneficiary households as model households are the key health extension workers' output efficiency indicators and have an impact on child mortality reduction (Bilal et al., 2011), none of the reviewed studies explored the determinant factors affecting the health extension programme beneficiary households' graduation at the national level[3].

Thus, empirical evidence on the factors responsible for inter-regional differentials in under-five child mortality needs to be identified. The efficiency of the Ethiopian health extension programme, as well as the potential determinant factors influencing disparities in technical efficiency levels, needs to be evaluated and identified, respectively. Furthermore, identifying key determinant factors affecting the health extension programme beneficiary households' graduation is crucial in reducing child mortality variations among regions and should be examined. Information on these crucial research gaps remains scarce and is in its infancy stage at the national level and a detailed study is needed. This study, therefore, aims to address these important knowledge gaps.

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[3] Graduation refers to certifying of the health extension program beneficiary households who have been able to adopt basic health knowledge and skill and are able to practice more than 75 percent of the health intervention packages of health extension programme after being trained for approximately 196 hours basic healthcare services, using theoretical and practical courses of the programme (FMoH, 2010; CNHDE, 2011).

1.2. The rationale for the study

While Ethiopia made improvements in reducing the overall under-five child mortality rate at the national level, it was noted that there were wide inter-regional variations both in infant and under-five child mortality rates as well as rate of reduction in under-five child mortality rate among the Ethiopian regions (CSA & IFC International, 2012; 2016; CSA & ORCMacro., 2000; & 2006; Abebaw, 2013; Assefa et al., 2013). Most importantly, the regional variations in child mortality are more pronounced for under-five child mortality rate rather than for the infant mortality rate (Assefa et al., 2013; Bedane et al., 2016; CSA & ICF International, 2012).

Among the regional studies, Dejene & Girma (2013) indicated that the gender of the child, maternal age at the first birth, child's birth spacing, and multiple children were significantly affecting the under-five child mortality. Deribew et al. (2007) revealed that the maternal educational level, improved breastfeeding practices, immunisation coverage, and shorter birth spacing between children were also found to affect the under-five child mortality. Gizaw (2015) further indicated that the child's gender, maternal educational level, and region of residence were the major factors affecting the under-five child mortality. Furthermore, Regassa (2012) also examined the determinant factors affecting the infant mortality in a rural Southern region of Ethiopia. He found that maternal age, antenatal healthcare services, immunisation coverage, and exclusive breastfeeding practices were significantly affecting the infant mortality rate.

In addition, among the national level studies, Mulugeta (2011) indicated that mother's level of education, mother's age at first birth, total number of under-five children, access to clean water, access to modern toilet facilities, and access to electricity were negatively affecting the child mortality. Whereas the child's gender, type of birth, house's floor type, and type of cooking fuels used were positively affecting the child mortality. Moreover, Negera et al. (2013) found that the gender of the child, birth spacing, access to modern toilet facilities, maternal educational level, and maternal marital status were the major determinant factors affecting the infant and under-five child mortality rates. Bedane et al. (2016) further indicated that child's birth size, type of birth, mother's educational level, mother's age at first birth, and breastfeeding status were the major determinant factors affecting the under-five child mortality.

However, none of these reviewed studies explored the determinant factors explaining the inter-regional differentials in either infant or under-five child mortality at the national level. Most importantly, much less is known about the determinant factors explaining the regional disparities in under-five child mortality in the Ethiopian context. The Ethiopian health extension programme contributed significantly in reducing the country's overall child mortality (FMoH, 2015). The programme's main objective is to provide a basic healthcare service focusing on reducing child and maternal deaths through improving access to and utilisation of basic healthcare facilities that are available to the majority of the country's population both at the household and community levels. In addition, the programme intends to graduate more rural households by providing them training on the basic healthcare services, which, in turn, are expected to improve their health status and influence their society's overall health status (FMoH, 2015). Despite the considerable contribution that the health extension programme made in reducing the overall child mortality rate and other health-related indicators (FMoH, 2015), its overall efficiency and productivity growth at the national level was not evaluated. Moreover, the overall national throughput rate of graduating the health extension programme beneficiary households as model households was very small with considerable disparities across regions of the country (FMoH, 2015/16).

Thus, the Ethiopian local studies (Dejene & Girma, 2013; Deribew et al., 2007; Gizaw, 2015; Regassa, 2012; Bedane et al., 2016) considered the geographical region as an independent variable to examine its effect on the infant and under-five child mortality indicating that infant and under-five child mortality rates varied substantially across regions. The determinant factors affecting the overall child mortality differentials might tend to mirror the inter-regional differentials and thus, almost none of the reviewed studies examined the major determinant factors affecting the inter-regional differentials in the infant or the under-five child mortality rate at the national level. Hence, although a large body of literature is available on the domains of determinant factors affecting the infant and the under-five child mortality in Ethiopia, much less is known about the relative contribution of these determinant factors in explaining the inter-regional differentials in the infant and/ or the under-five child mortality in rural setting of Ethiopia. In addition, studies on determinant factors influencing the health extension programme beneficiary households' graduation and the efficiency and productivity growth of the Ethiopian health extension programme are still scanty and are in their infancy stage at the national level.

Therefore, the determinant factors affecting the inter-regional differentials in the infant and/or under-five child mortality, the efficiency and productivity growth of the community-based health extension programme, and the determinant factors influencing the community-based health extension programme beneficiary households' graduation need further rigorous studies. Hence, these are the rationale behind the reason as to why this study examine the determinant factors affecting the inter-regional under-five child mortality, evaluate the efficiency and productivity growth or changes of the community-based health extension programme, and identify the determinant factors influencing the community-based health extension programme beneficiary households' graduation.

1.3. The overall objective of the study

This study aims at exploring primarily the determinant factors affecting the inter-regional differentials in under-five child mortality, programme efficiency, and assessing the factors affecting graduation of the community-based health extension programme beneficiary households in rural settings of Ethiopia.

1.3.1. The specific objectives

There are three interdependent and core specific research objectives of this study. These are:

i. To examine the major determinant factors affecting the inter-regional differentials in under-five child mortality;

ii. To evaluate the efficiency of the Ethiopian community-based health extension programme; and;

iii. To identify the determinant factors influencing the community-based health extension programme beneficiary households' graduation.

1.4. Scope and significance of the study

The present study was restricted to Ethiopia's rural areas and was carried out based on a cross-sectional secondary data obtained from the regional health bureaus and federal ministry of health, Ethiopia. Despite the marked progress that Ethiopia made in health and health-related outcomes, none of the reviewed studies explained the relative contribution of determinant factors affecting the inter-regional variations in child mortality, as well as evaluated the efficiency and productivity growth (changes) of the community-based health extension programme at the national level. Moreover, much less is also known about the determinant factors affecting the community-based health extension programme beneficiary households' graduation in rural areas of Ethiopia.

Therefore, the present study is the first of its kind in the Ethiopia's context to explore the major determinant factors affecting the inter-regional differentials in under-five child mortality, evaluate the efficiency and productivity changes of the community-based health extension programme, and examine the key determinants of the community-based health extension programme beneficiary households' graduation at the national level.

Therefore, the significance of this study is to:

(a) Provide valuable insights on policy guidelines to improve the overall Ethiopian health programme;

(b) Suggest guidelines on enhancing access to and utilisation of the country's basic healthcare services for the federal ministry of health, regional health bureaus, health managers, stakeholders, development practitioners, federal and regional governments; and

(c) Providing empirical information that could be utilised as an input in achieving the country's sustainable development goal of reducing under-five child mortality rate to less than 25 deaths per thousand births by 2030.

1.5. Outline of chapters of the thesis

This thesis has seven chapters.

- ***Chapter One*** presents an overview of the overall background of the study and states the research knowledge gaps**.** It also explained the study's rationale, scope, and significance.
- ***Chapter Two*** provides a brief overview of the economic profile and primary healthcare system of Ethiopia. It also briefly explains Ethiopia's demographic, socio-economic status, and discusses the health extension programme focusing on the health extension workers, health posts, and graduation of the health extension programme beneficiary households.
- ***Chapter Three*** presents the reviews of related literature and an integrated conceptual framework guiding the present study.
- ***Chapter Four*** describes the statistical methods and data sources employed to address the specific research objectives of this study.
- ***Chapter Five*** reports the major results of the research findings of the entire study.
- ***Chapter Six*** presents a discussion of results of the research findings in comparison with other previous empirical studies' findings.

- ***Chapter Seven*** presents summary of main findings, makes conclusions, and potential insightful policy recommendations. It also reports possible research directions for further study and presented the overall limitations of the study.

1.6. Conclusion

This chapter presents the overall background of the study. It further provides a detailed explanation why this study was carried out by stating specific objectives that this study needs to address.

CHAPTER TWO

ETHIOPIA'S ECONOMIC AND PRIMARY HEALTHCARE SYSTEMS

2.1. Introduction

This chapter presents an overview of Ethiopia's profile in terms of demography and geography, administrative structure, socio-economic context, unemployment status, educational status, health status, and the structural primary healthcare system of the country. The economic profile of Ethiopia is discussed focusing on the socio-economic situation of the country mainly since post-1991. Much emphasis is also placed on the developmental issues such as Gross Domestic Product (GDP) and its growth rate over the years, the contribution of the various sectors to the country's GDP, and the poverty status of the country. In addition, the chapter provides an overview of the Ethiopian health status and the progress that the country made mainly in reducing the overall child mortality rate.

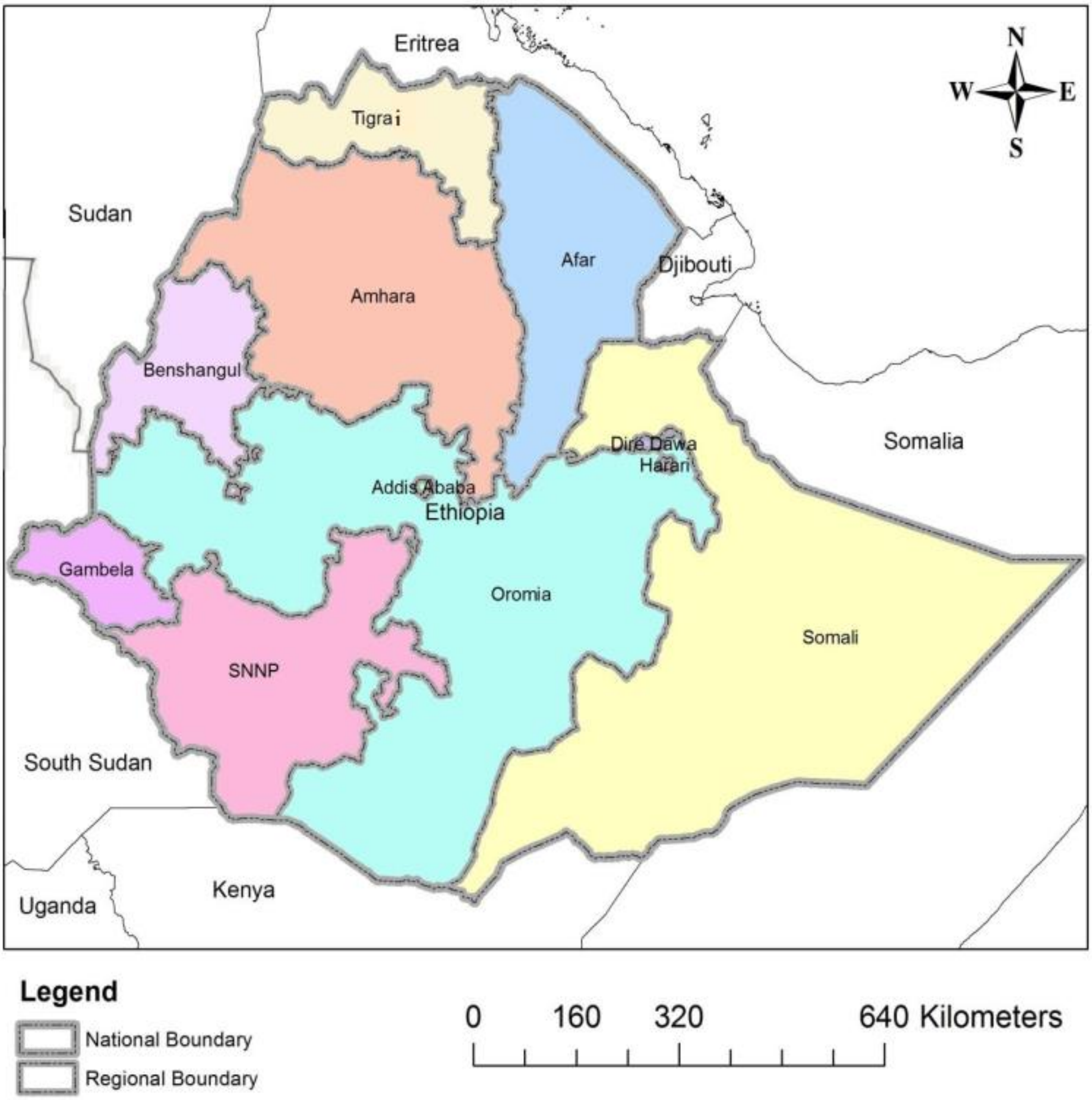
The chapter is outlined as follows: Section 2.2 presents a brief overall profile of Ethiopia (demographic and geographic). Section 2.3 provides the structure of the primary healthcare system of Ethiopia. Section 2.4 presents a summary of the chapter.

2.2. Demographics and geography of Ethiopia

Ethiopia is a country situated in the horn of East Africa with a total area of over one million square kilometres. It shares a border with six neighbouring countries, namely; Eritrea to the north, Kenya to the south, Sudan to the west, South Sudan to the southwest, and Somalia and Djibouti to the east. After Nigeria, Ethiopia is the second most populous country in Africa with a population of over 99.4 million inhabitants in 2015 (WHO, 2016). The majority of the population of Ethiopia (83 percent) live in rural areas of the country. About 43 percent of the total population of the country is under fifteen years old (Wang et al., 2016). The overall national annual natural population growth rate was 2.31 percent in 2015/16 (NBE, 2015/16). At the national level, the household size for rural areas (5 persons per household) was larger than the urban counterparts (3.6 persons per household), with an average national household size per household of 4.6 in 2016. Moreover, at the national level, about 75 percent of the households were headed by men, while the remaining 25 percent were headed women. Most importantly, nearly half of the Ethiopian population is under the age of fifteen years old (CSA & ICF International, 2016).

2.2.1. Administrative structure

Ethiopia is officially known as the Federal Democratic Republic of Ethiopia (FDRE) and is a parliamentary republic with the prime minister as head of the government (FMoH, 2010). Ethiopia is a multi-ethnic and a diverse country in its religion, culture, and climatic makeup, and thus, for administrative purposes, the country is subdivided into nine regions. As displayed in Figure 2.1, the regions are Tigrai, Afar, Amhara, Benshangul-Gumuz, Oromia, Harari, Gambella, Somali, and Southern Nations, Nationalities, and Peoples' (SNNP) region. Addis Ababa, the capital of the country, and Dire-Dawa are the two administrative cities (FMoH, 2010).



Source: Adigrat University, Department of Geography and GIS (2017)

Figure 2. 1: Location and map of Ethiopia with its administrative regions

The regions of the country are also subdivided into zones, and the zones are further subdivided into districts, which are known as "*weredas*" decentralised administrative units. Finally, the "*weredas*" are further subdivided into sub-districts or villages, which are known as "*kebelles*", the smallest administrative units in the context of Ethiopia. Amharic is the federal official language; nevertheless, each region has its own administrative official language (FMoH, 2010).

2.2.2. Ethiopia's socio-economic context

Since the downfall of the Derg regime in 1991, the present Ethiopian government (FDRE) has followed a market-oriented and "Agricultural Development Led Industrialisation, ADLI" development policy. The economy of the country largely depends on agriculture and therefore, the agriculture sector remains its backbone (NBE, 2015/16). It accounted for 85 percent of the total employment of the country (UNDP, 2013; Wang et al., 2016). In addition, the agricultural sector also accounted for 41 percent of the Gross Domestic Product (GDP), and 74 percent of the total export of the country in 2015 (UNDP, 2016). Ethiopia's economy grew by 9.8 percent between 2010/11 and 2015/16 (NBE, 2015/16).

Ethiopia is one of the fastest growing economies in the world and the country registered an average annual growth rate (real GDP) of 8 percent in 2015/16. Of this growth of 8 percent, 3.1 percent came from the industrial sector, 4 percent from the services sector, and 0.9 percent from the agricultural sector (NBE, 2015/16). While the contribution of the agricultural sector to real GDP decreased by 2.5 percent in 2014/15 to 4 percent in 2015/16, the sector remained as the major source of livelihood for the majority of the rural population (NBE, 2015/16) (see Table 2.1). Over the last decade (2009 - 2015), on average, the Ethiopian annual economic growth rate was 10.3 percent (WDI, 2017). The average Gross National Income (GNI) per capita in US Dollar for an Ethiopian was 590 in 2015, which remains quite low when compared to the Sub-Saharan African countries such as Seychelles, Botswana, Swaziland, Ghana, Sudan, Mauritius, and Kenya, with GNI per capita (in US Dollar) of 14,680, 6,460, 3,280, 1,480, 1,920, 1,370, and 1,340, respectively over the same period (WDI, 2017). In terms of the Human Development Index (HDI), Ethiopia also improved its economic status from 0.283 in 2000 to 0.435 in 2013, while in 2014, the human development index improved to 0.441, which is 58.3 percent higher than the index was in 2000 (WDI, 2017). Despite its remarkable progress in economic growth, Ethiopia is still among the poorest countries in the world countries. Accordingly, Ethiopia's human development index value for 2015 is 0.448, ranking 174th out of 188 countries and put the country in the lowest human development index category. Between 2000 and 2015, Ethiopia's human development index value increased from 0.283 to 0.448, an increase of 58.2 percent (UNDP, 2016). Ethiopia's 2015 human development index of 0.448 is below the average of 0.497 for countries in the low human development index group and below the average of 0.523 for countries in Sub-Saharan Africa (UNDP, 2016).

Table 2. 1: The real GDP and sectoral contribution to real GDP

Measured in Birr (in billion)	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16
Real GDP	475.6	517.0	568.0	627.0	692.0	747.0
Growth rate in real GDP	11.4	8.7	9.9	10.3	10.4	8.0
Sectoral contribution to real GDP (in percent)						
Services	5.6	4.4	4.1	5.8	5.2	4.0
Industry	2.0	2.1	2.8	2.2	2.7	3.1
Agriculture	4.2	2.2	3.1	2.3	2.5	0.9

Source: National Bank of Ethiopia, 2015/16; Note: Birr is the Ethiopian currency

Most importantly, Ethiopia is considered to be one of the under-developed countries in the world, with one of the highest poverty levels in the world. For example, in 2000, about 44 percent of Ethiopians were living below the national poverty line and declined to less than 30 percent in 2011 (WB, 2015). Furthermore, evidence indicated that the poverty rate further declined to 23.5 percent in 2015/16. Of this 23.5 percent, about 25.6 percent were in rural areas, while 14.8 percent were in urban areas (GoE, 2017). Despite the progress Ethiopia has made in reducing the poverty rate, the income inequality remains a persistent challenge to the population of the country, with an increasing trend in the Gini Coefficients of 0.28, 0.30, 0.33, and 0.33 in 2000, 2005, 2011, and 2015/16, respectively (GoE, 2017; WB, 2015). The income inequality is higher in urban areas (0.38) than in rural areas counterparts (0.28) (GoE, 2017). Compared to the Sub-Saharan Africa average poverty rate (41 percent), the overall poverty rate of Ethiopia remains low (WDI, 2017). Despite the steady economic growth, unemployment remains a major challenge in Ethiopia, with the national unemployment rate standing at 4.5 percent, with 37.82 percent lower than the rate for Sub-Saharan Africa in 2015 (UNDP, 2015).

The total government expenditure on health increased from 4.4 in 2000 to 4.9 percent in 2014, with an annual average increase of 11.36 percent (WHO, 2015a). At the national level, health expenditure has increased from 2.4 billion (Ethiopian Birr) in 2006/07 to 24.5 billion (Ethiopian Birr) in 2015/16, at an average annual growth rate of 30.6 percent. The average per capita health expenditure also increased from 16.1 US Dollar in 2007/08 to 20.8 US Dollar in 2010/11 and further to 28.7 US Dollar in 2013/14, which is very low compared to the sub-Saharan Africa average of 98 US Dollar per capita health expenditure in 2014, and has resulted in considerable personal out-of-pocket health expenditure, which is relatively higher for poorer households (FMoH, 2014b; UNICEF, 2017).

2.2.3. Educational status

Education remains one of the most fundamental aspects of social and economic development. It enhances capabilities, and is strongly related to socio-economic factors (CSA, 2016). Accordingly, Ethiopia has given due emphasis to education and has made notable progress in terms of quality and coverage across its regions (NBE, 2015/16). The overall educational level has a significant effect on the use of modern healthcare services, the acceptability of health practices, and the spread of diseases. The Ethiopian population's literacy status is, however, very low (FMoH, 2005a). The overall adult literacy rate in Ethiopia increased from 25 percent in 1995/96 to 46.7 percent in 20101/11 (39 percent for female and 62 percent for male) (GoE, 2015). The adult literacy rate for Ethiopia was slightly increased to 49 percent in 2015. Compared to the average adult literacy of the sub-Saharan Africa (62 percent), the adult literacy rate for Ethiopia remains the lowest (FMoH, 2015/16).

2.3. Structure of the primary healthcare system in Ethiopia

Until 1991, the largest part of the Ethiopian population had limited access to basic healthcare services, which was considered a major cause of health problems in the country. The lack of adequately trained health professionals, inadequate funding sources, and the high illiteracy rate, which in particular, prevents the spreading of information on modern healthcare practices, also all contribute to the healthcare problems of the country. These factors were also the major reasons why most of the Ethiopian population was excluded from access to basic healthcare services (Kloss, 1998; TGE, 1993). In addition, the health system of the country was focused on curative healthcare service provision and was mainly found in the urban setting areas of the country (Ofcansky & Berry, 1991). To provide basic healthcare services and to reach most of the rural communities of the country, the Ethiopian government established the first national policy in 1963 during the imperial regime. This national policy focused on preventative and curative healthcare services by expanding health centres and health stations to provide essential healthcare services making the urban-biased equitable. This policy, however, could not realise its objective of reaching the majority of rural people in providing basic healthcare services. This was mainly owing to severe resource constraints faced by the imperial government of the country (Kloss, 1998).

Following the 1974 revolution, during the Derg regime, a ten-year national health programme (1984/85-1993/94) was developed, which focused on prevention and control of disease, which took into consideration the rural community of the country. The major goal of the programme was to expand and consolidate the child and maternal healthcare services provision, focusing on immunisation of children under two years of age and on pregnant mothers. In addition, during the stated periods, the programme planned to reduce infant and child mortality rate from 145 and 274 to 95 and 150 per thousand births, respectively (Kloss, 1998). The policy however failed to attain its intended goal due to urban-based health resources distribution, the absence of active community participation, the ongoing civil war, and the highly centralised administrative political system of the regime (Kloss, 1998; TGE, 1993). Since 1991, following the downfall of the Derg regime, the present Ethiopian government (FDRE) revised the national health system of the country that took into consideration the wide-ranging health and health-related issues such as food availability, population dynamics, acceptable living conditions, and other crucial factors affecting health (TGE, 1993).

In 1993, the current Ethiopian government revised the national health policy, which gave due emphasis to the decentralising of the national health system in providing basic healthcare services based on promotive, preventative, and selective curative principles (FMoH, 2010). The policy fully reorganised the healthcare services delivery system as contributing positively to the country's overall socio-economic development efforts (TGE, 1993). Its major themes were democratisation, decentralisation, and equitable healthcare service distribution by expanding the basic healthcare system to the most rural poor and under-served communities, with special emphasis on women and children's health (TGE, 1993). Despite the major improvement that Ethiopia made in the healthcare systems of the country, the healthcare needs of most of the people remained unaddressed (FMoH, 2012/13).

In 1997, aligned to the national health policy frameworks, the Ethiopian government developed a twenty-year perspective national development programme, which is known as the Health Sector Development Programme, HSDP. The HSDP was further subdivided into a series of five-year subsequent strategic plans (namely, HSDP I: 1997/08 - 2001/02, HSDP II: 2002/03 - 2004/05, HSDP III: 2005/06-2009/10, and HSDP IV: 2010/11 - 2014/15) (FMoH, 2010). The programme aimed at providing comprehensive and integrated basic healthcare services both at household and community-level health facilities. The programme shifted the focus of the healthcare system from predominantly curative healthcare to more preventative and promotive healthcare as well as prioritised the healthcare needs of the rural inhabitants. The evaluation of the HSDP I and II phases showed notable progress in coverage and utilisation of basic healthcare services of the healthcare system of the country (FMoH, 2010).

Despite the notable improvement obtained from the programme, the Ethiopian healthcare system remained inadequate in providing the basic healthcare services to the largest rural population of the country at grass roots level (FMoH, 2010). The major challenges of the healthcare system of the country included limited access to healthcare services, widespread poverty, low basic healthcare service utilisation, and inadequate access to clean water and sanitation facilities (FMoH, 2010). The higher cost associated with the expansion of standard healthcare services and the lack of higher-level health professionals such as doctors continued to be the main challenges to address the health problems of most of the rural people within the existing socio-economic situation of the country. The standard healthcare system under the HSDP model could not address the major challenges of health problems of the rural communities of the country. As a result, the overall levels of child and maternal mortality appeared unlikely to have shifted significantly. For this reason, maternal and child mortality, as well as the incidence of the major killers such as HIV/AIDs and malaria, continued to be among the world's highest. Therefore, the present Ethiopian government was forced to restructure the former national healthcare system to significantly address the healthcare needs of most of the people of the country (FMoH, 2015).

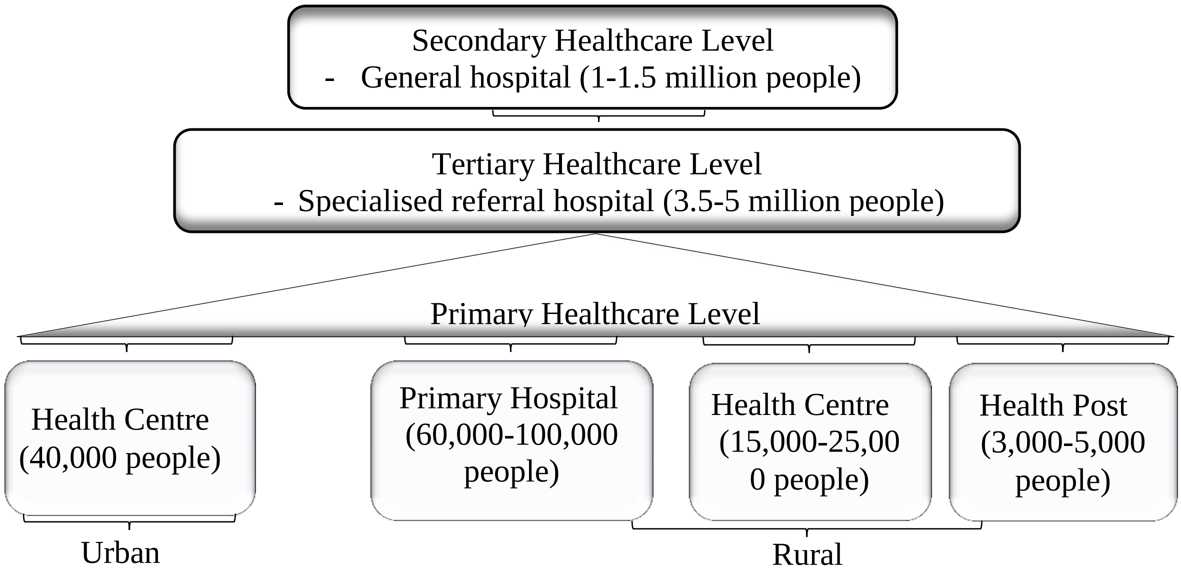
As illustrated in Figure 2.2, the present Ethiopian healthcare system has three levels of healthcare services delivery to its citizens. These are:

1) The primary healthcare level (also known as Primary Health Care Units, PHCU), which consists of a referral primary hospital, five health posts, and one health centre, forming a base for the healthcare system of the country. There are two health extension workers per health post to provide basic healthcare services to a 3000 - 5000 rural population, while one health centre serves 15,000 - 25,000 people. A primary hospital provides healthcare services

for a total of 60,000 - 100,000 people while the urban health centres provide healthcare services to 40,000 people.

2) The secondary healthcare level includes a general hospital that serves a total population of 1 - 1.5 million. Moreover, it serves as a referral base for the primary hospital.

3) The tertiary healthcare level, which refers to the specialised referral hospital that serves a total population of 3.5 - 5 million (FMoH, 2010).



Source: Own elaboration and development using data from FMoH (2010)

Figure 2. 2: Organisational structure of the Ethiopian health system

2.3.1. Ethiopia's health status

Compared to the other developing countries, Ethiopia's health status is poor. Although Ethiopia made remarkable gains in many health indicators (such as child mortality, maternal mortality etc.), the majority of the country's health problems remain largely preventable communicable diseases and nutritional disorders (FMoH, 2005a). For example, the national average of full immunisation coverage for under-five children increased from 86.4 percent in 2013 to 90.9 percent in 2014, with significant variations across regions, ranging from the highest, namely 95 percent in the Oromia region, to the lowest, namely 55.2 percent in the Gambella region. The proportion of women aged 15 – 49 who received antenatal healthcare services from a skilled health personnel has increased from 34 percent in 2011 to 62.4 percent in 2016, with considerable variations across regions, ranging from 14.4 percent in the Gambella to 95 percent in the Tigrai region. The institutional deliveries have increased from 10 percent in 2011 to 26 percent in 2016 at the national level (CSA & ICF International, 2016). The total number of deaths of pregnant women also declined from 31,000 in 1990 to

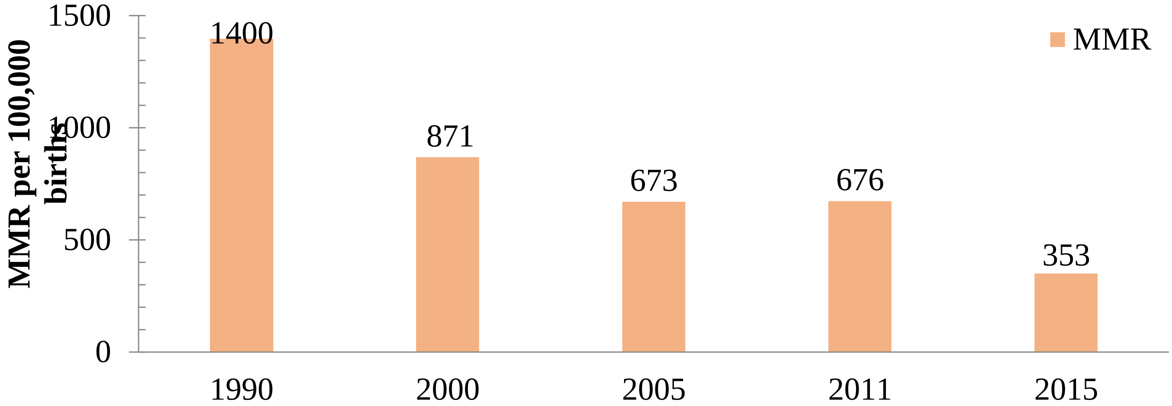
11, 000 in 2015, with an annual average rate of reduction of 65 percent (FoMH, 2015/16). Furthermore, the average use of modern contraceptive at the national level was 69.9 percent, ranging from the highest 97.2 percent in the Amhara region to the lowest 5.7 percent in the Somali region. Moreover, the proportion of households who used modern or improved latrines increased from 38 percent in 2011 to 43.3 percent in 2014, ranging from 67.9 percent in Amhara region to 1 percent in the Afar region (CSA & ICF International, 2012; FMoH, 2016).

Ethiopia also made remarkable progress in life expectancy, literacy, child, and maternal health (CSA & ICF International, 2012). On the other hand, the coverage of postnatal healthcare services declined slightly from 90 percent in 2013 to 89.3 percent in 2014 at the national level. Moreover, the HIV-positive pregnant mothers who received Antiretroviral (ARV) declined from 64.9 percent in 2013 to 62.1 percent in 2014 (FoMH, 2015/16). The overall improvements that Ethiopia made in health outcomes enabled the country to remarkably improve the life expectancy of its citizens. Accordingly, the average life expectancy at birth for both sexes rose from 45 years in 1990 to 65 years in 2015 (UNDP, 2016; WHO, 2016). Between 1990 and 2015, Ethiopia's life expectancy at birth increased by 17.5 years (UNDP, 2016). Overall, in Ethiopia, the average total fertility rate (number of children per woman) declined from 5.5 children per woman in 2000 to 4.6 children per woman in 2016, a reduction of 0.9 children (CSA and IFC International, 2016). The fertility rates however remain higher in rural areas (5.2) than in urban areas (2.3) among women of all age groups where the total national fertility rate was 4.6 children per woman in 2016. Most importantly, the fertility rate varies across regions of Ethiopia; the highest being 7.2 children per woman found in the Somali region, and the lowest being 3.5 children per woman found in the Gambella region. Moreover, fertility varies with education and economic status. Women with no education have more children (5.7), than women with more than secondary education (1.9 children), with an increase of 3.8 children (CSA & ICF International, 2016).

In terms of access to clean or improved drinking water and sanitation facilities, the proportions of population who have access to these facilities remain quite low in Ethiopia. According to the recent report by World Development Indicators (2017), only 57 percent of the country's population has access to improved drinking water. Furthermore, at the national level, only 28 percent of the Ethiopian population has access to improved sanitation facilities. These figures were much lower than other Sub-Saharan Africa countries' access to improved drinking water and sanitation services such as Seychelles, Swaziland, Mauritius, and Rwanda, with 96 and 98 percent; 74 and 58 percent; 58 and 40 percent; and 76 and 62 percent of access to improved drinking water and sanitation facilities, respectively (WDI, 2017).

2.3.2. Maternal mortality

Ethiopia paid more attention to maternal and child health in its national health development programmes and sustained efforts are being made to reduce both maternal and child mortality rates. As indicated in Figure 2.3, the maternal mortality ratio, MMR (maternal deaths per 100,000 births) estimate declined from 871 deaths in 2000 to 353 deaths per 100,000 births by 2015 (CSA & ORCMacro, 2006; UNIGME, 2015). On a global level, the rate of maternal mortality has decreased by approximately 44 percent over the past 25 years, to an estimated 216 maternal deaths per 100,000 births in 2015, from maternal mortality ratio of 385 in 1990. The annual average number of maternal deaths decreased from 532,000 in 1990 to 303,000 in 2015, a nearly 43 percent rate of reduction between 1990 and 2015 (WHO, 2015b).



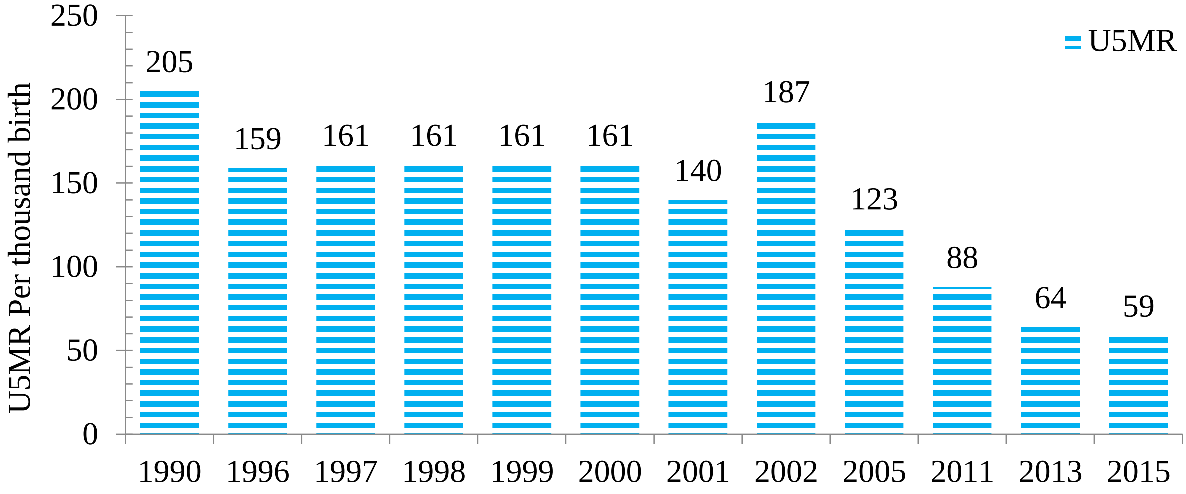
Source: Own elaboration using data from CSA & ICF International (2016, 2012); CSA & ORCMacro. (2000; 2006); UNIGME (2015)

Figure 2. 3: Trends in estimates of MMR (maternal deaths per 100,000 births) in Ethiopia between 1990-2015

Although the magnitude of maternal mortality remains relatively high, Ethiopia is not among the eighteen countries where maternal deaths remained very high in 2015. They are: (Central African Republic (1,500 maternal deaths), Somalia (1,390 maternal deaths), Chad (1,350 maternal deaths), Nigeria (1,180 maternal deaths), South Sudan (1,150 maternal deaths), Guinea-Bissau (1,090 maternal deaths), Malawi (1,080 maternal deaths), Burundi (1050 maternal deaths), Liberia (1,030 maternal deaths), Gambia (1,030 maternal deaths), Democratic Republic of the Congo (1,010 maternal deaths), Mauritania (984 maternal deaths), Guinea (927 maternal deaths), Côte d'Ivoire (909 maternal deaths), Cameroon (881 maternal deaths), Mali (823 maternal deaths), Niger (752 maternal deaths), and Kenya (754 maternal deaths)) (WHO, 2015b).

2.3.3. Levels and trends of child mortality in Ethiopia

As illustrated in Figure 2.4, the remarkable progress that Ethiopia has made in improving child health status enabled the country to reduce its overall under-five child mortality from 205 deaths per thousand births in 1990 to 59 deaths in 2015, a 71 percent reduction over the 25 years. Thus, Ethiopia is among the few Sub-Saharan African countries that achieved its Millennium Development, MDG goal-IV, in reducing the under-five child mortality rate by two-thirds, three years ahead of the deadline (UNIGME, 2015). However, as indicated in Figure 2.4, the trend of decline was not consistent. A huge decline in under-five child mortality was recorded from 1990 (205 deaths per thousand births) to 1996 (159 deaths per thousand births), no reduction was observed between 1997 and 2000. The under-five child mortality then rate increased to 187 deaths per thousand births in 2002 but gradually declined to 59 deaths per thousand births in 2015, a nearly 50 percent rate of reduction between 2005 and 2015 (CSA & ICF International, 2016; 2012; CSA & ORCMacro, 2006; UNIGME, 2015). On a global level, considerable progress has been made in reducing under-five child deaths. Accordingly, the global under-five mortality rate has decreased from 91 deaths per thousand births in 1990 to 43 deaths in 2015, a 53 percent rate of reduction (UNIGME, 2015).



Source: Own computation (CSA & ICF International, 2012; CSA & ORCMacro, 2006; MoFED, 2004; UNIGME, 2015)

Figure 2. 4: Trend of under-five child mortality rates between 1990 and 2015 in Ethiopia

2.3.4. Health extension programme in Ethiopia

In Ethiopia, the community-based health worker programme, which is currently known as the health extension programme, has a wide-ranging history and has been in place for several years dating back to the Alma-Ata Declaration era, in 1978 (Ghebreyesus et al., 1996). The Tigrai region, one of the Ethiopia' regions, had employed about 3,000 community-based health extension workers in early 1980 during the civil war in order to provide certain basic healthcare services to their rural communities. They were chosen by their communities to receive training mainly in the field of child, maternal, and environmental health, as well as in malaria diagnosis and treatment. When the civil war ended in 1991, the programme was deferred (Ghebreyesus et al., 1996)[4]. As indicated earlier (see section 2.3), the evaluation of HSDP I and II indicated that although the health extension programme improved the health status of many citizens of the country, it was criticised for being highly centralised in urban areas and could not provide basic healthcare services to the largest rural population of the country. As a result, the programme failed to enhance the universal primary healthcare coverage of the country (FMoH, 2010)**.**

The Ethiopian government launched the health extension programme in accordance with the basic principles of primary health care (PHC) in 2004. Its aim was to provide basic healthcare services that drew heavily on the principles of Primary Health Care and community-based health approaches (Dynes et al., 2012; FMoH, 2010). The Ethiopian community-based health extension programme, or simply the health extension programme is a flagship healthcare service providing programme aimed at improving health outcomes of the households and communities by ensuring universal healthcare services coverage of the country in the context of scarce resources. The programme is the cornerstone of the country's primary healthcare system, which gives priority to the prevention and control of communicable diseases by means of active community participation, with the goal of providing equitable access to basic healthcare services. Most importantly, the health extension programme is the main vehicle for achieving Ethiopia's health and health-related MDGs. The primary aim of the programme is to improve primary healthcare services in rural areas of the country by means of provision of an innovative community-based approach focusing on child and maternal health (FMoH, 2008).

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[4] Community Health Workers (CHWs) are defined as "members of the communities where they work, should be selected by the communities, should be answerable to the communities for their activities, and should be supported by the health system but not necessarily be a part of its organisation, and have shorter training than professional workers" (WHO, 1989, pp. 16).

The Ethiopian health extension programme includes 16 packages under four major categories of healthcare services provisions. These categories are:

i) Hygiene and environmental sanitation include personal hygiene, clean water supply and safety measures, proper and safe excreta disposal, food hygiene and safety measures, liquid and solid waste disposal, healthy home environment, and control of rodents and insects.
ii) Disease prevention and control including HIV/AIDS and other sexually transmitted infections, tuberculosis prevention and control, and malaria prevention and control.
iii) Family health services include child and maternal health, family planning, nutrition, immunisation, and adolescent reproductive health.
iv) Health education and communication.

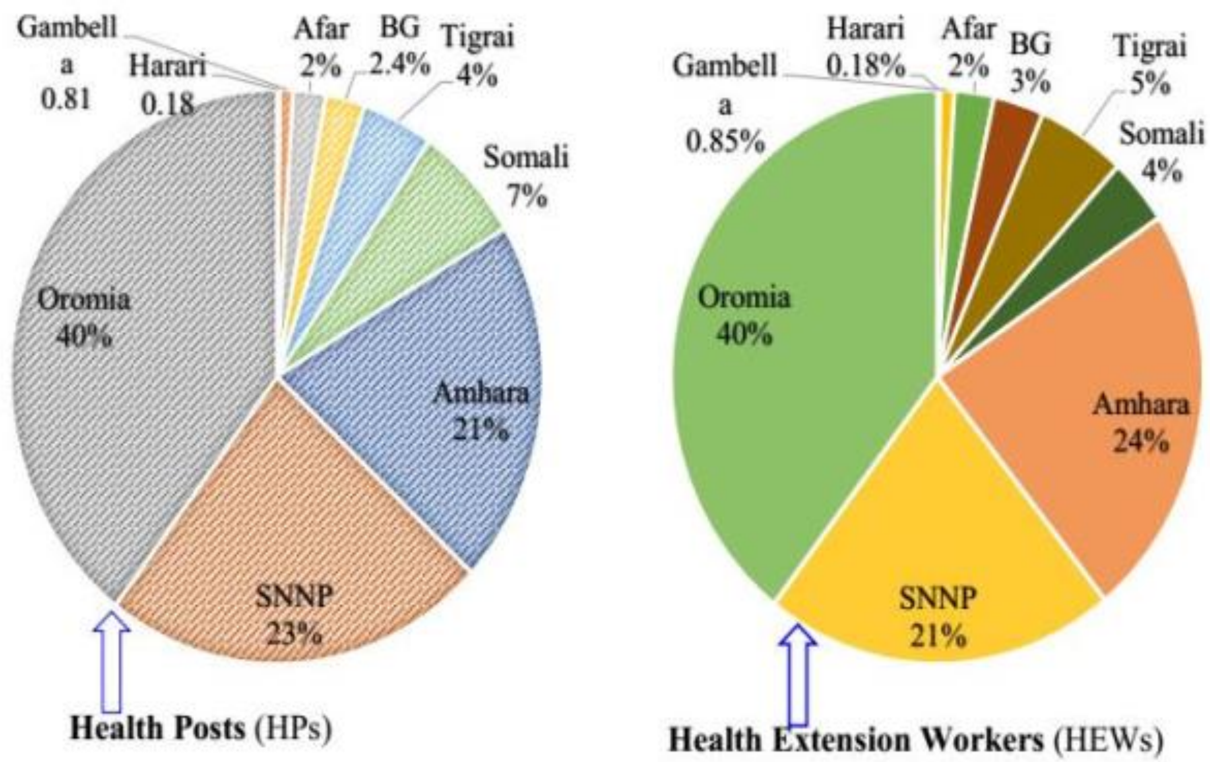
To provide these packages, the health extension workers employed three modes of healthcare service delivery (house-to-house visits, community outreach, and health post-based healthcare service provisions). The packages were put together according to the need and the existing real critical health situation of the rural communities of the country (FMoH, 2015, Wang, et al., 2016).

2.3.4.1. Selection and training of health extension workers

The health extension workers are the major drivers of the Ethiopian health extension programme. They are selected by the community and are recruited based on the nationally agreed criteria that include being residents of the village in which they are working, female older than 18 years who have at least grade 10, knowledge of the local language of the community, and willingness to go back to the village and provide packages of basic healthcare services of the health extension programme to their respective community (FMoH, 2005b). The health extension workers are given an extensive training for one year, both on theoretical coursework and practical field work on basic healthcare services of the health extension programme. Upon their graduation, as key drivers for the implementation of the programme, they are then deployed in pairs to their respective home village's health post as government-salaried workers to provide basic healthcare services of the programme to their respective communities (FMoH, 2015).

The expansion of the physical health infrastructure, mainly the health posts is crucial in implementing the Ethiopian health extension programme. Since the inception of this programme, there has been a significant increase in the aggregate number of health posts from the baseline of 6,191 in 2004/05 (FMoH, 2010). In 2014, the number of health posts reached 16,447, achieving over 100 percent of the national target of 15,000 health posts (FMoH, 2015/16). The health extension programme setup is an institutional framework for the expansion of the national healthcare interventions to household and community levels by means of provision of basic healthcare services provided by the health extension workers in the health post (FMoH, 2014a).

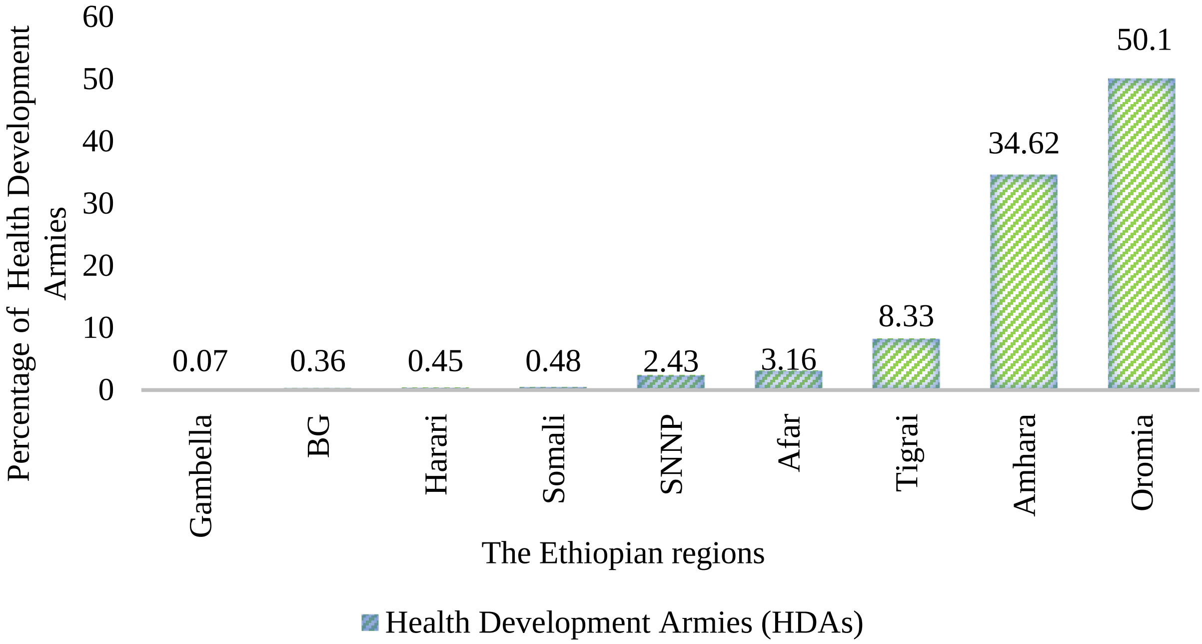
As indicated in Figure 2.5 (left side), although the country achieved 100 percent of its national target of constructing health posts, there were significant variations in the percentage of the health posts across the regions. The percentage of health posts ranges from the highest; nearly 40 percent of these were in the Oromia region, followed by 23 percent in the SNNP region, to the lowest 0.18 percent of which were found in the Harari region.



Source: Own computation using data from FMoH (2015/2016; 2016)

Figure 2. 5: The aggregate percentage of regional health posts and health extension workers

Most importantly, the overall national target of the health extension programme was to select, train, and deploy a total of 30,000 health extension workers, two health extension workers to every health post of each "*kebelles*" based on the proportional population size of the regions of the country in 2009 (FMoH, 2008). Hence, the actual cumulative number of 42,258 health extension workers had been trained and deployed to 16,447 health posts across regions of the country by 2014. Furthermore, by 2014, a total of 360,629 health development armies (HDAs) were trained by the health extension workers at the national level in order to support the health extension workers in providing basic healthcare services to their respective communities. There were significant variations in the number of trained health development armies across regions of the country. As displayed in Figure 2.6, Oromia had the highest, at 50.1 percent while the Gambella region had the lowest, at 0.07 percent of the total number of



health development armies (FMoH, 2014a).

Sources: Own computation using data (FMoH, 2014a)

Figure 2. 6: Percentage of Health Development Armies, by region (2014)

2.3.4.2. The graduation of health extension programme beneficiary households as model households

One of the objectives of the Ethiopian health extension programme is training and graduating of the health extension programme beneficiary households as model households as a means of enhancing access to and utilisation of basic healthcare services of packages of the programme to the remaining largest number of rural people (Bilal et al., 2011; FMoH, 2014a). Thus, the health extension programme beneficiary graduates as model households are those households that

i) are trained with basic skills and knowledge on the packages of basic healthcare services of the health extension programme for about 96 hours;

ii) are able to manage their own practices and implement 75 percent of packages of the basic healthcare services of the programme after they were trained by the health extension workers within three months; and

iii) are also able to influence their families and communities to implement the same practices on the packages of basic healthcare services of the health extension programme (Bilal et al., 2011; FMoH, 2014a).

Although the health extension programme was launched in 2004, training and graduation of the programme beneficiary households as model households only started in 2006/07 by graduating 64,966 health extension programme beneficiary rural households at the national level (Wang et al., 2016). In 2008, a total of 953,040 health extension programme beneficiary households had graduated as model households. By 2010, about 4,061,532 health extension programme beneficiary households had been trained and graduated as model households, with a throughput rate of 26 percent at the national level (FMoH, 2008; 2010). By 2014, an additional 947,119 of the health extension programme beneficiary households had been trained and graduated as model households by health extension workers at the national level (FMoH, 2014a).

As illustrated in Table 2.2, the overall national throughput rate of graduating health extension programme beneficiary households as model households was 7.2 percent, with considerable disparities across regions of the country. For example, the throughput rate of graduating health extension programme beneficiary households ranges from the highest, of nearly 20 percent in Southern Nations and Nationalities of People region, followed by 17 percent in the Tigrai region to the lowest of 0.28 percent in the Somali region. In Tigrai region, the throughput rate of graduating health extension programme beneficiary households of the Afar region was 0.42 percent (FMoH, 2014a).

Table 2. 2: The throughput rate of the health extension programme beneficiary graduates as model households, by region (2014)

Region	Enrolled	Graduated	Throughput rate (in percent)
Tigrai	734,600	125,908	17.14
Afar	262,400	1102	0.42
Amhara	3,545,600	120,256	3.39
Oromia	4,840,400	123,284	2.55
Somali	751,200	2134	0.28

Region	Enrolled	Graduated	Throughput rate (in percent)
Benshangul-Gumuz	117,800	9,476	8.05
SNNP	2,808,800	571,969	19.94
Gambella	41,600	710	1.71
Harari	15,600	1,907	12.2
Total	13,118,000	947,119	7.22

Source: Own computation using data (FMOH, 2014a)

2.4. Conclusion

The Ethiopian economy was characterised by steady growth over the last decade, with a declining rate of poverty. However, the income inequality measured by the Gini coefficient among the citizens widened. In addition, unemployment remains a major challenge with the national unemployment rate standing at 16.5 percent in 2012/13. Although the Ethiopian population's literacy status is very low, the adult educational status improved over time. The overall health status of the country also improved during the same time, for example, the under-five child mortality was reduced due to the significant contribution of the health extension programme to the overall improvement of the health status of citizens of the country.

CHAPTER THREE

REVIEW OF LITERATURE AND CONCEPTUAL FRAMEWORK

3.1. Introduction

This chapter reviews relevant literature on determinant factors of inter-regional differentials in child mortality, efficiency and productivity changes of the community-based health workers programmes, as well as determinant factors affecting the community-based health workers programmes beneficiary households' graduation. The chapter also reviews some of the previous studies and summaries of their major findings are presented in Appendix A, Table A-1 and Table A-2. In addition, this chapter presents an integrated conceptual framework guiding the present study.

The chapter is outlined as follows: Section 3.2 presents a review of the literature focusing on the determinant factors affecting inter-regional differentials in child mortality. Section 3.3 provides a review of related literature on the efficiency and productivity changes of the community-based health worker programmes. Section 3.4 presents a brief overview of the determinant factors influencing the community-based health worker programmes beneficiary households' graduation or graduation of households from the programmes. Section 3.5 provides the synthesis of an integrated conceptual framework putting in context on how the overall study had been addressed. The last section 3.6 presents the summary conclusions of the overall reviewed literature along with certain basic limitations.

3.2. Determinants of inter-regional differentials in child mortality: A review of the empirical literature

Measurement or evaluation of disparities in infant and under-five child mortality rates was less explored within most developing countries (Gayawan et al., 2016). In less developed countries, very few studies were carried out on determinants of disparities in infant and under-five child mortality rates within countries (Macassa et al., 2003). Hence, this chapter reviewed some of the growing studies mainly examined the differentials in infant, child, and under-five child mortality rates across states, provinces, or regions in developing countries were reviewed.

As illustrated in Table A-1 of Appendix A, the within-country studies showed the presence of pronounced differentials in infant and under-five child mortality rates. For example, in rural India, Jain (1985) examined the factors explaining the regional differences in infant mortality rate using the multiple linear regression method. Results indicated that the regional variations in infant mortality rate were mainly due to differences in the maternal level of education; use of electricity, use of safe drinking water, child's birth delivery by health personnel, household's poverty status, and the child's vaccinations. Combined, these factors reduced 77 percent of the regional variation in infant mortality rate in rural India. The household's poverty status and maternal level of education jointly reduced 60 percent of the regional disparities in infant mortality. Moreover, among the individual determinant affecting the infant mortality, the medical healthcare at birth and during postnatal periods together reduced 64 percent of the regional disparities in infant mortality rate. Interestingly, the poverty status of the household alone reduced 16 percent of the regional differentials in infant mortality rate. It can, therefore, be concluded that improving households' poverty status and maternal education level could significantly minimise the regional differentials in infant mortality rate in rural India. However, this study examined the regional variations in infant mortality by grouping the provinces into some geographical regions (north and south regions) instead of examining the sources of variations among the provinces. The infant mortality rate could significantly vary among the provinces of the geographically formulated regions (north and south regions).

Another study by Choudhury (2015) provides evidence on the regional differentials in infant mortality rate as measured by parental education using data from the Indian demographic and health survey for the year 2005 - 2006. The analysis was made using a binary logistic regression model. The key objective of the study was to explain the effect of parental education on infant mortality rate across regions of the country. The findings of the study indicated the negative and significant association between a mother's level of education and the rate of infant mortality. The overall infant mortality for Empowered Action Group (EAG) states were over 60 deaths while for most non-EAG states was 40 deaths per thousand births[5]. A woman who had an exposure to mass media reduced the EAG and non-EAG regional differences in infant mortality rate by 26.4, percent. Similarly, a woman with primary educational level reduced 20 percent of the EAG and non-EAG regional differences and a father with primary educational level reduced 25 percent of the EAG and non-EAG

[5] Based on the rate of fertility and sociodemographic, the Indian government has classified the states into two regions, which are known as Empowered Action Group, EAG and non-EAG regions or states. The purpose of classifying the states into EAG and non-EAG regions was to introduce area-specific interventions for better healthcare outcomes of the country and to limit the growth of the population of the country to a manageable proportion (Choudhury, 2015).

regional differences in infant mortality rate. Altogether a woman who had exposure to mass media and decision-making power explained the regional difference in infant mortality by about 25 percent. Thus, the study concluded that parental education mainly maternal education, mother's exposure to mass media, and the socio-economic status of the households could significantly reduce the infant mortality between the two regions of India (EAG and non-EAG regions). This study, however, could not address the other potential determinants such as the child's birth size, the child's birth order, the gender of the infant, and maternal age at first birth explaining the regional variations in infant mortality rate. Most importantly, the study classified the provinces into two groups (EAG and non-EAG) instead of examining the regional variations among the provinces of India because the provinces could have different rates of infant mortality within the categorised regions of the EAG and non-EAG states.

In India, Mukhopadhyay (2015) examined the temporal regional variations in infant mortality rates across the states using data from the 2012 National Rural Health Statistics from the governments of India. Using a multiple linear regression, the study explained some of the determinant factors affecting the regional differentials in infant mortality. Findings of the study revealed that there were significant variations in infant mortality among the Indian states. The results of the regression analysis found that the per capita income, female literacy, and number of doctors in health centres (percentage) were the most significant determinants of the regional disparities in infant mortality. The findings further indicated that female literacy rate and per capita income were negatively related to infant mortality rate. In addition, the percentage of medical doctors in health facilities (health centres) affected positively infant mortality and was also the source of the regional variations in infant mortality. Therefore, the study concluded that the regional variations in infant mortality in India were mostly a result of the socio-economic disparities across states of the country. Furthermore, the study concluded that improving maternal universal basic education could significantly minimise the observed regional mortality differentials in infant mortality rate of the country. This study, however, could not explain the relative contribution of these as well as other potential factors (such as birth size, maternal age at first birth, the child's birth spacing, and the child's birth order) that explain the regional differentials in infant mortality rates of the country.

Another neonatal-based health outcome indicator study by Patel and Sharma (2013) examined the inter-state neonatal mortality rate disparities in India. The study employed data from Indian national family health survey of 2005 - 2006. The data were analysed using a multiple linear regression across the states of India. The findings revealed that the inter-state differences in neonatal mortality rate were explained by home child delivery, higher child's birth order, mothers whose Body Mass Index (BMI) was less than 17 and women between the age 15 to 49, households in the lowest wealth index quintile, and women who received antenatal healthcare services by health professionals. It can, therefore, be concluded that improving the maternal body mass index, enhancing maternal antenatal healthcare services, and households' wealth status could significantly minimise the disparities in neonatal mortality rate across states of the country. Furthermore, although the study indicated that these determinants were the sources of neonatal mortality rate variations across the Indian states, their relative percentage contribution to the inter-state gaps was not explicitly reported. Another limitation of the study was that determinant factors such as parental education, the child's birth size, the child's birth spacing, maternal age at first birth, and maternal exposure to mass media that could explain the variations in neonatal mortality rate were not examined.

Using a Least Square Dummy Variable (LSDV) model, Uttam (2015) examined the determinants of the inter-state variations in infant mortality rate in the Northeast of India. The study employed data from District Level Household and Facility Survey DLHS-II (2002 - 2004) and DLHS-III (2007 - 2008). The results of the analysis indicated that though the infant mortality rate increased from 2002 - 2004 (31.5 deaths) to 2007 - 2008 (34.67 deaths per thousand births), the inter-state differences in infant mortality declined over the stated periods. The percentage of households who had access to modern toilet facilities and home child delivery were the two most determinant factors affecting the inter-state variations in infant mortality. Moreover, an illiterate married woman, with pregnancy-related complications, and a home-based delivery assisted by professionals altogether reduced the variations in infant mortality by 88 percent. It can, therefore, be concluded that there were significant variations in infant mortality across the states of the country. Enhancing maternal educational level could significantly reduce inter-state differentials. The antenatal healthcare service, improved breastfeeding practice, maternal age at first birth, birth size, birth spacing, and households' wealth status could give a complete picture of the study, however, this study could not explicitly explain the relative contribution of individual factors in reducing or widening the inter-state variations in infant mortality rate of India.

In Sri Lanka, Chaudhury et al. (2006) examined the inter-district disparities in infant mortality rate using data from the Registrar's General Department, Family Health Bureau and the Medical Statistics Unit of the Ministry of Health. The data were analysed using a multiple linear regression model. The results of the regression analysis indicated that access to healthcare services (33 percent), lack of access to clean drinking water (16 percent), low birth weight (13 percent), and utilisation of antenatal healthcare services (8 percent) reduced the district variations in infant mortality rate. It can, therefore, be concluded that improving the birth size, access to healthcare services, and access to safe drinking water could significantly reduce the infant mortality rate disparities across districts of the Sri Lankan states. This study, however, was limited in its scope as it was not be nationally representative study. In addition, some important proximate (maternal age at birth, birth spacing, the gender of the child, and the child's birth order) and socio-economic (the households' wealth status, parental education, and place of child delivery) factors were not included during the analysis, which could potentially explain the disparities in infant mortality across districts of the country.

Perhaps the most comprehensive study, in the areas of determinants of variations in child mortality by ecological region, is the one conducted by Goli et al. (2015) in Nepal. To examine the determinants of regional variation in child mortality, the study employed an Oaxaca-Blinder decomposition technique based on the Cox-Proportional hazard regression using Nepal Demographic and Health Survey data. The results of the regression indicated that children in mountainous areas had a higher probability of dying than children of the same cohort living in the other two areas (Hill and Terai). Furthermore, the results of the decomposition analysis revealed that the decomposed covariates explained 40 percent of the overall regional variation in under-five child mortality while the largest 60 percent of the components of the gap remained unexplained. The results of the detailed decomposition analysis further revealed that parental educational level (34 percent), the households' wealth status (25 percent), the households' place of residence (16 percent), higher child's birth order along with shorter birth spacing between children (less than 24 months) (11 percent), mother's employment status (5 percent), mother's religious affiliation and mother's liberty on healthcare decision (3 percent) reduced significantly the regional variations in under-five child mortality. It can, therefore, be concluded that the substantial variations in under-five child mortality could significantly be minimised by enhancing mainly maternal education and households' wealth status. Thus, this study suggested that the differences in under-five child mortality should be addressed from an ecological region outlook. Other potential factors such as place of child delivery, antenatal healthcare services, the child's birth size, and maternal age at first birth could also explain the regional differentials in under-five child mortality; however, this study did not address these in their analysis.

Another study by Dev et al. (2016) examined the topographical variations of infant mortality rate in the three ecological zones of Nepal using the logistic regression model. The findings indicated that the three ecological zones differ significantly in their infant mortality rate reduction. The infant mortality rate was significantly higher for the Mountain ecological zone than that of the Hill and Terai ecological zones; a result consistent with the findings of Goli et al. (2015) above. Similarly, the relative risk of infant mortality among the population living in the mountain ecological zone was significantly higher for mothers who perceived the distance to the nearest health facilities as a major problem, as compared to the other two ecological zones. The maternal level of education, household's economic status, and the number of infants or children that the mother had was also major determinants of infant mortality rate and regional variations in infant mortality. The study concluded that there were significant variations in infant mortality rates across three ecological zones of Nepal. Therefore, improving access to healthcare services as well as improving transport to health could substantially minimise the regional variations. This study, however, could not quantify the relative contributions of these factors to the infant mortality disparities across the three ecological zones of the country. In addition, the perception of distance to the nearest health facilities that was considered as a determinant was subjective, because it was measured based on the mothers' perceived self-reports.

In rural China, Wang et al. (2012) carried out an empirical study on the geographical variations in infant mortality using data from the national children mortality surveillance network of 1996 - 2008. For purpose of their study, they divided the 12 years into three time periods, namely 1996 - 2000, 2001 - 2005, and 2006 - 2008. The data was analysed using the Woolf method to identify the determinants of infant mortality rate that explain variations across the three regions of China (remote western, coastal and inland regions). Although the three regions significantly reduced their infant mortality from 1996 to 2008, there was a considerable regional variation in the annual progress rate of infant mortality. The findings further revealed that the child's sex, low birth size, pneumonia, injuries, birth asphyxia, and diarrhoea were the major contributors to the regional variations in infant mortality accounting for 80 percent of the regional variations. The study further revealed that there were considerably increased variations in infant mortality in the coastal and remote western regions in 2001 - 2005, but not in 2006 - 2008 when compared to the inland region. Moreover, they indicated that the highest regional disparities were observed for postneonatal mortality. Besides, in a remote region, access to healthcare services was substantially lower than for the other two regions. It can, therefore, be concluded that the variations in infant mortality across the regions can significantly be minimised by addressing birth asphyxia, pneumonia, birth size, and diarrhoea. In addition, improving access to healthcare services can also reduce the regional variations in postneonatal mortality. The basic limitation of this study lays in quantifying the relative individual percentage contribution of these factors in explaining the regional disparities in infant mortality rate in rural China.

Another study by Khosravi et al. (2007) assessed the child mortality differentials among the Iranian provinces using the Iranian demographic and health survey data for 2004. The data was analysed using the multiple linear regression method. The findings revealed that the rates of child mortality varied substantially across the provinces, ranging from 25 deaths (Gilen and Tehran provinces) to 47 deaths per thousand births (Sistan and Baluchistan provinces). The findings of the study further indicated that GDP per capita, life expectancy, high literacy rate, and accessibility to healthcare services were the most important factors for variations in the child mortality rate across the Iranian provinces. It can, therefore, be concluded that improving the socio-economic status of the households and parental education level could significantly reduce child mortality, as well as the regional disparities in child mortality. This study, however, could not quantify the relative contribution of these determinant factors affecting the regional differentials in child mortality in Iran. Quantifying the determinants could help us to identify the most important one that substantially explains the regional variations in child mortality rate.

Terra de Souza et al. (1999) examined the disparities in infant mortality across municipalities in the state of Ceara Brazil, using data from the census of the state of Ceara for 140 municipalities and this was analysed using a linear regression model. The findings of the study revealed that there were significant variations in infant mortality rates across the municipalities of Ceara in Brazil. The study further indicated that female illiteracy rate (24.5 percent), women who received prenatal healthcare services (24.9 percent), under-immunised children (25.8 percent), children born to households who participated in growth monitoring (26.8 percent), children born to households with low-income level (35.6 percent), children born to households who do not have sufficient water supply (36.3 percent), and sanitation facilities, (36.4 percent) reduced the variation in infant mortality across the municipalities. Altogether these factors reduced 41 percent of the inter-municipality disparities in infant mortality rate. It can, therefore, be concluded that improving the households' socio-economic status, adequate provision of water, and improved sanitation facilities could significantly reduce infant mortality, and could minimise the existing disparities in infant mortality among the Brazilian municipalities. This study, however, was limited in its scope because it was conducted in only one state of the country. Therefore, the findings of the study are not a nationally representative. Moreover, the other potential determinant factors such as parental educational level, the child's birth size, the child's birth spacing, and place of child delivery could have tended to mirror the inter-municipality variations; however, they received less attention.

Gayawan et al. (2016) attempted to explain the regional variations in infant and under-five child mortality rates among regions of the ten West African countries using the spatial extension of discrete-time survival model employing the countries' demographic and health survey data. The findings of the study revealed that there were substantial disparities in under-five child mortality rates among regions within these countries. Accordingly, access to electricity, improved toilet facilities, institutional child delivery, household economic status, and the mother's educational status were among the most important determinants of regional differences in under-five child mortality rates among regions within countries. The study firmly indicated that the variations in child mortality were more substantial than in infant mortality for most of the West African countries. It can, therefore, be concluded that enhancing households' economic status as well as the maternal education level could substantially decrease the regional variations in infant and under-five child mortalities within countries. This study, however, could not quantify the relative percentage contribution of each determinant factor that affects the regional variations within these countries in infant and under-five child mortality rates. It also did not indicate which factor was the most important in explaining the regional variation in infant and under-five child mortality rates for each country.

In Sudan, Farah & Preston (1982) examined the regional differentials in child mortality using the multiple linear regression model. The findings of the study show that the regional differential in child mortality was higher by 66 percent for the southern region than for the northern region of the country owing to the prevalence of malaria, a poor health system, poor parental education status, and low levels of household income. The study also indicated that there were disparities in child mortality among the provinces within these regions (the southern and the northern regions). It can be concluded that improving mainly the overall health system, parental education status, and households' economic status could decrease the disparities in child mortality across the regions. This study, however, could not explicitly quantify the relative contribution of each factor in explaining the regional disparities in child mortality. In addition, the study was made by grouping the provinces into regions (the south and the north regions) instead of examining regional variations among provinces, because the provinces could have a different level of child mortality within and across the regions.

Akuma (2013) evaluated the regional differentials in infant mortality using data from the 2009 Kenyan demographic and health survey. The regions were formulated by grouping the provinces of the country into two regions, namely the low and high-infant mortality regions based on the levels of infant mortality that the provinces had. The regional differences in infant mortality were analysed using a multivariate logistic regression model. The results of the study indicated that there were considerable regional disparities in infant mortality levels across the two regions. Moreover, the analysis shows that mothers with low educational attainment, the poor socio-economic status of households, and shorter birth spacing between children were the major determinants of infant mortality in the high mortality region, which would explain the regional variations in the infant mortality rate between the two mortality regions (low and high mortality regions). The study concluded that the sources of infant mortality differentials across provinces of Kenya were due to differences in the economic status of the households and social development of the regions (provinces) of the country. This study, however, could not explicitly indicate which factor and by which percentage explained or widened the regional differentials in infant mortality.

In Kenya, but for different health outcome indicators, Ikamari (2013) attempted to examine the neonatal and postnatal mortality disparities using data from the 2003 demographic and health survey. The data was analysed using the Cox-regression model to examine the regional neonatal and postnatal child mortality differentials. The results of the study indicated that there were substantial differences in neonatal and postnatal child mortality differentials across regions of Kenya (Eastern, North Eastern, Central, Western, Rift Valley, Coast, and Nyanza). The findings indicated that antenatal healthcare services, institutional delivery, birth spacing, the age of the mother at birth greater than or equal to 35 years, household's economic status, maternal education level, access to protected water sources, and improved toilet facilities were the major determinants of neonatal and postnatal child mortality and explained the variations in neonatal and postnatal child mortality across regions (provinces) of Kenya. It can, therefore, be concluded that the need for sustained efforts in improving mainly a household's economic status, maternal education level, and antenatal healthcare services could significantly reduce neonatal and post-neonatal mortality rates and regional mortality disparities of the country. This study, however, was not able to quantify the individual contribution of these determinants in explaining the regional variations in these health indicators (neonatal and postnatal child mortality rates).

Another similar study by Demombynes and Trommlerová (2016) examined some of the key driving factors that reduce regional disparities in infant mortality rate using data from 2008 DHS in Kenya. An Oaxaca-Blinder decomposition technique (O-B decomposition) was applied to examine the driving factors for reducing infant mortality rate across geographical zone of the country. Among the potential causes of variations in infant mortality rate, the substantial part of the reduction in postnatal mortality rate was significantly reduced by 39 percent of the regional gaps. The use of insecticide-treated bed-nets by a household reduced the regional differentials in postnatal mortality rate by about 58 percent. Furthermore, the study indicated that an augmented access to improved sanitation facilities reduced the regional gaps by about six percent. Thus, it can be concluded that increased widespread malaria prevention across the geographical zones can minimise the variations in infant mortality. The proportional regional differences in households' wealth status, maternal education, and maternal age at first birth in infant mortality could have tended to mirror regional variations; however, this study paid less attention.

In Malawi, using data from the three administrative districts, namely central, northern and southern, which are all districts from rural areas, predominantly agriculture, as sources of livelihood. The disparities in child mortality among the three regions (districts) were evaluated using the Poisson regression model. The findings of the regression analysis indicated that there were significant disparities in child mortality among regions of the country. When the factor of maternal level of education was added to the regression analysis, the results indicated that a mother with a primary school education reduced the risk of her child dying by 14.5 percent, compared to an illiterate mother. Most importantly, due to the inclusion of maternal level of education, the relative risk of child mortality in the southern and central regions reduced from 1.27 to 1.3 and from 1.32 to 1.21, respectively compared to the northern region. Similarly, when the use of improved latrines was added to the regression, the results of the regression analysis show that the use of improved latrines reduced the regional variations in child mortality rate of the country. As a result, the relative risk of child mortality in the southern and central regions reduced from 1.27 to 1.04 and from 1.32 to 1.06, respectively, compared to the risk in the northern region. It can, therefore, be concluded that maternal education level and use of improved latrine could substantially reduce child mortality and regional variation in child mortality (Baker, 1999). This study, however, could not explain the impact of some crucial factors such as households' wealth status, place of delivery, the child's birth size, the child's birth spacing, and family size that could explain the regional differentials in infant mortality, which could yield a complete picture of the study.

In Cote d'Ivoire, Assi (2014) assessed the determinant factors affecting the regional variations in under-five child mortality using data from the 2011 - 2012 Cote d'Ivoire demographic and health survey. The analysis of the obtained data was performed using the logistic regression model. The findings of the study indicated that there were considerable variations in the child mortality rate across the region of Cote d'Ivoire. The results of the regression analysis revealed that a woman with at least a secondary education level affected under-five child mortality positively. It can, therefore, be concluded that improving the maternal education could significantly reduce child mortality. This study, however, could not explain the relative percentage contribution of the sources of the regional variations in under-five child mortality; rather the researcher indicated that the level of under-five child mortality varied significantly across the region of the country. In addition, other potential factors such as households' wealth status, place of residence, place of child delivery, the child's birth size, and maternal age at birth that could have a significant impact on child mortality reduction and on minimising the regional variations in under-five child mortality rate did not receive much attention in the analysis.

In Mozambique, Macassa et al. (2012) examined the geographic disparities in under-five child mortality using data from the Mozambican 2003 demographic and health survey. The ten provinces were geographically classified into three regions, namely north, central and south regions. They applied the Cox-regression method to analyse the determinants of regional variations in the under-five child mortality rate. The study indicated that there were significant differences in under-five child mortality across regions. For example, child under age of five, whose mother was living in the north and the central regions had higher mortality risks than a child of the same cohort whose mother was living in the south regions. The study indicated that access to modern toilet facilities, sources of clean drinking water, household wealth status, parental educational level, and mother's region of residence were the major determinants of the regional differentials in under-five child mortality. Therefore, it could be concluded that an intervention that focuses on the under-five child mortality reduction should consider the significant regional disparities of the economic development of the country. Although this study attempted to examine the factors affecting the regional variations in the under-five child mortality rate by discussing the reviewed literature and indicating regions varied in their level of under-five child mortality, empirically, it could not explore the factors and to what extent each of these factors contributed to the geographic-specific variations in under-five child mortality. In addition, the analysis was based on grouping the provinces into some geographical regions (the north, central, and the south) instead of examining the sources of the variations among the provinces. This is because the provinces could have different levels of under-five child mortality within and across the geographically formulated regions (the north, central, and the south).

A study by Antai (2011) examined the regional differentials in the under-five child mortality rate using data from the Nigerian 2003 demographic and health survey. The study employed a multiple Cox-proportional hazard regression technique to examine the under-five child mortality differentials across the five regions of the country, namely North-Central, North-East, North-West, South-East, and South-South. The findings of the regression analysis indicated that there were considerable variations in under-five child mortality across the country's regions. The study further attempted to identify some of the major determinants of regional disparities in under-five child mortality. The higher proportion of mother with at most primary educational attainment, divorced mothers, high child's birth order, and the lower proportion of antenatal healthcare services were the main determinants of the regional disparities in under-five child mortality. In conclusion, the study found that improving the maternal economic status, mainly for those living in the disadvantageous regions of the country, could significantly reduce the regional disparities in under-five child mortality. In addition, different community-based health intervention aimed at improving child and maternal health status could substantially narrow down the regional variations in under-five child mortality in the country. This study, however, paid much less attention to quantifying the relative contribution of these determinants in explaining the regional disparities in under-five child mortality rate in the analysis.

Adedini et al. (2015) examined the sources of the regional differentials in infant and under-five child mortality in Nigeria using the Nigerian 2008 demographic and health survey. They applied the Cox-proportional hazard regression model to identify the determinants of the regional differentials in child mortality (infant and under-five child mortality rates). The findings of the study indicated that the differences in community infrastructure, households' wealth index, households' poverty status, place of child delivery, and place of residence among regions of the country were the major determinants of regional differentials in under-five child mortality. The proportional regional difference in the child's birth order, birth spacing, mother's level of education, and mother's age at marriage were the determinant factors affecting the regional disparities in infant mortality in Nigeria. This study, therefore, concluded that to substantially reduce the overall child mortality of the country, efforts should be exerted in addressing the sources of the regional variations in these important health indicators by focusing on the disadvantaged regions of the country. Although this study indicated the existence of regional variations in infant and under-five child mortality rates and identified some of the determinants of the regional disparities in infant and under-five child mortality rates, it could not quantify which determinant and to what extent it explained the regional gaps in infant and under-five child mortality rates. The components' gaps, including the explained and unexplained regional gaps remained unaddressed.

Similarly, in Nigeria another study by Anyamele et al. (2015) attempted to examine the differences in infant and under-five child mortality using pooled 2003 and 2008 data from the Nigerian demographic and health survey. The logistic regression model was applied to examine the regional differentials in infant and under-five child mortality. The findings indicated that Nigeria remains the highest in infant and under-five child mortality rates in the world as well as in Sub-Saharan Africa, with significant variations in infant and child mortality rates. The study revealed that though the trends for both infant and under-five child mortality rates showed a decline between 2003 and 2008, the rates of progress across the states varied substantially. The economic status of the households (wealth), religion, maternal educational level, use of healthcare facility, the gender of the child, and the number of live births were negatively related with infants and under-five child mortality rates in Nigeria. The study also indicated that these factors were among the major determinants in explaining the regional variations in infant and under-five child mortality rates. The study concluded that improving mainly the households' economic status and maternal educational level could significantly reduce infant and under-five child mortality rates as well as minimise the regional disparities in infant and under-five child mortality rates. The relative contribution of these factors, as well as the components gaps (both explained and unexplained), were not explicitly addressed in their analysis in explaining the regional differences in infant and under-five child mortality rates in Nigeria.

Byaro and Musonda (2016) assessed the regional disparities in infant and under-five child mortality rates using data from the four rounds of Tanzania demographic and health survey (1992, 1996, 2004 and 2010). A separate fixed effects model using the linear regression model was applied both for infant and under-five child mortality as dependent variables to examine determinants of variations in infant and under-five mortality across Tanzanian zones (the north, south, south highlands, and the central). The study revealed that despite the marked progress in infant and under-five child mortality rates across zones of Tanzania, there were substantial disparities over the different periods. Furthermore, results from the regression analysis indicated that the mother's level of education, modern breastfeeding practice, child immunisation coverage, child delivery by health professionals, and provision of antenatal healthcare services were the major contributors in reducing infant and under-five mortality and explaining the regional differentials of the country. The study noted that the importance of having an inter-sectoral approach, mainly between education and health sectors on improving the maternal level of education, antenatal healthcare services, institutional child delivery, and immunisation coverage could significantly reduce the regional variations of infant and under-five mortality. Therefore, the study concluded that improving the maternal educational level and healthcare services could reduce child mortality and minimise the regional variations in infant and under-five child mortality. This study, however, did not examine the relative individual contribution of these determinant factors in explaining the observed regional variations in infant and under-five child mortality rates in Tanzania.

Ghaffar and Bhuyan (2000) examined the factors responsible for explaining the regional disparities in child mortality rate for Libya, North-Eastern part region, using discriminant analysis. They initially classified the seven localities found in the North-Eastern of the country into three sub-regions, namely, Benghazi, Derna, and Tobruk. The findings of the study indicated that maternal age at marriage (under-age marriage), parity, the socio-economic status of the household; multiple children, mother's modern breastfeeding practice, and parental educational level were the major determinants of regional variation in child mortality in Libya. In conclusion, this study indicated that improving the socio-economic status and parental level of education could significantly reduce the regional disparities in child mortality**.** This study, however, examined the regional variations in child mortality by grouping the localities into some geographical settings instead of examining the sources of variations in child mortality among the localities themselves. This is because the localities could have different rates of child mortality within and across the already geographical formulated regions. In addition, this study paid much less attention to quantify the relative individual percentage contribution of the determinant factors affecting the regional gaps in child mortality that could have tended to mirror the regional differentials.

The studies focused on examining the regional variations in infant and under-five child mortality in Ethiopia were based on the regions' level of infant and under-five child mortality instead of examining the relative contribution of each factor in explaining the regional differentials. For example, a local study by Tessema (2008) attempted to examine the observed infant and under-five child mortality differences between the Afar and the Somali regions using data from the Ethiopian 2005 demographic and health survey. The data was analysed using qualitative (descriptive statistics) methods. The descriptive findings of the study indicated that the differences in the proportion of poverty status of the households, healthcare system of the regions, epidemic diseases, maternal healthcare facilities, and family healthcare services were the major determinants responsible for the two regional variations in infant and under-five child mortality rates in Ethiopia. It can, therefore, be concluded that enhancing the poverty status, healthcare system, and maternal healthcare facilities could significantly improve the regional disparities in infant and under-five child mortality. The scope of this study was very limited and thus, its findings could not be nationally represented. In addition, this study failed to examine to what extent that these factors were explaining the existing regional gaps in infant and under-five child mortality rates in Ethiopia.

Another study by Bedane et al. (2016) also attempted to examine the under-five child mortality differentials using the Ethiopian 2011 demographic and health survey. The data was analysed using a binary logistic regression model. The findings of the regression analysis revealed that maternal age at first birth, the child's birth size, maternal level of education, multiple births, improved breastfeeding practice, and the child's birth index negatively affected the under-five child mortality risk and explained the regional disparities in under-five child mortality. It can, therefore, be concluded that improving the maternal level of education and use of healthcare services could significantly reduce under-five child mortality. This study, however, could not quantify the relative contribution of each determinant factor in explaining the regional variations in under-five child mortality as well as the components gaps (explained and unexplained parts) of the regional gaps in under-five child mortality in Ethiopia. Simply, the region was considered as a categorical independent variable to indicate the significant difference in the under-five child mortality rate across the regions.

Similarly, another study by Negera et al. (2013) attempted to analyse the trends and determinants in disparities of infant and under-five child mortality across regions using pooled datasets from the Ethiopian 2000, 2005, and 2011 demographic and health survey. The data was analysed using the Cox-regression method to examine the determinants of disparities in infant and under-five child mortality rates. The study indicated the steady rates of reduction both in infant and under-five child mortality rates across time periods (2000, 2005, and 2011). Furthermore, the findings of the regression analysis indicated that maternal level of education, the gender of the child, birth size, birth spacing, access to an improved latrine facility, and maternal marital status were the major determinants of infant and under-five child mortality. The study further indicated that significant variation was pronounced for the under-five child mortality rate than for the infant mortality rate across regions of the country. Thus, improving mainly maternal level of education and healthcare services could significantly reduce infant and under-five child mortality rates. This study, however, paid less attention to explicitly quantify the relative individual contribution of the factors in explaining the regional variations in infant and under-five child mortality rates as well as the components gaps (explained and unexplained parts) of the regional gaps in their analysis.

In summary, findings of most of the reviewed studies confirmed the existence of substantial differentials in infant, child, or/and under-five child mortality within the studied countries. Accordingly, the regional differentials in child mortality were explained largely due to the differences in households' economic status, GDP per capita, life expectancy rate, parental level of education, households' poverty status, mother's exposure to mass media, place of birth delivery, the child's birth order, birth spacing, child's birth size, use of modern contraceptives, households' travel distance to health facilities, and antenatal healthcare service visits, among others. However, the review literature varied significantly in terms of the methodology that each reviewed study employed and most of the reviewed studies were done in different countries with a different scope.

3.3. Review of literature on the efficiency and productivity changes of community-based health worker programmes

Despite the growing interest in evaluating the efficiency of primary healthcare services programmes or community-based health worker programmes in developing countries (Amado & Santos, 2009; Hollingsworth et al., 1999; Kruk & Freedman, 2008), most previous studies focused on the evaluation of the efficiency and productivity of hospitals (Cheng et al., 2015; Kakeman et al., 2016; Kirigia & Asbu, 2013). There are some studies which examined technical efficiency and productivity changes of the health units as decision-making units (Herna´ndez and San Sebastia´n, 2014; Zeng et al., 2011; Kirigia et al., 2007) while some studies evaluated the technical efficiency of the health units and explained the determinants of the variability in the technical efficiency estimates among the health units (Marschall & Flessa, 2009; Akazili et al., 2008a). However, most previous empirical studies evaluated only the technical efficiency of the health units (Satyanarayana et al., 2012; Qorbani et al., 2017; Kawakatsu et al., 2012; Wangalwa et al., 2012; Kirigia et al., 2004; Kirigia et al., 2011; Renner et al., 2005; Akazili et al., 2008b; Stekelenburg et al., 2003; among others) of the health units. This section of the chapter, therefore, reviewed the efficiency and productivity growth studies focusing on the community-based health worker programmes in developing countries, and their brief summary findings are also reported in Table A-2 of Appendix A.

In Guatemala, a quantitative study by Herna´ndez and San Sebastia´n (2014) examined the technical and productivity changes of the health posts used as decision-making units for the community-based health worker programme. The analysis was based on primary data collected for 34 health posts from 19 districts in Alta-Verapa, Guatemala for the year 2008 and 2009. The study employed one input (number of auxiliary nurses) and five output (number of: new patients attended, children less than two years old, children receiving a third dose of the DPT vaccine, and family planning users). An output-oriented Data Envelopment

Analysis (DEA) technique based on the variable-returns to scale (VRS) assumption was applied to evaluate the technical efficiency of the health posts. The DEA-based Malmquist index was also applied to examine the productivity changes of the health posts. The findings of the DEA analysis indicated that there was a significant increase in healthcare services outputs by 50 percent and the mean number of the community-based health workers per health post had increased by 36 percent in 2009. The technical efficiency estimates of the health posts varied among the health posts and over periods of time. The findings of the decomposition analysis further indicated that the increased proportion of outputs being produced (provided) were not in proportion to the increase in inputs being employed by the sample health posts from 2008 to 2009. In addition, about 66 and 35 percent of the sample health posts were scale efficient in 2008 and 2009, respectively. Whereas the remaining 44 and 65 percent of the health posts were scale inefficient in 2008 and 2009, respectively, all of them exhibited decreasing returns to scale (DRS). Moreover, the results of the Malmquist productivity analysis revealed that the overall productivity change of the sample health posts increased by four percent over the two-year study periods mainly due to an increase in healthcare services outputs. Therefore, it can be concluded that although most of the health posts were operating below their optimal scale size, their productivity changes or growth were improved by 4 percent. The reasons behind the variations in technical efficiency estimates among the health posts, however, were not explained further, which is the basic limitation of the study by Herna´ndez and San Sebastia´n (2014)

Zeng et al. (2014) examined the technical efficiency of the Rwandan rural health centres while providing healthcare services for human immunodeficiency virus/acquired immunodeficiency syndrome, (HIV/AIDS) affected communities. The analysis of the study was based on primary data collected from a total of 26 health centres for the years 2006 and 2007. Using four inputs (number of HIV/AIDS full-time or equivalent personnel, number of non-HIV/AIDS full-time equivalent personnel, percentage use rate of community-based health insurance, and amount of non-personnel expenditure on HIV/AIDS) and three outputs (the number of clients receiving VCT services, the number of participants in prevention of mother-to-child transmission, and the number of AIDS patients receiving ART) variables, the study evaluated the technical efficiency of the Rwandan rural health centres. The study employed Data Envelopment Analysis and DEA-based Malmquist methods to analyse the technical efficiency and productivity of the health centres, respectively. The study revealed that about 42.31 percent of the health centres were technically efficient in 2006, with an average technical efficiency estimate of 82 percent, while about 30.77 of them were technically efficient in 2007, with average technical efficiency estimates of 74 percent, with significant variations among the health centres. Despite the substantial variations in technical efficiency, the findings of the Malmquist productivity analysis revealed that the overall productivity growth of the health centres was 15.6 percent due to technological progress over the two study periods. The study concluded that the high use of community-based health insurance by the Rwandan rural households in the health centres could significantly enhance the HIV/AIDS healthcare service. This study, however, employed a small sample size, which might not be represent the country and as a result, would affect the efficiency estimates. In addition, the study did not examine the external factors that explained the technical efficiency variability among the health centres.

In the Seychelles, a study by Kirigia et al. (2007) examined the efficiency and productivity changes of the 17 health centres using cross-sectional secondary data from annual health statistics reports for the periods 2001 to 2004. The study employed two inputs (total number of doctor hours and nurse hours) and three outputs (number of patients dressed, domiciliary cases treated, and maternal and child health visits) variables[6]. The estimation of the efficiency and productivity changes of the health centres were made using an output-oriented DEA and Malmquist productivity methods, respectively. Findings of the decomposition analysis indicated that there were significant variations in technical and scale efficiency estimates of the Seychelles' health centres. The study further revealed that the overall average technical efficiency estimates of the health centres using variable returns to scale were 93, 92, 92 and 96 percent in 2001, 2002, 2003, and 2004, respectively. Moreover, the average scale efficiency estimates of the health centres were 90 percent for 2001, 93 percent for 2002, 92 percent for 2003, and 95 percent for 2004. In addition, the study showed that about 59 percent in 2001, 47 percent in 2002, 53 percent in, and 59 percent in 2004 of the health centres were technical efficient. Whereas the remaining 31 percent for 2001, 53 percent for 2002, 47 percent for 2003, and 31 percent for 2004 of health centres were relatively technically inefficient. Furthermore, the finding of the Malmquist analysis revealed that the overall productivity change of the health centres improved by only 2.4 percent due to

[6] To increase degrees of freedom, the researchers combine the number of: family planning clinic visits, maternal and child health visits, antenatal healthcare visits, post-natal healthcare visits, Pap-smear visits, under-five children fully immunized, and under-five children participating in school health programme into an output variable known as FMAPPP. This is because of the smallness of the population the health centres (Kirigia et al., 2007).

mainly technical efficiency progress. The study noted that the importance of the institutionalisation of the evaluation and monitoring of the efficiency of the health centres could significantly help to improve the overall efficiency of the Seychelles' health sector. Although this study indicated the existence of technical and scale efficiency variations among the health centres, it did not examine the determinant factors influencing the technical efficiency disparities among the health centres that could have helped Seychelles' health centres to significantly improve their efficiency.

Marschall & Flessa (2009) examined the technical efficiency of 20 Center de Sante'et d Promotion Social (CSPS) of Nouna health district, Kossi province, Burkina Faso using cross-sectional data obtained from Nouna Health District Household Survey for the year 2003. An output-oriented DEA technique was applied to evaluate the technical efficiency of CSPS using four inputs (vaccination costs, personnel costs, costs of CSPS building, and CSPS equipment depreciation) and four output (number of general consultations, immunisation, deliveries at health facilities, and special healthcare services such pre-and post-natal healthcare services and family planning) variables. In addition, to explain the sources of disparities in technical inefficiency among the health units, the Tobit regression model was also applied. The findings of the DEA analysis revealed that there were considerable variations in technical and scale efficiency levels among the Center de Sante'et d Promotion Social, CSPS. The average technical and scale efficiency estimate of the health centres was 91 and 97 percent, respectively. About 70 percent of health centres were scale and technical efficient while the remaining 30 percent of them were scale and technically inefficient. Furthermore, the results of the regression analysis indicated that households' travel distance to the nearest health centres affected significantly the technical efficiency estimates of the health centres. Thus, the study concluded that the technical inefficiency estimates of the health centres could be improved by enhancing poeples' access to healthcare services provision instead of downsizing or shutting down of the health centres. The study also noted that socio-economic and cultural factors might also affect the relative technical efficiency of Center de Sante'et d Promotion Social. This study, however, could not be generalised to Burkina Faso due to its limited scope as it was carried out at the district level. In addition, the study employed a small sample size to evaluate the technical efficiency of the Center de Sante'et d Promotion Social. Most importantly, other potential factors such as the health personnel staff experiences, monthly salary, professional level of the health worker, and marital status received much less attention in this study that could possibly explain the technical efficiency variations among the Center de Sante’et d Promotion Social.

Another study by Akazili et al. (2008a) evaluated the technical and allocative efficiency of the Ghanaian public health centres using primary data collected from 113 sample health centres in 2005. The efficiency evaluation was based on three input variables (the number of staff, cots, and beds, costs for recurrent consumables and supplies) and five output variables (the number of outpatient visits, under-five children fully immunised, antenatal healthcare, child delivery at health facilities, and family planning visits). The technical and allocative efficiency estimates were analysed using an input-oriented DEA technique. In addition, a binary logistic regression was also employed to examine the factors affecting technical efficiency variations among the health centres. The findings from the DEA analysis indicated that 78 percent of the health centres were technically inefficient. Moreover, the study showed that there were geographical disparities in technical efficiency estimates and thus, the middle belt region had a higher number of technically inefficient health centres than the other two regions (the coastal and western) of the country.

Furthermore, Akazili et al. (2008a) evaluated the allocative efficiency of the health centres and found that 88 percent of these were allocative efficient while the remaining 12 percent of them were not allocative efficient. In addition, the total efficiency of the sample health centres was computed and only 4 percent of them were both allocative and technical efficient while 50 percent of them were estimated to be less than 50 percent technical efficiency. Furthermore, the findings of the regression analysis indicated that the age of health centres and staffs' incentives were the main determinants of technical efficiency disparities among the public health centres. Thus, the study concluded that most of the health centres were over utilising resources while delivering healthcare services to their communities since most of them were technically inefficient. Moreover, the staff of the health centres should be offered appropriate incentives to operate at the efficient frontier. Health centres with 100 percent technical efficiency levels were considered as technical efficient while health centres with less than 100 percent were known as technically inefficient. This study, however, did not report the relatively technically inefficient health centres that could have different levels of technical efficiency. Thus, applying the logistic regression model could not be an appropriate regression technique as it yields biased estimates; rather the Tobit or ordinary least square regression technique could be the appropriate regression models to examine the variations in technical efficiency estimates among the health centres.

Satyanarayana et al. (2012) evaluated the efficiency of the rural healthcare centre programme in the Chikmagalur District, Karnataka, India. The study employed cross-sectional secondary data obtained from the National Rural Health Mission centre, District health office Chikmagalur District, Karnataka, for 27 health care centre programmes of NRHM (2008-2010). The study used 11 input variables (number of: doctors, ANMs, nurse-midwife, health assistant, administrative staff, laboratory assistant, population size, age of the programme, users under-five years of age, male and female health workers) and four output variables (number of: doctors encounter, health assistant encounters, ANM's encounters, and total encounters) to examine the efficiency of the programme. The data was analysed using the DEA technique. For purpose of the analysis, they categorised the health care centre programmes into three subcategories, namely, community health centres (CHCs), primary health centres (PHCs), and sub-centres (SCs). The findings of the DEA analysis revealed that the highest 66.66 percent of the sub-centres followed by 63.63 percent of primary health centres were technically efficient programmes, while the health centres had the lowest proportion of 42.87 percent technical efficient programmes. Overall, about 59.25 percent of the Indian rural healthcare centre programmes were relatively technically efficient while the remaining 40.75 percent of them were technically inefficient. It can, therefore, be concluded that to improve the efficiency of the technically inefficient healthcare centre programmes, they have to increase the level of output without increasing the available level of inputs. This study, however, was limited in its scope, as it evaluated the efficiency of the programme at the district level and thus, it might not reflect the real impact of the programmes at the national level. In addition, the source of the technical efficiency variability of the healthcare centres was not properly addressed. Furthermore, it did not examine the productivity change of the programme over periods of time.

In Iran, a study by Qorbani et al. (2017) evaluated the technical efficiency of the primary healthcare system for the coverage rate of diabetes mellitus in rural areas of Iran. The study employed cross-sectional secondary data obtained from multiple sources of the Non-Communicable Disease Surveillance Survey, Health Census database, and the Census data and household survey for all provinces in 2008. The study considered the rate of diabetes treatment coverage as an output variable, while health centre, physician, and ‘Behvarz’ workers all measured per thousand population (density) were employed as input variables. In addition, the age of households, the rate of urbanisation, and households' wealth index were employed as contextual variables to examine the sources of technical efficiency variations among the primary healthcare system. Estimation of the technical efficiency of the primary healthcare system was computed using a Stochastic Frontier Analysis (SFA). The findings of the SFA analysis showed that the diabetes treatment coverage was about 67 percent at the national level with significant disparities in the rate of coverage across the provinces, which ranged from 44 percent in the Ilam to 81 percent in the Semnan province. Furthermore, findings of the analysis revealed that the national average technical efficiency estimate of the primary rural healthcare system was estimated to be 87.84 percent with significant variations across the provinces of the country, which also ranges from 59.65 percent in Chaharmahal and Bakhtiaril to 98.28 percent in Markazi. Moreover, the findings indicated that among the predictors, Behvarz worker per thousand populations had a significant impact on the coverage of the diabetes treatment across the provinces of the country. The study, therefore, concluded that there were considerable disparities in technical efficiency estimates across the provinces although the Iranian rural healthcare system was considered as relatively efficient in the coverage rate of the diabetes mellitus treatment. Thus, using the Behvarz healthcare workers, the primary healthcare system could enhance the coverage rate of the diabetes mellitus treatment of the Iranian rural population. This study, however, paid much less attention to the inclusion of some important determinant factors such as the age of the Behvarz healthcare workers, a region of residence of the Behvarz healthcare workers, and their monthly income that could have an impact on the technical efficiency variations of the primary rural healthcare system of the country. In addition, it did not evaluate the productivity changes or growth of the primary healthcare system of the country over periods of time.

In Kenya, a local study was undertaken by Kawakatsu et al. (2012) to identify the factors that affected the community-based health workers' efficiency in Kisumu district using a cross-sectional data collected from 13 community-units for 172 community health workers in 2010. The indicator that the study used to identify the efficient (inefficient) of community health workers was based on the community-based health workers' reporting rate. A community-based health worker who had reported her work every month to her supervisor for the last three months prior to the survey was considered as an active community-based health worker. Otherwise, she would be considered as a non-active community health worker.

The findings of the study further indicated that 61 percent of the community health workers were active community-based health workers, while the remaining 39 percent of them were non-active. The study indicated that there were significant differences in training participation, financial income, and mean age between the active and non-active-community health workers. Most importantly, this study attempted to explain the difference in inefficiency among the community health workers using a logistic regression model. Results from the regression analysis indicated that the age of the community-based health worker had a positive and significant effect on their performance. In addition, the refresher training given to the community health workers had a positive impact on their efficiency. A community-based health worker who received a refresher training course was found to be an efficient community-based health worker (active community-based health worker). The study concluded that a sustained refresher training provision to the community-based health workers could significantly improve the community-based health workers' performance. This study, however, was limited in its scope which was focused at the district level of the country and thus, the findings of the study might not be nationally representative.

Similarly, Wangalwa et al. (2012) examined the Kenyan performance of community health worker programme using pre-and-post interventions. The study employed data from 19 villages for 266 respondents (133 each for the pre-and post-interventions) of mothers whose children ages were younger than 23 months. The analysis of data was made using the pre-and post-test univariate analysis (Fisher's exact test technique) to examine the percentage of changes in neonatal and maternal healthcare practices based on the four-plus antenatal healthcare services visits (ANC), skilled delivery with professionals, post-natal visits, exclusive breastfeeding, and women who were counselled and tested for HIV at antenatal healthcare services and knew their HIV status. The findings of the analysis indicated that there was a significant increase in antenatal healthcare service visits, skilled delivered with professionals, post-natal visits, exclusively breastfed, and a woman who counselled and tested for HIV at antenatal healthcare service visits and knew her HIV status. There was a substantial enhancement in basic maternal and neonatal healthcare practices that indicated the community-based healthcare services strategy could be an appropriate platform for providing community-based healthcare interventions. The scope of this study, however, was very limited as it had been conducted at village level of the country and thus, its findings might not be nationally representative. In addition, examining the sources of the variability of the efficiency estimates could have provided important insights in improving the efficiency of the programme, but this study could not address this gap.

Another study by Kirigia et al. (2004) evaluated the technical efficiency of 32 public health centres in Kenya using the DEA technique. The analysis of the efficiency was made using 11 input variabless (number of beds, administrative staff, clinical officers, nurses, physiotherapist, occupational therapy, public health officer, dental technologist, laboratory technical, laboratory technologist, and non-wage expenditures) and nine output variables (number of: immunisation visits, outpatient visits, family planning visits, antenatal healthcare service visits, malaria visits, diarrhoeal visits, urinary tract infection visits, sexual transmitted infections visits, and intestinal worm visits). The findings of the analysis demonstrated that 56 percent of the public health centres were technically efficient, while the remaining 44 percent of them were technical inefficient, with differences in the levels of technical efficiency estimates. The average technical efficiency estimate of the technically inefficient health centres was 65 percent. Moreover, the study indicated that about 59 percent of the health centres were scale efficient while the remaining 41 percent of them were scale inefficient. The study noted that the technical efficiency estimates of the Kenyan health centres were similar to the health units of other developing countries. Thus, the study concluded that the technically inefficient health centres should increase their outputs with the existing level of input to operate at the efficiency frontier. Despite the significant variations in technical efficiency among the health centres, this study did not examine the factors that explained the technical efficiency variability among the health centres. In addition, it did not evaluate the efficiency changes (productivity changes or growth) of the primary healthcare system of the country over periods of time.

In Sierra Leone, Kirigia et al. (2011) evaluated the relative efficiency of 36 maternal and child health posts (MCHPs); 22 community health centres (CHCs) and 21 community health posts (CHPs) using cross-sectional data of 2008. Employing the DEA model for health units, the analysis of efficiency was computed using the two input variables (the number of community health officers and administrative staff) and three output variables (the number of health education sessions, the number of outpatients treated, and the number of vector control activities). The findings of the DEA analysis revealed that there were significant variations in technical and scale efficiency levels among and within the health units. The findings further indicated that about 66.7 percent of the community health posts, 59.1 percent the community health centres, and 77.8 percent maternal and child health posts were relatively technical efficient under the variable returns to scale assumption, with differences in the technically efficiency estimates. The results of the analysis further indicated that about 66.67 percent of the community health posts, 31.8 percent of the community health centres, and 52.8 percent of the maternal and child health posts were scale efficient. The figure implied that the 33.33 percent of the community health posts, 68.2 of the community health centres, and 31.8 percent of the maternal and child health posts could raise their levels of outputs to be technically efficient with the present level of inputs utilisation. The study indicated that the substantial number of technically inefficient health units could significantly be improved by the optimal use of the scarce resources (inputs). Thus, the utilisation of the scarce resource needed serious attention both at the national and district levels to significantly improve the overall efficiency of the health units. This study, however, paid less attention to examine the sources of the technical efficiency variations among the health units. Moreover, it did not evaluate the efficiency changes (productivity growth or growth) of the health units over certain time periods because it was based a single time period survey.

Another study by Renner et al. (2005) examined the technical efficiency of 37 public peripheral health units using data from the planning and information department at the ministry of the health system for the year 2000 in Sierra Leone. The technical efficiency was computed using four inputs and six output variables and analysed using an output-oriented DEA technique based on the variable returns to scale assumption. The four inputs were the number of technical staff, capital inputs, subordinate staff, and material and supplies. The six outputs variables were the number of health education sessions, child delivery, family planning visits, under-five fully immunised children, growth monitoring visits, and ante-and post-natal healthcare services. The technical efficiency was analysed using an output-oriented DEA technique based on the variable returns to scale assumption. The findings from the DEA analysis indicated that 41 percent of the health units were technically efficient while the remaining 59 percent of them were technically inefficient with overall average technical efficiency estimates of 78 percent. Furthermore, the study revealed that 35 percent of the health units were scale efficient, while 65 percent of them were scale inefficient, with an average scale efficiency level of 72 percent. The study concluded that the major form of scale inefficiency was the decreasing returns to scale as most of the health units (65 percent) were operating below their optimal scale. Thus, with the present low level of technical efficiency estimates, there was less likelihood of achieving the health targets of the country such as the

Abuja and Millennium Development Goals targets by scaling up healthcare interventions at the regional level. Despite the variations in technical efficiency among the health units, this study, however, could not address the determinant factors that affect the technical efficiency variations among the sample health units.

The technical efficiency of health centres was evaluated by Akazili et al. (2008b) using primary data, which was collected from 89 sample health centres in Ghana. Using four input variables (number of clinical staffs, non-clinical staff, number of cots and beds, and costs ofdrugs and other consumables) and five output variables (number of outpatients visits, antenatal healthcare service visits, deliveries at health facilities, under-five fully immunised children, and family planning visits), the efficiency analysis was made by an input-oriented DEA technique based on the variable returns to scale assumption. The findings of the analysis revealed that 65 percent of the sample health centres were technically inefficient with an average technical efficiency level of 57 percent. This implies that they could possibly reduce their present level of inputs by 43 percent to produce the same level of outputs and operate at the efficient frontier. Moreover, the 79 percent of the health centres were scale inefficient with an average scale efficiency level of 86 percent, suggesting that they could potentially increase their outputs provision by 14 percent using their current scale size and operating at their optimal scale size. The study noted that the health centres employed more inputs than needed to produce the optimal level of outputs because most of them were found to be technically inefficient while delivering basic healthcare services. Thus, the sizeable wastage of inputs should possibly be minimised in order to enhance the technical efficiency of the health centres. Although this study evaluated the technical efficiency of health centres and indicated the exisitence of variations in technical efficiency estimates among the health centres; it did not explain the determinant factors affecting the significant variations in the technical efficiency estimates among the health centres.

A cross-sectional descriptive analysis study by Stekelenburg et al. (2003) examined the poor performance of the community-based health workers using data from 86 members of the community, 27 community-based health workers, and nine staffs members of health centres in rural ‘Kalabo’ district, the western province of Zambia. The performance of the community-based health workers was analysed using descriptive data analysis based on three indicators, namely the community health workers' quarterly reporting rate (active community-based health workers versus non-active community-based health workers); the provision of drugs to health centres; and availability of health equipment. Accordingly, the findings of the study indicated that 43 percent of community health workers were active community-based health workers while the remaining 57 percent of them were non-active community-based health workers. About 37 percent of the community-based health workers and 74 percent of the members of the communities revealed that the health centres had a lack of adequate drugs, which resulted in the programme to function poorly. The inadequate, irregular, and uneven provision of drugs to health centres might not have a direct effect on the programme; however, they are important contributors to the poor performance of the community-based health workers. It can, therefore, be concluded that the provision of adequate drugs and health equipment into the health centres could significantly improve the poor performance of the community-based health workers. The representativeness and generalisability of the findings of this study at the national level would be difficult because it was limited in its scope as it had been conducted at district level of the country.

In Ethiopia, most of the health extension programme studies (Amare, 2013; Gebrehiwot et al., 2015; Fetene et al., 2016; Kelbessa et.al., 2014; Medhanyie et al., 2016; Negusse et.al., 2007; Tesfa & Jibat 2014; Workie & Ramana, 2013, among others) did not give due attention to the efficiency and productivity changes of the programme at the national level. In 2007, at an initial stage of the health extension programme, a study by San Sebastián & Lemma (2010) evaluated the technical efficiency of the health posts using primary data collected from 60 health posts in seven rural districts in the Tigrai region, Ethiopia. The study employed two input variables (number of health extension workers and voluntary health workers) and eight output variables (number of health education sessions, child deliveries, antenatal healthcare service visits, under-five children treated diarrheal cases, family planning visits, visits made to households by the health extension workers, new patients treated, and malaria cases treated). In addition, it employed a Tobit regression model to examine the determinants of the technical efficiency variations among the health posts. The analysis of the findings revealed that there were variations in technical and scale efficiency estimates among the sample health posts. The overall average technical and scale efficiency estimates of the health posts were 57 and 95 percent, respectively. Moreover, about 25 percent of the health posts were technically efficient, while the remaining the 75 percent of them were relatively technically inefficient. Furthermore, the study indicated that about 45 percent of the health posts had technical inefficiency estimates of 42 percent, which implies that they could probably produce an additional 58 percent of outputs with the present level of inputs to operate at the efficient frontier. None of the regressed variables had a significant effect on the disparities in the technical efficiency among the health posts. This study, however, was carried out at a micro-regional level. It evaluated the efficiency of health posts at an initial stage of the programme and might not have indicated the real impact of the programme. Furthermore, the number of the health extension programme beneficiary graduates was not considered as an important output variable while evaluating the technical efficiency of the health posts. Moreover, the productivity changes of the health posts were not examined. Thus, the overall findings of this study could not be nationally representative.

In Iran, Javanparast et al. (2011) examined the factors influencing the performance of the community health workers perspectives on their contribution to rural health and well-being using primary data collected from the community-based health workers from 18 provinces of the country. A descriptive statistics analysis was applied to analyse the obtained data. The descriptive analysis indicated that despite the Iranian community health workers having a better understanding of health, the high workload, inadequacy of a supervisory system, lack of incentives, and poor support methods of the community-based health workers were the most significant factors affecting the performance of the Iranian community health worker programme (the Iranian "*behvarz*" programme). The sustained relationships between the community health workers and rural communities, motivated community-based health workers, and the community health workers' high-level knowledge and skills on the basic healthcare services were the most crucial factors that enhanced the performance of the behvarz programme to provide better quality healthcare services to their communities. The study concluded that improvement with regard to the workload, the inadequate supervisory system, and incentive mechanisms for the community-based health workers could significantly enhance the performance of the behvarz programme in the rural areas of the country. This study, however, did not examine the technical efficiency of the community-based health workers programme. Moreover, it did not explain the relative contribution of each factor in explaining the efficiency variability of the community-based health workers programme; rather this study indicated qualitatively those factors affecting the performance of the programme. Most importantly, this study failed to indicate which provinces were performing better in comparison to the others.

Similarly, Condo et al. (2014) examined the determinants of Rwanda's community health workers system using descriptive analysis. Cross-sectional primary data was collected from both 108 community-based health workers and 36 programme beneficiary households (lactating, pregnant, and reproductive-age women) in 2011 from three districts based on their level of food security (i.e. low, middle, and high). The findings of the qualitative analysis revealed that high workload, irregular training, inadequate supervision, and level of education of the community-based health workers were the major sources of efficiency variations among Rwanda's community-based health workers. In conclusion, addressing and understanding these barriers (mainly the high workload, irregular training, and inadequate supervision of the community-based health workers) in the context of performance-based financing could significantly improve the performance of the community-based primary healthcare system in Rwanda. This study, however, did not evaluate the performance of the programme and merely indicated the performance variations among the community-based health workers. In addition, the scope of this study was limited as it had been conducted at the district level of the country and thus, its findings might not be nationally representative.

Sharma et al. (2014) assessed the factors that influenced the performance of the community-based health workers, which are known as Accelerated Social Health Activists (ASHA) from sixteen villages of Udaipur district in Rajasthan in rural settings of India. An inductive approach was applied to analyse the collected data from the Accelerated Social Health Activists', ASHAs' co-workers, and representatives of the healthcare system. They categorised the factors into three (the professional, personal and institutional factors) based on how these factors could affect the performance of the Accelerated Social Health Activists. Among the professional factors, incentive mechanisms, poor training provision, ASHAs' knowledge, and skills in health promotion, selection, placement of Accelerated Social Health Activist, job security, and accountability were affecting ASHAs' performance. The ASHAs' education status, being a resident of the village where they work, family background, ASHAs' health status (absenteeism from work due to frequent pregnancies and other maternal health issues) were the personal factors affecting their performance. Among the institutional factors, reporting and supervision mechanisms, poor health infrastructure due to inadequate medical supply, and poor healthcare services provision were affecting their performance. In conclusion, the study revealed that the performance of Accelerated Social Health Activists was affected by a variety of factors and thus, addressing and understanding the factors (professional, personal and institutional) could significantly improve their performance. This study, however, was limited in its scope as it had been carried out at a district level of the country, and therefore, the results might not be nationally representative. In addition, it did not evaluate the performance of Accelerated Social Health Activists and as a result, it did not indicate the level of performance variations among them.

Haines et al. (2007) reviewed the determinants of the disparities in the efficiency of a community-based health workers programme and categorised these factors into four types. First, health system factors, which included the use of effective healthcare interventions, appropriate health policy, adequate supervision, and payment mechanisms which could affect the efficiency of the community-based health worker programme. Second, the community factors (such as health infrastructure, transport facilities) were also affecting efficiency of the community health worker programme. Third, the national factors, which included national poverty levels, corruption levels, and the political will of governments, were found to affect the efficiency of the community-based health workers programme. Fourth, the international factors, which included technical assistance, research studies that lead to improved healthcare interventions provision, and policies and strategies of donors, were affecting the efficiency of the community health worker programmes. This review, however, did not indicate the performance variations among the community-based health worker programmes. In addition, it did not indicate the relative individual contribution of the reviewed determinant factors in explaining the performance variations in the community-based health workers programmes.

In a review of the literature, Prasad and Muraleedharan (2008) indicated that gender of the community-based health workers, the nature of employment, community-based health worker's educational level, and duration of training on basic healthcare services given to community-based health workers, number of offspring that a community-based health worker had, population size that the community-based health workers served, and the community-based health workers' workload were the major factors affecting the performance of the community-based health workers. Although this review identified some of the major determinants of the community-based health workers, it did not indicate the performance variations among the community-based health workers. In addition, it did not indicate the relative individual contribution of the reviewed determinant factors affecting the performance variations among the community-based health workers.

A systematic review of qualitative study by Bigirwa (2009) assessed the factors affecting the performance of the community-based health workers while providing basic healthcare services to their respective communities. The review identified the community-based health worker's experience in relation to healthcare interventions, the community-based health workers' level of education, erratic medical provisions, the length and intensity of training provided to the community-based health workers, the range of healthcare services that the community-based health worker delivered, population size coverage, long distance to work, insufficient payment, the absence of career development structure, poor communication skills and socio-economic status of the community-based health workers as the major factors affecting the performance of the community-based health workers. This review shared the limitation of the Prasad and Muraleedharan (2008) review.

Likewise, Shakir (2010) reviewed the factors affecting the performance of the community-based health workers. The review indicated that the inadequate supervision given to them, absence of incentives, inadequate (inconsistent) of resources provision, insufficient training given to the community-based health workers, the absence of community involvement in designing the community-based health worker programme, and the undefined job description of the community-based health workers were the major determinants of the performance of the community-based health workers. This review, however, did not indicate the performance variations among the community-based health workers. In addition, the review did not indicate the relative individual contribution of the reviewed determinants in explaining the performance variations among the community-based health workers.

Moreover, Christopher et al. (2011) reviewed the impact of the community-based health workers on providing basic healthcare services to the society. The review indicated that the efficiency of the community health worker programmes could be affected by place of work (rural versus urban), healthcare services setting (home to home or being in office), type of work or intensity of work, cultural, and environmental background of the society. In addition, the proportion of the community-based health workers per a given population, the payment and incentives mechanisms, the community-based health workers' level of educational, marital status, religion affiliation, the selection criteria utilised to select the community-based health workers, the gender of the community-based health workers, ethnicity of the community health workers, duration and mode of training given to the community-based health workers, and the adequacy of supervision on the community health workers were among the factors which influenced the efficiency of the community-based health worker programme. This review shared the limitation of the Shakir's (2009) reviews.

Jaskiewicz and Tulenko (2012) assessed the factors that increase the productivity of the community-based health workers. The review identified that a reasonable community-based health workers' workload, an optimum geographical distance to be covered by the community-based health workers, the availability of adequate medical equipment at the health facilities, adequate supportive supervision given to the community-based health workers, and the respect that community-based health workers received from their community were the major contributing factors that enabled them to increase their productivity. Thus, these factors enabled the community-based health workers to provide improved and quality healthcare services to their respective communities more effectively. This review, however, did not indicate the performance variations among the community-based health workers. Moreover, it did not indicate the relative individual contribution of the determinant factors affecting the performance variations among the community-based health workers.

3.4. Determinant factors of throughput of the community-based rural programmes: A review of the evidence

Bazezew (2012) analysed the household level graduation from the Productive Safety Net Programme (PSNP) in the Gaint district, in the Amhara region of Ethiopia using a logistic regression model for data collected from 201 sample households in 2011. The findings of the regression analysis revealed that income (non-farm income), total production, livestock, and the per capita income had a positive and significant association with the households' probability of graduation with differences in the levels of significance. Therefore, it can be concluded that improving the total crop production, per capita income, and non-farm income of the households could enhance their graduation rate from the programme. This study, however, paid less attention to the inclusion of other potential factors such as income from remittance, number of dependents, households' access to irrigation, parental education level, households' land size, among others, can add substantial insights into the study. Moreover, the scope of this study was very limited as it was conducted at the district level and thus, its findings might not be nationally representative.

Gebresilassie (2013) also examined the determinant factors affecting graduation of the Ethiopian Productive Safety Net Programme beneficiary households in the eastern zone of Tigrai, Ethiopia, using primary data collected from a total sample of 400 rural households in 2013[7]. The data was analysed using a logistic regression analysis. This study's findings indicated that irrigable land, literacy of head of the household, use of an integrated

[7] PSNP stands for Productive Safety Net Programme in the Ethiopian context

agricultural package, access to credit, saving practices, non-government follow-up, access to petty trading, and livestock holding positively affected the graduation of the households. In contrast to this, a household with a larger family size was less likely to graduate as model household. It can, therefore, be concluded that improving the savings practice (culture), encouraging the households to participate in petty trading, and in an integrated agricultural package could significantly improve households' graduation. The scope of this study, however, was limited as it was conducted at a micro-region of the country and thus, its findings might not be nationally representative. Nevertheless, substantial insights can be gained from this study by including factors such as households' off-farm income, remittance, and farm income in the regression analysis that could have an impact on the households' probability of graduation.

Hailu & Seyoum (2015) assessed factors affecting households' graduation from the productive safety net programme in the Southern zone of Tigrai, Ethiopia. The study employed primary data collected from 235 sample households and this was analysed using a binary logistic regression model. The results of the regression analysis revealed that male-headed household (gender), access to credit, number of dependents, natural calamities, and irrigation use had a positive and significant impact on households' probability of graduation. The results of the regression analysis revealed that family size affected negatively the probability of household's graduation. A household with a relatively larger family size was less likely to graduate as model household. The study concluded that encouraging households to engage in irrigation use and allowing households which had a larger number of dependants to become affiliated with the programme could enhance the throughput rate of households' graduation. This study, however, was limited in its scope as it was carried out at zonal level and, therefore, its findings might not be nationally representative. In addition, it could not examine the impact of some demographic (such as family size, maternal age) and socio-economic (such as households' off-farm income, remittance, a savings culture, among others) factors that could have an impact on the households' probability of graduation.

Another study by Wedajo & Lerong (2017) in the Babile district of the Oromia region of Ethiopia examined factors influencing graduation productive safety net programme beneficiary households. The study employed primary data collected from 120 rural households in 2016 and analysed this using a binary logistic regression model. Findings of the study indicated that gender of the household, family size, irrigable land, access to credit, and drought affected positively the probability of households' graduation. The study concluded that encouraging that has a larger family size and assisting them to make use irrigation schemes could enhance the throughput rate of the programme's graduation. This study, however, paid less attention to the inclusion of other potential factors such as households' off-farm income, maternal age, parental education level, households' land size, and households' access to irrigation that could have an impact on the households' probability of graduation. Moreover, the scope of this study was very limited as it was conducted at the district level and thus, its findings might not be nationally representative.

Hence, a brief summary report of the reviewed literature focused on regional differentials in child mortality, the efficiency of the community-based health worker programmes, and the factors affecting the community-based health worker programmes beneficiary households' graduation presented in Appendix A, Table A-1 and Table A-2.

3.5. The conceptual frameworks

This section of the chapter reviews and discusses some of the conceptual frameworks focusing on the determinants of child mortality and the efficiency measurement evaluation of community-based health workers programme. As indicated in Figure 3.1, an integrated conceptual framework was developed to provide guidance on addressing the research gaps, which was stated as specific objectives of this study. These gaps, as indicated in the first chapter of this thesis, ought to be addressed.

i. A conceptual framework explaining the level of child mortality disparity

There are other influencing factors other than biological incident, such as socio-economic, demographic and environmental factors (Fotso & Kuate-Defo, 2006; Masuy-Stroobant, 2001). This implies that children under-five years old are not only dying because of the official causes (biological incident) of child death (malaria, sepsis, diarrhea, tetanus, and others), but they are also dying because of many other crucial factors, for instance, limited access to clean water, children born into poor households, low maternal education, undernutrition, and children belonging to rural households, among others. To reduce under-five child deaths from preventable diseases, it requires tackling not only the medical causes of a child death, but also the socio-economic, environmental, and proximate factors that increase a child's risk of early death (UNICEF, 2015a). Medical experts have focused on the biological causes of a child's death, while omitting the socio-economic and environmental factors that can lead to this (Mosley & Chen, 1984). Thus, Mosley and Chen (1984) give greater emphasis to the combined effect (of both medical and social) factors that effect on child mortality, particularly in developing countries.

Of the existing illustrative conceptual frameworks for child mortality (Adedini et al., 2015; Houweling & Kunst, 2010; Macassa et al., 2011; Mosley & Chen, 1984), that was developed by Mosley & Chen (1984) is perhaps the most comprehensive and often employed in the context of child mortality in low and middle-income countries (Masuy-Stroobant, 2001). Mosley and Chen's (1984) framework is the most commonly employed theoretical framework in many health and social studies, incorporating research methodology utilised by medical and social researchers (Akuma, 2013; Baker, 1999; Jain, 1985; Masuy-Stroobant, 2001). This framework considered the direct and indirect factors which have an immediate influence on a child's death. Mosley & Chen identified fourteen factors that could potentially affect child mortality in developing countries. The determinants were classified into direct (proximate) and indirect (environmental and socio-economic) factors. The direct factors have an instant effect on child mortality rates, while the indirect ones have an indirect effect. The socio-economic factors comprise six factors, which such as personal preventive measures, maternal working status, maternal education, place of residence, place of child delivery, intentional and accidental injuries. There are four environmental factors which include types of dwelling, access to improved sanitation, safe drinking water, and energy. Four of the proximate factors are the child's birth spacing, maternal age, the child's gender, and the child's birth order. Therefore, the core objective of the Mosley & Chen's conceptual framework was to demonstrate that the socio-economic and environmental factors affect child mortality by means of the proximate factors that directly affect child mortality. Although the Mosley & Chen's conceptual framework was mainly developed to explain the determinant factors of child mortality in developing countries, it is limited in the sense that it does not indicate how these factors may be used to explain the inter-regional variations in child mortality within a particular country.

Another conceptual framework by Macassa et al. (2011) attempted to explain the variations in child mortality in sub-Saharan Africa. This framework considered the philosophies that Mosley and Chen's outlined in their framework but incorporated some social factors such as culture, structure, and society's social system as major determinants of child mortality. They indicated the importance of proximate, socio-economic, environmental as well as the social factors in explaining the variations in child mortality across the sub-Saharan African countries. They acknowledged the importance of the social factors in their framework to explain and redress the variations in child mortality. They indicated that the social factors, along with the other socio-economic and environmental factors, indirectly affected the child mortality risk through the proximate factors. This framework, however, did not explain the relative percentage of individual factors (proximate, socio-economic, environmental, and social factors) in explaining the variations in child mortality across and within the sub-Saharan African countries as their relative contributions could vary significantly in explaining the regional variations and disparities between countries in child mortality.

Houweling & Kunst (2010) developed a conceptual framework based on the Mosley & Chen framework to explain the determinants of the disparities in child mortality in developing countries. They attempted to explain the determinants of the variations in child mortality and indicated that there were considerable disparities in the magnitudes of child mortality among the countries under examination. Similar to the Mosley & Chen's findings, the impact of socio-economic factors on child mortality was through the proximate factors (direct factors). Consequently, they noted that the inequalities in socio-economic and proximate factors could result in intra-country variations in child mortality. However, the framework did not explain the relative percentage contribution of each factor in explaining the regional variations in child mortality.

One of the most referenced studies is that of Adedini et al. (2015) who examined the regional differentials in infant and under-five child mortality in Nigeria. This study adopted a modified framework from the Mosley and Chen study as a basis for their work while examining the regional variations both in infant and under-five child mortality. The study considered the individual level factors (such as maternal education, maternal age, birth spacing, the gender of the child, the child's birth order, and household's wealth status). It also included community level factors (such as households' poverty status, antenatal healthcare, access to electricity, access to safe drinking water, a region of residence, place of residence, and place of child delivery) to conceptualise their impact on infant and under-five child mortality. The findings of this indicated that these factors had a strong association with the infant and under-five child mortality. However, their modified conceptual framework did not indicate how each of the proximate, socio-economic, and environmental factors could explain the regional variation in infant and under-five child mortality. They rather indicated that the regional variations were examined based on the different levels of infant and under-five child mortality that each region had.

In summary, the Mosley & Chen's framework was the most commonly employed conceptual framework and thus, it can be concluded that most of the reviewed frameworks developed their theoretical and conceptual frameworks based on this. Most importantly, although all the earliest reviewed conceptual frameworks explained the relationships between each factor (the proximate, socio-economic, environmental, and social factors) and child mortality, however, almost none has explicitly explained and indicated how individual factors elucidate the regional variations in child mortality.

ii. Conceptual frameworks of the efficiency of the decision-making units

In the context of production, the evaluation of efficiency focused on the healthcare services organisations commonly referred to as decision-making units (DMUs). Examples of the decision-making units consist of banks, health posts, health centres, and hospitals, among others (Jacobs et al., 2006). A simple production function of the microeconomic concept was applied while evaluating the efficiency of the decision-making units. Efficiency is a term commonly employed in economics and is defined as the optimal use of available inputs (resources) (Shone, 1981). Alternatively, Farrell (1957) defined efficiency as producing the maximum possible outputs (healthcare services in this case) from a given set of health inputs.

The efficiency measures have three interrelated categories. These are:

i) Technical efficiency which refers to the optimal possible production of outputs from a given set of inputs.
ii) Allocative efficiency which refers to the ability to select input mix to produce a certain number of outputs at minimum cost, given the prices of inputs and available production technology.
iii) Total economic efficiency. If a decision-making unit employs all its inputs in a technical and an allocative manner, it can be said that it achieved its total economic efficiency (Coelli et al., 1998; Worthington, 2004).

The evaluation of efficiency of the organisations is commonly computed by dividing all valued outputs with all valued inputs, which is mostly applied to various disciplines such as economics, business, health economics, and engineering, among others (Coelli et al., 1998; Copper et al., 2006; Jacobs et al., 2006). A decision-making unit, with an estimate technically efficiency value of 100 percent is defined as technically efficient. Less than this is defined as technically inefficient. A decision-making unit can be allocative or technical efficient or both, but due to its scale of operation, the decision-making units may not be optimal. Most importantly, the decision-making units involved may be too large (or too small) in their scale of operation. Accordingly, a technically efficient decision-making unit operating at decreasing or increasing returns to scale could enhance its technical efficiency estimates by changing its scale of operation that is maintaining the same input mix but altering its scale of operations. However, if the primary production technology was at constant returns to scale technology, the decision-making unit will automatically be scale efficient (Coelli et al., 1998).

Worthington (2004) developed a theoretical framework on how an organization (healthcare services organisation) can evaluate its efficiency along with its three classes (technical, allocative, and total economic efficiency). Worthington (2004) clearly noted the steps that are to be taken when analysing and measuring the efficiency of a healthcare organisation with a given set of input and output variables. In the first step, the author indicated the choice of an efficiency measurement model based on the nature of the inputs and outputs variables and the theoretical nature of the techniques or advantages and disadvantages of the techniques. In the second step, careful selections of input and output variables are outlined to evaluate the efficiency of healthcare service organisation. As the third step, the determinant factors affecting the variations in technical efficiency estimates among the healthcare service organisations were explained. Although the theoretical framework explained how to analyse and measure the efficiency of the healthcare service organization, the author could not integrate the framework with the inter-regional differentials in child mortality. This framework, however, did not indicate which efficiency measures (technical, allocative, and total economic efficiency) were to be considered as a dependent variable to explain the determinants of variations in efficiency among the healthcare service organisations.

Eunice (2013) developed a conceptual framework, which is known as a health production model, to analyse the efficiency of the health system. In addition, the author attempted to understand and explain the key drivers of the efficiency of the healthcare service delivery. This framework employed three input variables (such as equipment, number of human resources, and number of available adequate medicine) and three output variables (such as the number of vaccinated children, treated patient, and number of beds filled) to analyse and measure the efficiency of the health system. The author further employed factors such as education, environment, population, and behaviour (personal hygiene, use of bed net, alcohol use, etc.) to explain the determinants of disparities in the technical efficiency among the healthcare services providers. The framework indicated how the health system could measure efficiency and explained the determinants of the variability in technical efficiency among the healthcare services deliveries. This framework, however, did not integrate with child mortality disparities within a particular country to how the efficiency of a health system could be affected by child mortality disparities within that particular country or region. In addition, the framework did not indicate either the computed technical efficiency estimates employed as dependent variables were based on the constant or variable returns to scale assumptions.

Renner et al. (2005) examined the efficiency of the health units in the Pujehun district, Sierra Leone and developed a conceptual framework that guided their empirical study. They employed multiple-input variables (such as capital, material, and supplies, technical, and subordinate staffs members) and multiple-output variables (such as the number of health education sessions, fully immunised children, child deliveries, growth monitoring, ante-and post-natal healthcare visits) to evaluate the technical efficiency of the health units. The framework indicated how the multiple-outputs were produced or provided by the multiple-inputs being employed. This framework, however, did not indicate how the variability in technical efficiency among the health units could be explained by employing some contextual factors. In addition, the framework did not indicate how the technical efficiency of the health units could affect the child mortality by integrating with the technical efficiency of the health units that affected child mortality.

In conclusion, the reviewed theoretical and conceptual frameworks clearly indicated how one may analyse and measure the efficiency of the decision-making units using various multiple-inputs and multiple-outputs variables. Most of the authors' works that were reviewed indicated how the contextual determinants explained the variability in technical efficiency among the decision-making units by employing or proposing appropriate inferential statistics.

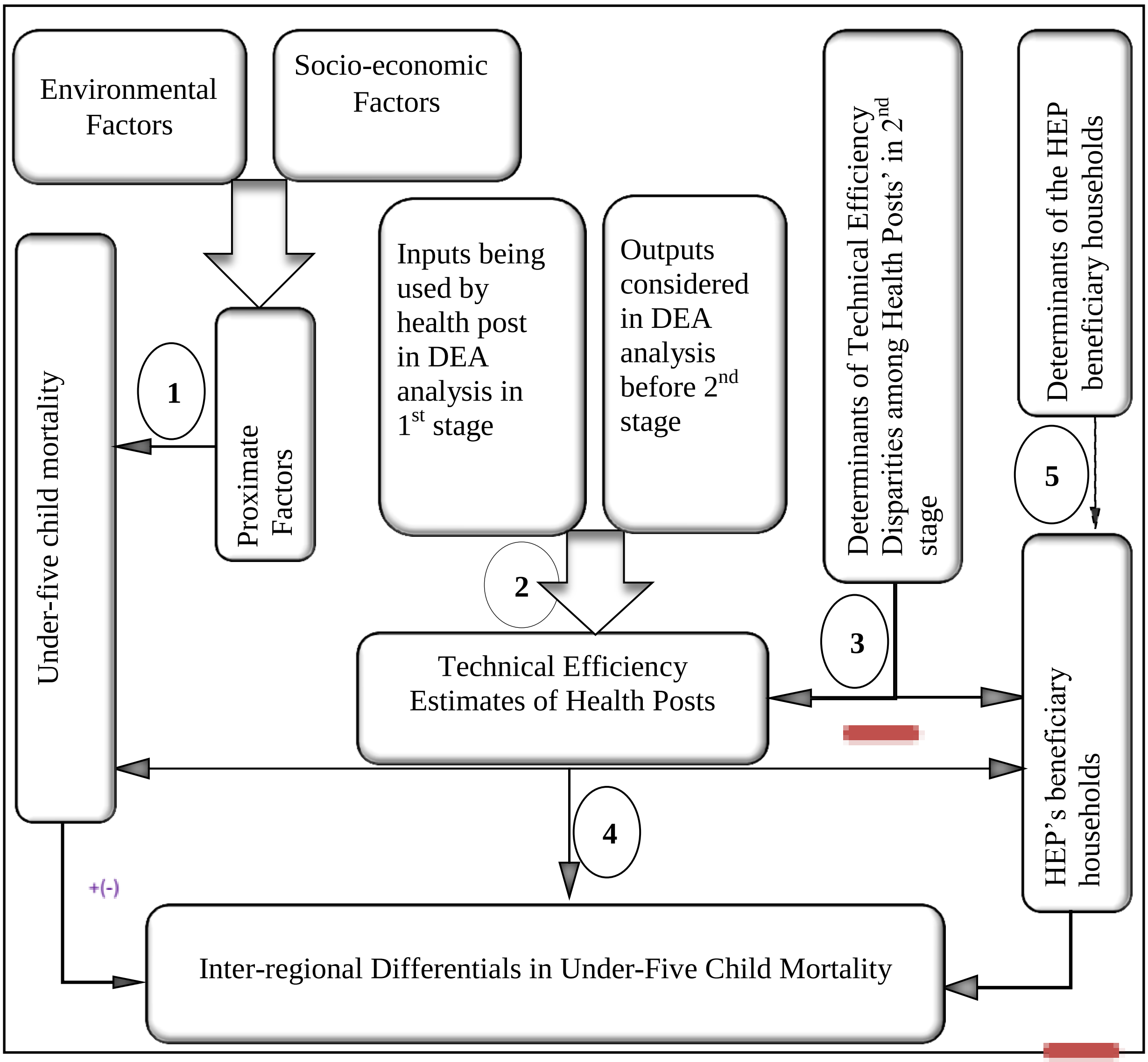
iii. An integrated conceptual framework employed for this study

There is a paucity of explanations regarding the development of an integrated framework that concurrently shows the factors affecting the inter-regional gaps in under-five child mortality, evaluate efficiency of the decision-making units, as well as the determinant factors affecting the variations in technical efficiency among the decision-making units. Unlike the theoretical and conceptual frameworks discussed and explained earlier, this study developed an integrated conceptual framework, as illustrated in Figure 3.1, which draws mainly upon the works of Mosley and Chen (1984), Eunice (2013) frameworks, and the Worthington (2004) theoretical framework to structure this study comprehensively.

The Mosley and Chen's framework considered health as well as socio-economic factors as determinants of child mortality risks. This framework was the basis for almost all other child mortality and related frameworks. Eunice' framework and Worthington's theoretical framework clearly indicated how to measure the efficiency of the decision-making units and attempted to explain the variability in technical efficiency among them. These frameworks (studies) constitute the rationale for the framework that was employed in this particular study. Therefore, it is through the lens of this integrated framework (Figure 3.1) that the interaction effect of the variables of interest was clearly elucidated and it addressed the stated specific objectives of this study. The integrated conceptual framework, as illustrated in Figure 3.1, described the direct and indirect factors that affected the under-five child mortality that conceptualised how each determinant factor affected the under-five child mortality, in turn, to explain the regional variations in under-five child mortality in Ethiopia. In addition, using health posts as decision-making units of the health extension programme, the framework indicated how to evaluate the efficiency and productivity changes of the health extension programme by employing multiple-inputs and multiple-outputs variables. Moreover, the study also examined the determinant factors affecting the disparities in the technical efficiency estimates among the health posts. The framework further indicated the factors that influence the health extension programme beneficiary households' graduation and how these factors also affect the efficiency of the health posts under analysis, which in turn affected the inter-regional differentials in under-five child mortality.

As indicated in Figure 3.1, the multiple interdependent paths (links) of the integrated framework clearly illustrated how the stated specific research objectives of this study were addressed. The dotted arrows and boxes of the figure indicate the factors affecting the under-five child mortality, which in turn explain the regional disparities in under-five child mortality, the factors explaining the disparities in technical efficiency among the health posts, and the determinant factors affecting graduation of the health extension programme beneficiary households. The factors affecting that have an impact on the regional variations in under-five child mortality, while the smooth arrows and boxes indicate the impact pathway or feedback links on their respective components of the framework.

The first link of the integrated framework indicated the relationship between the factors (socio-economic, environmental, and proximate factors) that affected the under-five child mortality rate, which in turn affected the inter-regional differentials in under-five child mortality.



Source: Own elaboration and representation with inputs mainly from Eunice (2013); Mosley and Chen (1984); and Worthington (2004) frameworks

Figure 3. 1: An integrated conceptual framework mapping for analysis of this study

The second link shows the multiple-inputs being used and the multiple-outputs being produced by the health posts to analyse and measure the relative technical efficiency of the health extension programme. To conceptualise the packages of basic healthcare services provided from the programme, specifying the possible combinations of the input and the output variables is a priori while estimating the technical and scale efficiency of the health posts (De et al., 2012; Dutta et al., 2014). Hence, a relatively technically efficient health post could provide more basic healthcare services to the largely rural communities and thus, be able to save the lives of many under-five children. The health posts' relative technical efficiency estimates might directly affect under-five child mortality rate as well as the regional variations in child mortality. A logical inference that may be drawn from the above is that the technically efficient health posts could reduce the inter-regional differentials in under-five child mortality rate. The estimated technical efficiency could vary among the health posts under analysis.

The third link of the framework showed that the estimated technical efficiency variations among the health posts might be affected by many external factors. As indicated in Figure 3.1, in turn, these factors could also affect the regional variations in under-five child mortality through their impact on the technical efficiency estimates of the health posts. The computed relative technical efficiency of the health posts indicated their level of performance in providing the packages of basic healthcare services to their respective communities. Accordingly, the relatively technical efficient health posts could provide enhanced basic healthcare services to the large population and as a result, the health status of the communities could significantly be improved, which in turn could save the lives of many under-five children.

The fourth link of the framework further indicated the factors explaining the differences in the technical efficiency among the health posts, which in turn have a reverse impact on the regional differentials in under-five child mortality rate. Therefore, regions with relatively more technically efficient health posts could have reduced their under-five child mortality rate compared to regions with relatively fewer technically efficient health posts. The technically efficient health posts could provide a relatively more enhanced package of basic healthcare services of the health extension programme to their respective large communities than the technically inefficient health posts, which could result in different levels of child mortality among regions of the country, Ethiopia.

Lastly, the fifth link of the framework indicated the determinant factors affecting the health extension programme beneficiary households' graduation. A health extension programme graduate household is expected to improve the overall health status of his/her families as well as his/her his neighbouring communities at large, by using the packages of basic healthcare services of the programme (Bilal et al., 2011; FMoH, 2015). Graduating a number of households as model households could imply that households are graduating with basic knowledge of and skills in basic healthcare services, which in turn the lives of many under-five children were saved. In turn, the inter-regional differential in under-five child mortality could be substantially minimised. Moreover, the factors that affect the graduation of the health extension programme beneficiary households might also affect the inter-regional variation in under-five child mortality and the technical efficiency estimates of the health posts. The health extension programme graduate households with basic knowledge of and skills in basic healthcare services of the health extension programme might improve the health status of their children and contribute to enhancing access to and utilisation of basic healthcare, resulting in reducing the inter-regional differentials in child mortality.

3.6. Conclusions

This chapter presented an overview of the literature focusing on the determinants of the inter-regional differentials in child mortality. The chapter also reviewed literature focusing on the efficiency and productivity changes of the community-based health worker programmes in developing countries. Concurrently, it also reviewed the factors affecting the disparities in technical efficiency estimates among the decision-making units (health facilities). Furthermore, the chapter presented a review of related literature on determinant factors affecting graduation of community-based programmes. Most importantly, the chapter provided an integrated conceptual framework developed for this study that guides how the stated specific objectives of the overall study would systematically be addressed.

The literature included in this review varied significantly in terms of the methodology that each reviewed study employed either a purely quantitative approach, qualitative approach, or a mixed-method approach. The quantitative and qualitative analyses examined different outcome variables of interest and were done in different countries with a different scope of the study. Most of the reviewed literature had some common features in the context of community-based health worker programmes. They employed the Data Envelopment Analysis technique to evaluate the efficiency of the health units used as decision-making units. They also employed various quantities of input and output variables, while evaluating the technical efficiency and productivity changes of the health units under analysis. In addition, most of the reviewed studies evaluated only the technical efficiency of the health units of the community-based health worker programmes. Furthermore, most of the reviewed literature attempted to examine the determinant factors affecting the inter-regional variations in child mortality, which were based on the magnitude of child mortality that the regions had, instead of examining the relative individual contribution of the factors affecting the regional variations in child mortality.

However, very few studies included in this literature review concurrently evaluated the technical efficiency of the health units, and examined the determinant factors affecting technical efficiency variations among health units using a two-stage Data Envelopment Analysis technique as a subsequent of the efficiency evaluation. Moreover, very few studies attempted to evaluate the productivity changes of the health units over time using the DEA-based Malmquist productivity index.

The findings of most of the reviewed studies confirmed the existence of substantial differentials in infant, child, or/and under-five child mortality within the studied countries. Accordingly, the regional differentials in child mortality were explained largely due to the differences in households' economic status, GDP per capita, life expectancy rate, parental level of education, households' poverty status, mother's exposure to mass media, place of birth delivery, the child's birth order, birth spacing, child's birth size, use of modern contraceptives, households' travel distance to health facilities, and antenatal healthcare service visits, among others. Furthermore, the chapter also reviewed the literature on the technical efficiency and productivity changes of the health units of the community-based health worker programmes. The evaluation of technical efficiency and productivity changes of the community-based health worker programmes were using health units, health posts, health centres or health facilities (institutions) as decision-making units. The technical efficiency and productivity changes of the health units were computed using multiple inputs and multiple outputs variables[8]. The findings of the studies indicated that the technical and

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[8] The input variables employed by the literature are the number of health extension workers, the number of doctor hours, personnel costs, the number of staff members, costs for recurrent consumables and supplies, number of administrative staff, number of public health officer, number of health education sessions, and the number of outpatients, among other. The output variables are the number of outpatient visits, family planning users, number of deliveries at health facilities, antenatal healthcare visits, and the number of under-five children fully immunised, among others.

scale efficiency estimates varied significantly among the health units of the community-based health worker programmes. In addition, the overall small average productivity change estimates varied substantially among the health units and over the time period. Furthermore, some of the reviewed studies also concurrently examined the factors that affected the disparities in the technical efficiency estimates among the health units as their subsequent studies. Among the factors, inadequate medical supplies to the health facilities, inadequate supportive supervision given to the community-based health workers, education level of the community-based health workers, community-based health workers' high workload, the number of the community-based health workers per a given population, households' poverty status, the intensity of training given to the community-based health workers, and absence of incentives were the major determinant factors affecting the variations in technical efficiency or performance of the health units of the community-based health worker programmes, or the community health workers.

Although this review was carefully specified, it was not free from limitations.

- First, although an extensive electronic database search was carried out, restricting the review to studies published in the English language would have reduced some of the potential literature, which is published in other languages.
- Second, the limited scope of the geographical coverage of some of the reviewed studies could have reduced their possibility of being nationally representatives. For example, most of the reviewed literature on determinants of regional variations in infant, child, and under-five child mortality rates were made by grouping the provinces, states, districts, or localities into a geographical setting or by formulating mortality-level regions based on child mortality rates instead of examining the sources of variations among the provinces, states, districts, or localities within the countries of study. In addition, most of the reviewed literature evaluated the technical efficiency of the community-based health worker programmes at a district, zone, provincial or micro-regional level, and, as a result, the findings of these studies might not be nationally representative and reflect the real impact of the community-based health worker programmes in their respective countries.
- Third, some of the reviewed literature has methodological limitations employed descriptive statistics to evaluate the efficiency of the decision-making units and to

examine the determinant factors affecting the regional disparities in infant and/ or under-five child mortality.

In summary, the reviewed literature revealed that there were significant regional or provincial, or inter-state disparities in infant, child, and/ or under-five child mortalities within the studied countries. The review further indicated that the community-based health worker programmes contributed significantly to improving health outcomes of the population, although most of them were limited in their scope. Moreover, the magnitude of the estimated technical efficiency and productivity growth varied significantly among the decision-making units and over time. In addition, some of the reviewed studies examined concurrently the determinant factors affecting the disparities in technical efficiency estimates among the decision-making units.

However, none of the reviewed literature examined the determinant factors affecting inter-regional differentials in under-five child mortality, evaluated the efficiency and productivity changes of the Ethiopian rural health extension programme, as well as examined the graduation determinants of the health extension programme beneficiary households in rural areas of Ethiopia at the national level. As indicated in the reviewed literature, most of the studies on determinant factors affecting inter-regional differentials in child mortality as well as technical efficiency and productivity changes measurement studies on the community-based health worker programmes were done outside of Ethiopia where this study was carried out.

The aim of this study, therefore, is to fill in and address these important research gaps by using appropriate inferential statistics measures, which are described in the following Chapter Four. Most importantly, several factors were drawn from the reviewed literature and included in the subsequent analysis of this study.

CHAPTER FOUR

STATISTICAL METHODS AND DATA SOURCES

4.1. Introduction

This chapter presented the data sources, theories, and the description of the statistical methods employed in this study to address the stated specific research objectives set out in Chapter One of this thesis. Each statistical method employed in conducting this study is discussed along with the rationale behind its choice. Based on the findings, insightful policy recommendations can be made to improve the overall health status of the rural societies in Ethiopia and thus, enhance their overall productivity status.

This chapter is divided into seven sections. 4.1 is the introduction. 4.2 describes the data sources used in this study. This is followed by a presentation of the sample design and sample sizes in section 4.3. Section 4.4 provides a description of variables employed, followed by statistical data analysis in section4.5. Section 4.6 presents the different statistical methods (approaches) employed in the study along with their model specifications that address the specific research objective as stated in Chapter One of this thesis. Finally, section 4.7 concludes the chapter.

4.2. Data sources

This study employs cross-sectional secondary data of birth's records obtained from the most recent round of the Ethiopian Demographic and Health Survey (EDHS, 2016) to examine the determinant factors affecting the inter-regional differentials in child mortality in rural Ethiopia. To estimate the efficiency and productivity growth of the Ethiopian health extension programme using health posts as Decision-Making Units (DMUs), this study also uses cross-sectional secondary data for the years 2013 and 2014 obtained from the regional health bureaus under the stewardship of the Federal Ministry of Health, Ethiopia. Furthermore, to examine the major determinant factors influencing the community-based health extension programme beneficiary households' graduation, this study also employs cross-sectional secondary data for the year 2014 obtained from the regional health bureaus under the stewardship of the Federal Ministry of Health, Ethiopia.

4.3. Sample design and sample sizes

Using EDHS (2016), the inter-regional differentials in under-five child mortality were examined. The analysis was based on 4,919 proportions of sample households from the nine administrative regions of rural Ethiopia. This dataset allows the author to examine the inter-regional differentials in under-five child mortality in rural settings of Ethiopia. The EDHS is a large-scale demographic and health survey carried out in nationally representative sample households throughout the country. The survey was conducted by the Central Statistics Agency (CSA) under the stewardship of the Federal Ministry of Health (FMoH), Ethiopia. The EDHS dataset incorporates information from a variety of sources for all regions in Ethiopia. The survey consisted of a questionnaire that was given as an important instrumental tool on households and on women to obtain comprehensive information on women and child health, birth histories, nutrition, and other related information.

The Ethiopian demographic and health survey employed a stratified two-stage cluster sampling technique to select the nationally representative sample households using quantitative and qualitative techniques of data collection. In the first-stage, a total of 645 enumeration areas (clusters) were selected of which 443 clusters were rural areas and 202 clusters urban areas. In the second-stage, based on a fixed sample take of 28 households per cluster, 16,650 sample households were identified and selected for interview from each cluster using a proportional probability sampling procedure. The sample consisted of 16,650 complete interviews with a national representative of women aged 15 to 49 years and who had had at least one live birth. Of these, 11,418 were in rural areas and 5,232 in urban areas. There were 14,195 complete interviews with men aged 15 to 49 years, of whom 9,723 were in rural areas and 4,472 in urban areas[9]. Thus, a total of 4,919 under-five child deaths were recorded in the sample households from each cluster, of which 4,200 and 719 were respectively from the rural and urban areas of the country.

However, the analysis presented in the present study was limited to deaths of 4,200 rural children below five years of age, of whom 57.17 percent (2,401) were male, while the remaining 42.83 percent (1,799) were female. In addition, a total of 4,139 rural sample households were also considered for further analysis from all regions of Ethiopia. Of these, 77.36 percent (3,202) were male-headed households, while 22.64 percent (937) were female-headed households. The participants' ages ranged from between 15 to 49 years. The reduction in the sample size was due to incomplete information in the surveyed households,

[9] The detailed description of the survey employed as secondary sources of data in this study such as the sampling procedure, data collection tools, sample design, and others are available in the report of the central statistical agency (CSA and ICF International, 2016) and the regional health bureaus of the Federal Ministry of Health, Ethiopia (RHB, 2013/14).

as well as the fact that urban sample households were excluded from the statistical analysis as this study focused only on the rural areas.

Furthermore, the study also employed secondary cross-sectional data obtained from the regional health bureaus for the years 2013 and 2014 to evaluate the technical efficiency and productivity changes of health posts using as decision-making units for the Ethiopian health extension programme in rural settings of Ethiopia. The survey employed a multistage sampling procedure technique. In the first stage, the regions were covered by the study survey. In the second stage, all zones of the respective regions were purposely selected in the survey. In the third stage, three districts from each selected zone of the regions were randomly selected using a systematic sampling technique. In the fourth stage, five villages from each selected district were also randomly selected based on a systematic sampling technique, and finally, data was collected from each health post of each village both for input and output variables. Data for input and output variables were obtained for a total of 2,000 sample health posts at the national level.

However, health posts with missing or incomplete information for the input and output variables for both the years 2013 and 2014 were excluded before executing the analysis, thereby reducing the sample size to a total of 1,552 health posts (Tigrai, n=161; Amhara, n=321; Oromia, n=601); SNNP, n=266; Gambella, n=52; Benshangul-Gumuz, n=129; and Harari, n=22). Note that, n represents the proportional subsample size of the health posts for their respective regions. Similarly, following the same sampling procedure techniques as explained earlier, a total sample of 4,244 rural households was systematically selected from their respective villages (*kebelles*) to examine the factors affecting the Ethiopian community-based health extension programme beneficiary households' graduation. Of these 52.63 percent (2,181) were the health extension programme beneficiary graduate households (HEP graduates) while, the remaining 47.37 percent (2,063) were the non-graduates, but were eligible for the health extension programme. Households with missing data were dropped, reducing the sample size to 3,197. Of these, the sample size for the health extension programme beneficiary households became 1,974 (61.75 percent) while that of the non-graduates was 1,223 (38.25 percent).

4.4. Description of variables

The dependent and independent variables employed in this study were contained in the 2011 Ethiopian Demographic and Health Survey (EDHS, 2016), as well as in the 2013 and 2014 regional health bureaus datasets (RHB, 2013/14). The inclusion of these variables was partly guided by the review of previous studies, the availability of comprehensive data, and objectives of the Ethiopian health extension programme.

4.4.1. Dependent variables

In the present study, the key parameter of outcome variable of interest is the under-five child mortality. The under-five child mortality rate is an important health indicator commonly used to measure the progress of the fourth Millennium Development Goal (MDG-IV: reducing under-five child mortality by two-thirds between 1990 and 2015). Thus, the present study employed the number of deaths of rural under-five children as the dependent variable to examine the factors that affected the inter-regional differentials in under-five child mortality rate, which is the first specific research objective of this study. Thus, the analysis of this study was restricted to a sample of rural children whose age ranged from 0-59 months. Furthermore, as outcome of variable of interest, the study also employed the technical efficiency estimates as the dependent variable to identify factors that influenced technical efficiency estimates variations among health posts. Moreover, the present study also used as the dependent variable a dummy variable that indicates whether the household was a health extension programme beneficiary graduate or not (the health extension programme graduates versus the non-graduates) to examine the major determinant factors which influenced the community-based health extension programme beneficiary households' graduation, which is the third specific research objective of this study.

4.4.2. Independent variables (covariates)

i) The covariates included in the regression analysis to explain the inter-regional differentials in under-five child mortality

To examine the inter-regional differentials in the under-five child mortality rate, the independent variables (covariates) employed were proximate, socio-economic, and environmental factors as presented and described in Appendix B, Table B-1. A number of previous studies highlighted the importance of various determinants (proximate, socio-economic, demographic, and environmental factors) in explaining infant and under-five child mortality differentials across various countries (Akuma, 2013; Caldwell, 1979; CSA & ICF International, 2012; CSA & Macro, 2006; Dev et al., 2016; Gupta, 1997; Hong et al., 2009; Khadka et al., 2015; Mosley & Chen, 1984; Negera et al., 2013; Regassa, 2012; Trussell & Hammerslough, 1983, among others). Thus, the selection of these covariates employed in this study was partly guided by the reviewed literature, partly by the theoretical foundation established from the reviewed literature, the impact of these variables on child mortality, partly by the availability of comprehensive data, and objectives of the Ethiopian health extension programme. Empirically, these selected independent variables are those known to explain the child mortality differentials as established in the reviewed literature. As presented in the integrated conceptual framework in Chapter Three of this thesis, the variables employed in the present study along with their descriptions are presented in Appendix B, Table B-1 to Table B-4.

The analytical framework suggested by Mosley and Chen (1984) to examine factors affecting child mortality in less developed countries was also considered in selecting the independent variables. In this study, as indicated in the integrated conceptual framework, the covariates or independent variables are grouped into three distinct classifications (the detailed summarised descriptions of these variables are reported in Appendix B, Table B-1):

a) Proximate factors include factors such as the child's age, the gender of the child, the child's birth order, a multiplicity of birth, birth size, birth spacing, and mother's age at the first birth[10].
b) Socio-economic factors include mother's use of contraceptives, antenatal visits, mother's present working status, parental (mothers and fathers) education level, gender of the households, and age of the household head, household size, antenatal healthcare services (ANC), mother's present working status, and household wealth index as a proxy measure for the household's economic status.
c) Environmental factors include factors such as access to toilet facilities, access to electricity, place of child delivery, access to safe drinking water, and household's region of residence.

ii) The input and output variables employed to evaluate the efficiency and productivity changes of the health posts

In healthcare efficiency studies, the selection of input and output variables for a healthcare service provider institution is done using mainly the production approach (Akazili et al., 2008a; Herna´ndez & San Sebastia´n, 2014; Kathuria & Sankar, 2005; San Sebastián & Lemma, 2010; Renner et al., 2005b). To measure the efficiency of the health posts using

[10] At birth, when a child size is 2500gram, the child is considered to have an average birth size while a child weighing less than 2500gram is considered to have low birth size. Similarly, when a child weighs more than average at birth size, the child is considered to have more than average birth size (Albrecht et al., 1996). Based on the recall of the sample respondents, child size at birth was used in our analyses as a proxy for birth weight since there was no detailed information on birth weight.

either a parametric or non-parametric technique, it is important to consider the three types of variables. These are the input variables, output variables, and the non-health system determinants (contextual variables) (Evans et al., 2001; Kathuria & Sankar, 2005; WHO, 2000). According to Manuel et al. (2013), the input and output variables included in the first-stage DEA analysis have to be standardised (adjusted) by the total rural population or inhabitants covered by the health extension programme (health post per 5,000 inhabitants). The importance of adjusting the input and output variables is to alleviate the potential distortions caused by the presence of considerable differences in the size of the health posts (Manuel et al., 2013).

The selection of input variables being employed and output variables being produced is a crucial step for the successful employment of Data Envelopment Analysis technique (De et al., 2012; Dutta et al., 2014). Thus, selection of input and output variables to measure the technical efficiency and productivity changes or growth of the Ethiopian health extension programme using health posts as decision-making units was guided partly by previous DEA healthcare efficiency studies (Akazili et al., 2008b; Herna´ndez & San Sebastia´n, 2014; Kathuria & Sankar, 2005; San Sebastián & Lemma, 2010; Renner et al., 2005, among others), availability of comprehensive data, and the objectives of the Ethiopian health extension programme. Therefore, this study evaluated the technical efficiency and productivity changes, or growth, of the sample health posts using two input variables and six output variables. It is crucial to elaborate the input and output variables employed in the efficiency estimation analysis using DEA technique because these variables could significantly affect the credibility and validity of the efficiency estimation analysis. Thus, a brief description of the input and output variables employed in the efficiency estimation is presented in Table B-2 of Appendix B. Furthermore, the non-health system determinants as independent variables were also employed to examine the determinant factors affecting the variations in technical efficiency estimates among the sample health posts. The outline of these independent variables, which are the determinant factors affecting the variations in the technical efficiency estimates among the health posts in the subsequent second-stage regressions analysis is presented in Appendix B, Table B-3.

iii) Variables employed in the empirical analysis of the determinants of health extension programme beneficiary households' graduation

The inclusion of the independent variables that could potentially explain the graduation determinants of health extension programme beneficiary households was partly guided by the reviewed literature (Bazezew, 2012; Cheng et al., 2015; DeAngelo et al., 2011; Gebresilassie, 2013; Giovagnoli, 2005; Hailu & Seyoum, 2015; Murray, 2014; Silver et al., 2008; and Yitayal et al., 2014), objectives of the health extension programme, and availability of comprehensive data. The summary description of these variables employed in the regression analysis can be found in Table B-4 of Appendix B.

4.5. Statistical data analysis

Both descriptive and inferential analysis techniques were applied to statistically analyse the obtained cross-sectional secondary data. Thus, the efficiency and productivity changes estimation analysis using the DEA technique and DEA-based Malmquist productivity index were computed by computer statistical software packages, which are known as the MaxDEA pro version 6.4 and DEAP version 2.1. These are the most commonly used type of efficiency and Malmquist productivity indices analysis software analysis packages (Coelli, 1998; Coelli, 1996). All data management and statistical analyses were computed using Stata statistical software package version 14. The study was adopting the user-written mvdcmp Stata command on nonlinear regression-based detailed decomposition technique of average outcome differentials proposed by Powers et al. (2011). In addition, different Stata commands were also applied to statistically compute the obtained data.

4.6. Model specifications

4.6.1. The Oaxaca-Blinder decomposition technique: The determinant factors affecting the inter-regional differentials in under-five child mortality

To identify the determinant factors that affect the inter-regional differentials in under-five child mortality, the statistical analysis that this study employed was based on three complementary estimation stages described as follows:

Stage I: Life-Table estimation technique

Following O'Donnell et al. (2008), the author computed the under-five child mortality rates using the “Life-Table” estimation technique produced using the user-written “ltable” Stata command. It primarily computed the probability of the cumulative survival function (S_p) at a given age interval while the corresponding probability of dying (D_p) was computed from the estimated probability of survival function. Thus, the probability of a child dying under the age of five in each region was computed by D_p= 1-S_p, expressed as deaths per thousand births (O'Donnell et al., 2008) (see Appendix C, Table C-1).

Stage II: A count data regression model

Since the response outcome variable is a count data variable (the number of under-five child deaths per thousand births), a count data model was applied to assess the factors that affected the deaths of under-five children across regions of Ethiopia. There are two basic count data models, and these are the Poisson and negative binomial regression models. When it comes to modelling count data variables, we usually begin with the Poisson regression model. Poisson regression is a generalised linear model where a response outcome variable takes non-negative integer values and is assumed to have a Poisson distribution conditional on an aggregated weighted the independent variables (Cameron & Trivedi, 1998; 1999).

a. Poisson regression model (PRM)

This assumes i number of deaths of under-five children per h individual household in $\dot{r}$ region ($\dot{r}$ =1,.,.,R) as dependent variable (U5MR$^{r}_{ih}$), conditional on the set of independent (explanatory or covariate) variables (X_{jr}) is with density function U5MR$^{r}_{ih}$~ Poisson (μ$_{ir}$) (Cameron & Trivedi, 1998; Cameron & Trivedi, 1999; Park & Lohr, 2010).

The Poisson regression model is given by:

$$\boldsymbol{Pr}(\boldsymbol{U5MR} = \boldsymbol{U5MR^{r}_{ih}}|\boldsymbol{x_{ir}}) = \frac{\boldsymbol{exp^{-\mu ir}\mu ig^{U5MR^{r}_{ih}}}}{\boldsymbol{U5MR^{r}_{ih}!}},\ \boldsymbol{U5MR^{r}_{ih}} = 0, 1,.,.,. N, \quad [4.1]$$

Where:

- $exp^{()}$ is the exponential function;
- x_{jr} are vector of explanatory variables;
- E (U5MR$^{r}_{ih}$ = U5MR$^{r}_{ih}|x_{ir}$) = μ$_{ir}$ measures the expected mean value of the count variable (U5MR$^{r}_{ih}$) or the conditional mean of the Poisson distribution.

Thus, the conditional mean is expressed as follows:

$$\mu_{\boldsymbol{ir}} = E\left(\boldsymbol{U5MR^{r}_{ih}}|\boldsymbol{x_{jr}}\right) = \boldsymbol{exp}^{(x_{jr}\beta_{jr})} \quad [4.2]$$

The dispersion parameter (μ$_{ir}$) is also the conditional variance value of a Poisson distribution and is equal to the conditional mean of the outcome variable (U5MR$^{r}_{ih}$), which is known as equi-dispersion (Cameron & Trivedi, 1998; O'Donnell et al., 2008).

Therefore, the conditional variance is given by:

$$Var(\boldsymbol{U5MR^{r}_{ih}}|\boldsymbol{x_{jr}}) = \mu_{\boldsymbol{ir}} = E\left(\boldsymbol{U5MR^{r}_{ih}}|\boldsymbol{x_{jr}}\right) \quad [4.3]$$

The sample counterpart (Sc) of the conditional mean ($E_{\beta^{P}_{jr}}$(U5MR$^{r}_{ih}$)) of the Poisson regression model (P) is expressed as:

$$\boldsymbol{Sc}(\hat{\beta}^{P}_{jr}, \boldsymbol{X_{jr}}) = \boldsymbol{U5MR}_{r,\hat{\beta}^{P}_{jr}} = \boldsymbol{N_r^{-1}} \sum_{j=1}^{N_r} \boldsymbol{exp}(\boldsymbol{X_{jr}}\hat{\beta}^{P}_{jr}) \quad [4.4]$$

The mean of $\mathrm{U5MR}_{r,\hat{\beta}^{P}_{jr}}$ should be a non-negative integer-values, however $X_{jr}\hat{\beta}^{P}_{jr}$ can assume any values which might result in negative values of the mean ($E\left(\mathrm{U5MR}^{r}_{ih}\middle|x_{jr}\right) = \mu_{ir}$). To avoid the negative mean values, the mean must be logarithmically transformed ($\eta_{ir} = \log(\mu_{ir})$) and this transformed mean should follow a linear function model ($\eta_{ir} = x'_{jr}\beta_{jr}$) (Cameron & Trivedi, 1998).

Taking the two necessary conditions into account, the log-linear model of the mean (μ_{ir}) can be rewritten as follows:

$$\boldsymbol{log}(\mu_{ir}) = \boldsymbol{x'_{jr}}\beta_{jr} = (\boldsymbol{X_{jr}})\,\beta_{jr} \quad [4.5]$$

Test of dispersion

The basis for testing for dispersion in the Poisson regression model is to determine the distribution of the relationship between the expected mean and conditional variance. The existence of over-dispersion or under-dispersion demonstrates that the Poisson regression model is an inappropriate model fit. Thus, in this study, following Hosmer et al. (1997); Hosmer and Lemesbow (1980) to determine the goodness-of-fit of the Poisson regression model, the Hosmer-Lemeshow's Chi-squared (χ^2_{HL}) goodness-of-fit test statistic was computed as:

$$\chi^2_{HL} = \sum_{j=1}^{g} \frac{\left(\sum_j y_{ij} - \sum_j \hat{\pi}_{ij}\right)^2}{\left(\sum_j \hat{\pi}_{ij}\right)\left[1 - \left(\sum_j \hat{\pi}_{ij}\right)/n_i\right]} \quad [4.6]$$

Where:

- y_{ij} is the dichotomous outcome variable of the i^{th}observation in the j^{th} subgroup,
- $\hat{\pi}_{ij}$ the expected probability of the i^{th}observation in the j^{th} subgroup,
- $n_i$is the number of sample observations in the j^{th} subgroup, g is the number of groups (g=10 in the present context), and $\chi^2_{HL}$is the estimate of Chi-squared with g-2 degrees of freedom.

A statistically significant Chi-squared test statistic indicates the model is not correctly specified, while a statistically nonsignificant test indicates the opposite.

A value of χ^2_{HL} greater than unity indicates the presence of over-dispersion (the expected mean is greater than the conditional variance). Whereas a value of χ^2_{HL} equal to unity signifies that the conditional mean and variance are equal.

Therefore, the presence of an over-dispersion indicates the Poisson regression model is not an adequate fit mode and is inappropriate for use as a statistical analysis technique in this study. The test of over-dispersion (dispersion parameter test) or the likelihood ratio tests for alpha (p-value < .05) at the national level as well as for each region were significantly greater than zero indicating that the conditional variance of the count outcome variable exceeds the expected or conditional mean (Var($\mathrm{U5MR}^r_{ih}|x_{jr}$) > μ_{ir}) (see Appendix C, Table C-2). When the conditional variance exceeds that of the expected mean of a count outcome variable, a Poisson distribution is known as over-dispersion, and a reasonable alternative is to use the negative binomial regression model to model the over-dispersed count data (number deaths of und of under-five children) (Cameron & Trivedi, 1999; Park & Lohr, 2010). Therefore, the regression analysis was instead based upon the negative binomial regression model.

b. Negative binomial regression model (NBR)

The Poisson regression model accounts for observed heterogeneity among the sample members by specifying the rate $\mu_i$as a function of the observed $x_i's$. The Poisson regression model could underestimate the amount of dispersion in the outcome variable of interest due to the presence of over-dispersion. Accordingly, the negative binomial model could alternatively address this problem by adding a dispersion parameter (α) that represents the extent of over-dispersion. The negative binomial and Poisson regression models have the same conditional mean, Var($\mathrm{U5MR}^r_{ih}|x_{jr}$) = μ_{ir} = E $\left(\mathrm{U5MR}^r_{ih}|x_{jr}\right)$ (Cameron & Trivedi, 1998; 1999) however, unlike with the Poisson regression model, the negative binomial regression model follows a two-parameter distribution (i.e. μ and α) and the conditional variance exceeds the conditional mean.

The conditional variance for negative binomial regression model is formulated as:

$$Var(\boldsymbol{U5MR}^r_{ih}|\boldsymbol{\mu}_{ir}, \boldsymbol{\alpha}) = \mu\,(\mathbf{1} + \mu\boldsymbol{\alpha}) \qquad [4.7]$$

In negative binomial regression model, the Var($\mathrm{U5MR}^r_{ih}|\mu_{ir}, \alpha$) = $\mu\,(1 + \mu\alpha)$ > $E(\mathrm{U5MR}^r_{ih}|x_{jr}) = \mu$, $\alpha > 0$

Thus, the fundamental negative binomial regression model for i number of deaths of under-five children per h individual household in $\dot{r}$ region ($\dot{r}$ =1,.,.,R), given a set of explanatory variables (X_{jr}), μ is the conditional mean and α is the dispersion parameter where the density function of $\mathrm{U5MR}^r_{ih}$~ binomial (μ_{ir}, α) is expressed as:

$$\boldsymbol{Pr(U5MR = U5MR^r_{ih}|\mu_{ir}, \alpha_i) = \frac{exp^{-\mu ir}\mu ig^{U5MR^r_{ih}}}{U5MR^r_{ih}!}},\ \boldsymbol{U5MR^r_{ih}} = 0, 1,.,.,. N, \qquad [4.8]$$

Thus, following the works of Cameron and Trivedi (1999), the negative binomial regression model for each region was computed by:

$$\boldsymbol{Pr(U5MR = U5MR^r_{ih}|\mu_{ir},\ \alpha_i) = \frac{\Gamma(U5MR^r_{ih} + \alpha^{-1})}{\Gamma(U5MR^r_{ih}+1)\Gamma(\alpha^{-1})}(\frac{\alpha^{-1}}{\alpha^{-1}+\mu})^{\delta^{-1}}(\frac{\mu}{\alpha^{-1}+\mu})^{U5MR^r_{ih}}} \qquad [4.9]$$

Where:

- is the gamma function;
- μ_{ir} is the conditional mean of U5MR$^r_{ih}$ per unit of exposure and;
- α represents the over-dispersion parameter.

The maximum-likelihood estimation technique (MLE) was employed to compute the regression coefficient estimates and their respective standard errors of those estimates computed by negative binomial regression model (Cameron & Trivedi, 1999; Hilbe, 2011; Zwilling, 2013). Hence, the logarithm of the maximum-likelihood estimation technique function is given by:

$$\pounds(\beta) = \sum_{i=1}^{n}\left(\boldsymbol{ln}\left[\Gamma\left(\boldsymbol{U5MR^r_{ih}} + \boldsymbol{\alpha^{-1}}\right)\right] - \boldsymbol{ln}\left[\Gamma\left(\boldsymbol{\alpha^{-1}}\right)\right] - \boldsymbol{ln}\left[\Gamma\left(\boldsymbol{U5MR^r_{ih}} + \boldsymbol{1}\right)\right]\right) - \boldsymbol{\alpha^{-1}}\,\mathbf{ln}(\mathbf{1} + \boldsymbol{\alpha\mu_{ir}}) - \boldsymbol{U5MR^r_{ih}}\,\mathbf{ln}(\mathbf{1} + \boldsymbol{\alpha\mu_{ir}}) + \boldsymbol{U5MR^r_{ih}}\,\boldsymbol{ln}(\boldsymbol{\alpha}) + \boldsymbol{U5MR^r_{ih}}\boldsymbol{ln}(\boldsymbol{\mu_{ir}})] \qquad [4.10]$$

Thus, besides the overall estimation at the national level, a separate negative binomial regression estimation was performed for each region under analysis to assess the relationship between potentially associated observable determinant factors represented by x_{jr} vector of explanatory variables, and the outcome variable of interest for the present study (number of deaths of under-five children) (see the coefficient estimates in Appendix C, Table C-3).

Stage III: The decomposition of the outcome variable of interest differentials after the negative binomial regression

Based on the computed estimates obtained from the negative binomial regression model, the author applied an extension of Oaxaca-Blinder (O-B) decomposition to the negative regression (count data) model to identify and quantify the major determinant factors affecting the inter-regional differentials in under-five child mortality. The regional differences can arise from variations in the distribution of the observable determinants of the under-five child mortality (characteristic effects) and their effects (coefficient effects) (Bauer & Sinning, 2008; Park & Lohr, 2010; Yun, 2004).

Since the outcome variable of interest for this study is given by a count data variable, (deaths of under-five children=0, 1, 3,. ,. ,. N), application of linear regression models-based O-B decomposition may not be an appropriate technique of decomposition analysis (Bauer et al., 2006). This, therefore, warrants the use of an extended nonlinear decomposition technique to count data modelling approach (Bauer & Sinning, 2008; Park & Lohr, 2010; Yun, 2004). The differences in the average deaths of under-five children for any two regions can be explained by a set of explanatory variables (O'Donnell et al., 2008). They consist of two components, namely:

i) the explained component which is the part of the outcome measure differential due to differences in the magnitude of observable determinants (covariates) across the two regions or groups (characteristics or covariates effect), labelled as EC) and
ii) the unexplained component which is the part of the outcome measure differences due to effects of these determinants or due to differences in estimated effects of these determinants across the two regions (coefficients effect) based on a regression model, labelled as UC) (Blinder, 1973; Fairlie, 2005; Oaxaca, 1973; Powers et al., 2011; Sen, 2014; Wagstaff et al., 2007)[11].

Suppose there are N number of deaths of under-five children ($\mathrm{U5MR}_{ih}^{r}$) (indexed, i = 1., ,., N_r) belonging to $\dot{h}$ household (h=1,. ,. ,. H) in R mutually exclusive and collectively exhaustive regions, $\dot{r}$ = 1,.,.,R, each region containing $N_{\dot{r}}$, X_{jr} is a vector of j observable explanatory variables (as described above), α_{jr} represents a vector of regression parameters to be estimated, and ε_{jr} denotes the error term.

For any linear regression model of healthcare services organisation like the Ethiopian health extension programme that is computed separately for the groups (Tigrai=TG and Harari=HR regions in this case denoted by r) and r = TG, HR, it is given by (Bauer et al., 2006):

[11] The detailed decomposition of the unexplained component both in linear and non-linear models don't have a simple meaningful interpretation for the included explanatory variables (coefficients effect) (Fortin et al., 2011; Jann, 2008).

$$\boldsymbol{U5MR_{ih}^{r}} = \begin{cases} \boldsymbol{X_{jTG}\alpha_{jTG} + \varepsilon_{jTG} \; if\ the\ child\ belongs\ to\ the\ Tigrai\ region\ (TG)} \\ \boldsymbol{X_{jHR}\alpha_{jHR} + \varepsilon_{jHR} \; f\ the\ child\ belongs\ to\ the\ Harari\ region\ (HR)} \end{cases} \quad [\mathbf{4.11}]$$

Accordingly, Blinder (1973) and Oaxaca (1973) developed the O-B decomposition for the difference in the under-five child mortality rate mean between two region samples as a linear additive regression model, specified as follows:

$$\boldsymbol{\widehat{U5MR}_{ih}^{(r=TG)} - \widehat{U5MR}_{ih}^{(r=HR)} = (\hat{X}_{TG} - \hat{X}_{HR})\hat{\alpha}_{TG} + \hat{X}_{HR}(\hat{\alpha}_{TG} - \hat{\alpha}_{HR})} \quad [4.12]$$

Where:

- $\widehat{U5MR}_{ih}^{(r=TG)} = N_r^{-1}\sum_{i=1}^{N_r} \mathrm{U5MR}_{ih}^{TG}$ and,
- $\widehat{X_{iTG}} = N_r^{-1}\sum_{i=1}^{N_r} X_{iTG}$

The application of a linear additive regression model might yield biased regression estimates (α_{jr}) because the outcome variable of interest ($\mathrm{U5MR}_{ih}^{r}$) is a count data, and thus, misleading the estimates of an extended Oaxaca-Blinder decomposition (Bauer et al., 2006). Thus, employing a negative binomial regression model for such a count data variable can be warranted to develop extension Oaxaca-Blinder decomposition for a count data model (Bauer et al., 2006). Therefore, following the works of Blinder (1973) and Oaxaca (1973), the author applied an extension of the Oaxaca-Blinder decomposition technique to a negative binomial regression model to identify and quantified the relative contribution of each explanatory variable (covariate) in explaining the under-five child mortality differentials between the two regions. The Oaxaca-Blinder decomposition aims at explaining the distribution of the outcome variable in question ($\mathrm{U5MR}_{ih}^{r}$) by a set of explanatory variables (O'Donnell et al., 2008; Oaxaca, 1973). It decomposes into characteristics or covariates and coefficients effects both at an aggregate and individual variable level to identify and quantify the relative contribution of each specific characteristic (Kaiser, 2013; Powers & Pullum, 2006; Powers et al., 2011; Wagstaff et al., 2007). In this study, this indicates how the inter-regional differentials in $\mathrm{U5MR}_{ih}^{r}$ can be explained by the separate contribution of the decomposed covariates.

Thus, based on the average values of the $\widehat{U5MR}_{ih}^{(r)}$ obtained from the negative binomial regression model, the Oaxaca-Blinder decomposition of the average outcomes values in under-five child mortality between the two regions, continuing with TG as reference category and HR as comparison regions for example, the estimation of the components of equation [4.12] can be computed as follows:

$$\hat{\Delta}_{NBR}^{TG,HR} = ln(U5MR_{ih}^{r=TG}) - \ln(U5MR_{ih}^{r=HR}) = \left[E\left(\hat{\alpha}_{jTG}^{NBR}, X_{jTG}\right) - E\left(\hat{\alpha}_{jTG}^{NBR}, X_{jHR}\right)\right] + \left[E\left(\hat{\alpha}_{jTG}^{NBR}, X_{jHR}\right) - E(\hat{\alpha}_{jHR}^{NBR}, X_{jHR})\right] \quad [4.13]$$

The conditional expectation $E\left(U5MR_{ih}^{r}|X_{jr}\right)$ of $U5MR_{ih}^{r}$ for nonlinear regression models evaluated at the parameter vector α_r varies from the linear prediction $\hat{X}_r\alpha_r$ (Bauer & Sinning, 2008). Thus, following the works of Bauer et al. (2006); Hirvonen (2016); Kaiser (2016); Park and Lohr (2010); Yun (2004); and Sinning et al. (2008) to accommodate nonlinear models the O-B decomposition for linear model equation [4.13] was alternatively expressed as:

$$\hat{\Delta}_{NBR}^{TG,HR} = ln(U5MR_{ih}^{r=TG}) - ln(U5MR_{ih}^{r=HR}) = \left[E_{\hat{\alpha}_{jTG}^{NBR}}(U5MR_{ih}^{r=TG}|X_{jTG} - E_{\hat{\alpha}_{jTG}^{NBR}}(U5MR_{ih}^{r=HR}|X_{jHR}\right] + \left[E_{\hat{\alpha}_{TG}^{NBR}}(U5MR_{ih}^{r=HR}|X_{jHR} - E_{\hat{\alpha}_{jHR}^{NBR}}(U5MR_{ih}^{r=HR}|X_{jHR}\right] \quad [4.14]$$

Where; the functional form of the negative binomial regression model was estimated at average values of the included explanatory variables.

i. An extension of detailed O-B decomposition to the NBR model

To examine the relative contribution of individual explanatory variables (covariates) to explained and unexplained components of the average differences in $\mathrm{U5MR}_{ih}^{r}$ requires a detailed decomposition analysis, because equation [4.14] computes only the aggregate decomposition (Blinder, 1973; Oaxaca, 1973). Thus, the explained (EC = characteristics or covariates effect) and unexplained (UC = coefficients effect) components gaps should further be decomposed into components, E_j and C_j (j = 1,.,.,J) that represent the contribution of individual explanatory variables to EC and UC, respectively (Jann, 2008; Kaiser, 2016; Powers & Yun, 2009). The very important point in Oaxaca-Blinder decomposition analysis is to estimate the relative contribution of individual explanatory variables to the overall disparities in the mean outcome variable of interest. This is achieved by performing a detailed Oaxaca-Blinder decomposition analysis to the nonlinear regression model (Kaiser, 2013, 2016; Powers et al., 2011). The detailed Oaxaca-Blinder decomposition analysis decomposed the explained and unexplained components gap as well as the relative individual contribution of the explanatory variable to the overall differentials in $\mathrm{U5MR}_{ih}^{r}$ across regions (Kaiser, 2016; Park & Lohr, 2010).

To quantify and identify the separate contribution of each explanatory variable to the inter-regional differentials in the under-five child mortality, let us consider Tigrai (superscript TG, used as a reference category) and Harari (superscript HR, considered as a comparison category) regions[12,13]. Therefore, following the works of Bauer and Sinning (2008); Park and Lohr (2010a); Powers et al. (2011); Yun (2004), the inter-regional differential in under-five child mortality between these two regions using average weights of a detailed Oaxaca-Blinder decomposition technique for each of the j covariates for each component (EC and UC) can be decomposed as:

$$ln(U5MR_{ih}^{r=TG}) - ln(U5MR_{ih}^{r=HR}) = \sum_{j=1}^{J} W_{\Delta X}^{j} \left[f\left(\hat{X}_{jh}^{TG}, \hat{\alpha}_{jh}^{TG}\right) - f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{jh}^{TG}\right)\right] + \boldsymbol{\sum_{j=1}^{J} W_{\Delta\alpha}^{J} \left[f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{ih}^{TG}\right) - f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{jh}^{HR}\right)\right]} \quad [4.15]$$

EC $= \sum_{i=1}^{J} W_{\Delta X}^{j} \left[f\left(\hat{X}_{jh}^{TG}, \hat{\alpha}_{jh}^{TG}\right) - f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{jh}^{TG}\right)\right]$ is the first bracketed segment on the right-hand side of equation [4.15] represents the explained component that the mean outcome differences in under-five child mortality due to differences in the observable characteristics across regions (characteristics or covariates effect)[14].

UC $= \sum_{i=1}^{J} W_{\Delta\alpha}^{j} \left[f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{jh}^{TG}\right) - f\left(\hat{X}_{jh}^{HR}, \hat{\alpha}_{jh}^{HR}\right)\right.$ is the second bracketed segment representing the unexplained component that measures the mean outcome differences in

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[12] Using the latest available estimates of the 2011 EDHS, the computed under-five child mortality rates for the Tigrai region were relatively lower with 54 deaths per thousand births compared to other comparison regions under analysis (Afar, Amhara, Oromia, Harari, Gambella, Benshangul-Gumuz, Somali, and SNNP) (see Appendix B, Table B-1).

[13] The same average outcome differentials with altered in sign can be computed from an alternative decomposition analysis by shifting the reference category and comparison regions which is known as the "indexing problem" (Bauer et al., 2007; Oaxaca & Ransom, 1988, 1994). Furthermore, unlike the decomposition for a linear regression model, the result of the detailed O-B decomposition for nonlinear regression models is more sensitive to ordering of explanatory variables in which they are entered into the decomposition analysis could affect estimates of the decomposition which is known as path dependency (Fairlie, 2005; Hirvonen, 2016; Powers et al., 2011). Yun (2004) and Nielsen (1998) proposed a solution to overcome the path dependence and identification by weighting the composition and coefficient components that are proportional to the overall contribution of individual explanatory variables or estimated coefficients components to the total differences in $U5MR_{ih}^{r}$. Thus, the detailed decompositions based on weighting the composition and coefficient components are free from the path dependency problem and the sequence (order) of the explanatory variables entered the decomposition (Nielsen, 1998; Powers & Pullum, 2006; Yun, 2004).

[14] The weights for the j explanatory variables for each EC and UC components gap in the detailed O-B decomposition technique are defined, respectively as follows (Park & Lohr, 2010; Powers et al., 2011; Yun, 2004): $W_{\Delta X}^{j} = \frac{(\hat{X}_{TG_j} - \hat{X}_{HR_j})\alpha_{TG_j}}{\sum_{j=1}^{J} \alpha_{TG_j}(\hat{X}_{TG_j} - \hat{X}_{HR_j})}$; and $W_{\Delta\alpha}^{j} = \frac{(\alpha_{TG_j} - \alpha_{HR_j})\hat{X}_{TG_j}}{\sum_{j=1}^{J} \hat{X}_{TG_j}(\alpha_{TG_j} - \alpha_{HR_j})}$. The estimates of weights ($W_{\Delta X}^{j}$and $W_{\Delta\alpha}^{j}$) are computed based on the estimated coefficients obtained from NBR model at average values of the regressed explanatory variables where the sum of each weight category ($\sum_j W_{\Delta X}^{j}$ and $\sum_j W_{\Delta\alpha}^{j}$) are equal to unity, that is $\sum_j W_{\Delta X}^{j} = \sum_j W_{\Delta\alpha}^{j} = 1$ (Powers & Yun, 2009).

under-five child mortality due to differences in returns of these observable characteristics across regions (coefficients effect).

The contributions of the decomposed variables could sum up to the aggregate characteristics effect, that is, $EC = \Delta^{x} = \sum_{j=1}^{J} w_{\Delta x}^{j} EC$. The separate contribution of the individual explanatory variable to explained and unexplained components, respectively are $EC_{jr} = W_{\Delta X}^{j} EC$ and $UC_{jr} = W_{\Delta\alpha}^{j} UC$. Thus, the covariate weights (characteristics effect) ($EC_{jr} = W_{\Delta X}^{j} EC$) reflect the relative separate contribution of individual covariates to EC as determined by the magnitude and size effect of the regional differential, weighted by the impact of the covariates in the reference region. Whereas, the coefficient weights (coefficients effect) ($UC_{jr} = W_{\Delta\alpha}^{j} UC$) reflect the relative separate contribution of individual covariates to UC as determined by the magnitude and size effect of the regional differential, weighted by average values of the covariates in the comparison region (Powers & Pullum, 2006).

4.6.2. Models for evaluating the efficiency and productivity changes of the health posts used as decision-making units of the health extension programme

Within the broad scope of healthcare services, several institutions applied efficiency estimation techniques. According to Worthington, (2004, pp. 19) “All efficiency estimation assumes that the production frontier of the fully efficient organisation is known. As this is usually not the case, the production frontier must be estimated using sample data”. Thus, although an appropriate target against which efficiency performance of Decision-Making Units (DMUs) (in the present study context, health posts represent the DMUs) being evaluated is chosen, some basic points need to be identified ahead of estimating the efficiency estimates. These are the following: the efficiency estimation technique; specification of the functional form of the efficiency frontier; identifying input and output variables to develop the efficiency frontier; and data measurement (Eunice, 2013; Mester, 2003). The most commonly employed efficiency estimation techniques are categorised into two approaches. The regression-based approaches common in the efficiency measures under the parametric frontier approach include the Stochastic Frontier Analysis (SFA), the Thick Frontier Approach (TFA), and the Distribution-Free Approach (DFA) (Hussey et al., 2009). Under the non-parametric frontier approaches, there are two efficiency estimation techniques under a non-parametric approach, namely the Data Envelopment Analysis and the Free-Disposable Hull Analysis (FDHA) (Jacobs et al., 2006). The Stochastic Frontier

Analysis and Data Envelopment Analysis are the two most commonly employed efficiency estimation techniques, which are known as frontier analysis and they compare health posts' use of actual inputs and outputs to efficient combinations of multiple inputs and outputs (Hussey et al., 2009). The key difference between the SFA and DEA approaches is that the former states a specific functional form for the production function while the latter does not. These two techniques also employ different estimation techniques to compute the ‘‘efficiency frontier’’ of efficient combinations used for comparison (Hussey et al., 2009). The efficiency frontier identifies the boundary to a series of possible observed production levels and the extent to which the health posts lies below or above the efficiency frontier (Cooper et al., 2007; Jacobs et al., 2006) [15]. Thus, the Stochastic Frontier Analysis and the Data Envelopment Analysis approaches are briefly explained below.

A. The Parametric approach: Stochastic Frontier Analysis

The most commonly employed parametric frontier approach, the SFA, is used mainly when there is only one output production technology (single output variable). This approach assumes the mathematical form of the model and data and uses an econometric method to measure the technical efficiency of the health posts. The functional form of the parametric frontier approach is the stochastic production function. Unlike the Data Envelopment Analysis, the Stochastic Frontier Analysis divides the distance to the efficiency frontier into random error and inefficiency. The main advantage of the Stochastic Frontier Analysis is that it considers the error term into its regression function. However, the Stochastic Frontier Analysis is limited, as it demands a prior mathematical functional specification in the production function and the distributional form of the inefficiency term (Jacobs et al., 2006). Unlike the Data Envelopment Analysis technique, the Stochastic Frontier Analysis evaluates the efficiency of the decision-making units or healthcare services providing organisations against some theoretical benchmark (Worthington, 2004).

B. The Non-Parametric approach: Data Envelopment Analysis

The Data Envelopment Analysis is a non-parametric technique of measuring the relative efficiency and productivity of production function based on multiple inputs and outputs produced by the units of analysis commonly known as decision-making units that involve the use of non-parametric mathematical Linear Programming Problem (LPP) (Jacobs et al.,

[15] The efficiency frontier was computed based on the output oriented VRS DEA technique, which the frontier that the health posts should be able to reach it by reducing their inefficiency level. The amount by which a health post lies below the efficiency frontier can be considered as a measure of its inefficiency (Laura, 1998).

2006). The Data Envelopment Analysis technique estimates the efficiency levels of health posts, which are considered as decision-making units in producing outputs using multiple inputs. It is the most commonly employed and an increasingly popular non-parametric frontier approach, which makes use of linear programming techniques to compute the relative efficiency levels of the health posts (Chattopadhyay & Ray, 1996; Laura, 1998; Theodoridis & Psychoudakis, 2008). It adopts the notion of Pareto-efficiency of decision-making units (Siddharthan et al., 2000).

The Data Envelopment Analysis freely provides further information in terms of peers and targets. The technical efficient health posts are called peers, with which a relatively technical inefficient health post is compared (Coelli et al., 1998). These health posts are normally functioning at a similar scale size, which helps us to compare the HP_0 itself to similar health posts that are performing relatively better. The values of the inputs being used, and the outputs being produced are the targets of the health post that it should be able to achieve once it becomes technically efficient (Laura, 1998). Unlike the SFA, the DEA compares the relative technically efficient health posts to other health posts under analysis, but not against a theoretically based benchmark (Worthington, 2004). Since its development in the 1970s, the Data Envelopment Analysis was applied to measure the relative technical efficiency in healthcare sectors. A large number of previous studies that applied the Data Envelopment Analysis model on healthcare sector efficiency measure noted that the Data Envelopment Analysis technique is a valuable and useful statistical package analysis tool (Yu, 2011).

This study, therefore, employed the DEA technique based on the Farrell (1957) applications to evaluate the technical efficiency of the health posts that use similar inputs to yield similar outputs, and to make a comparison with their relative neighbours (Huang & McLaughlin, 1989). The estimated efficiency frontier consists of efficiently performing health posts and is supposed to dominate (envelope) the other health posts that remain below the efficiency frontier and in relative terms are performing inefficiently (Jacobs et al., 2006).

The choice of comparative efficiency analysis techniques is vital, while estimating the relative efficiency because they are essentially different from each other and consequently they produce different estimates (Sarafidis, 2002). There are potential strengths in computing the relative technical efficiency of the health units used as decision-making units using Data Envelopment Analysis technique:

a) The DEA technique is the only technique that computes the relative efficiency in the absence of price information for input and output variables (Ray, 2004);
b) The DEA technique does not make any assumptions in the functional form of how input and output variables are related (Chattopadhyay & Ray, 1996);
c) The DEA technique makes a simple comparison of a particular health post (a relatively efficient one) with other health posts in the system (Coelli et al., 1998);
d) Most importantly, in contrast to the parametric approaches, mainly with the Stochastic Frontier Analysis, the Data Envelopment Analysis technique can simultaneously handle multiple inputs and outputs with each being expressed in different units of measurement (Chattopadhyay & Ray, 1996; Hollingsworth, 2008; Jacobs et al., 2006; Worthington, 2004);
e) The estimated technical efficiency under the Data Envelopment Analysis technique decomposes into the scale and technical efficiency. It further identifies which health posts are operating at constant, increasing or decreasing returns to scale by incorporating the non-increasing returns to scale (NIRS) into the system (Kumar & Gulati, 2008); and
f) The Data Envelopment Analysis technique can provide a numerical measure of the relative technical and scale efficiency of the health posts, and indicates the areas of potential improvements by means of either reduction of inputs or increased outputs or a mix of both (Kumar & Gulati, 2008).

However, the drawbacks of the Data Envelopment Analysis technique are as follows:

a) The Data Envelopment Analysis technique is a deterministic model that does not consider the error term in its functional model (Coelli et al., 1998);
b) The Data Envelopment Analysis considers all deviations from the efficiency frontier to be due to inefficiency (Sarafidis, 2002);
c) The DEA technique presumes all deviations from the efficiency frontier to be the result of inefficiency and cannot isolate the technical efficiency from random noise (Chattopadhyay & Ray, 1996; Worthington, 2004);
d) The efficiency estimates under the DEA are extremely sensitive to the outliers and to measurement error (Coelli et al., 1998; Ramírez-Valdivia et al., 2011); and
e) In the Data Envelopment Analysis technique, biased efficiency estimates can be obtained due to inclusion or exclusion of certain input and output variables (Coelli et al., 1998; Jacobs et al., 2006; Worthington, 2004).

The efficiency of the health posts can be computed either by constant or variable-returns to scale DEA technique. The use of the Data Envelopment Analysis technique in the efficiency measurement studies was explained by looking at its empirical and theoretical considerations (advantages). In general, the efficiency is computed by employing linear programming function that compares similar health posts or units using a set of inputs to produce a set of outputs. The Data Envelopment Analysis identifies how well a health post is operating relative to its peers, not to a theoretical maximum benchmark (Worthington, 2004). The following sub-sections (4.6.2.1 to 4.6.2.4) presented the derivation of the efficiency and productivity estimation technique utilised in this chapter.

4.6.2.1. The CCR DEA efficiency estimation model

A two-stage DEA technique was applied to measure the relative technical efficiency of the health posts in this chapter. In the first-stage, the Data Envelopment Analysis technique estimates the technical efficiency of health posts by computing an efficiency frontier[16]. Then, each health post is given a technical efficiency level by means of a multiple outputs and inputs ratio comparison of a health post on the relative efficient frontier.

Mathematically, the relative technical efficiency of each health post is given by the ratio of the weighted outputs to the weighted inputs (Yu, 2011), that is:

$$\frac{\text{Sum of Weighted Health Services Outputs}}{\text{Sum of Weighted Health System's Inputs}} = \frac{U_1Y_1}{V_1X_1} + \frac{U_2Y_2}{V_2X_2} + \cdots \frac{U_{si}Y_{si}}{V_{mi}X_{mi}} = \frac{\sum_{s=1}^{S} U_S x Y_{S,i}}{\sum_{m=1}^{M} V_m x Xm_{,i}} \quad [4.16]$$

The choice of an appropriate functional form and objective for the efficient frontier measurement including multiple inputs and output variables selection and measurement is the next decision in the DEA technique (Mester, 2003). The choice of either input or output orientation is not as it is in the econometrics estimation technique; the DEA techniques under a constant return to scale (CRS) assumption compute the efficiency of health posts, based on the ratio of all outputs being produced to all inputs being utilised by the health posts (Coelli, 1996). Although there are a number of various ways to formulate a Data Envelopment Analysis technique (SCRCSSP, 1997), simple mathematical formulation of the DEA technique with CRS assumption (CCR model) and VRS assumption (BCC model) along with an objective function of maximising the outputs for a given level of inputs consumption (output-expanding orientation) using linear programming problem, was adopted.

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[16] In stage-one, the technical and scale efficiency estimates of the health posts will be computed. In the second-stage, using the estimated technical efficiency as dependent variable, the determinants of the variability in technical efficiency among the health posts will be computed as a subsequent efficiency measurement study.

The Data Envelopment Analysis technique makes use of the linear programming approach because the DEA adopts weights to each health post that maximises its estimated relative efficiency, and this subject to the constraint that none of the health posts has an efficiency level greater than 100 percent (Sarafidis, 2002). The Data Envelopment Analysis technique would then allow attaching different weights for each health post in such a way that each health post's relative technique efficiency compares in the most favourable way with the remaining health posts. The DEA technique would refuse the technical efficiency estimates of a particular health post if it produces a technical efficiency level greater than 100 percent for any other health post. By means of this mechanism, the DEA has developed an envelope of health post that is most efficient at each set of attached weights to the utilised inputs and produced outputs (Sarafidis, 2002). The Charnes-Cooper-Rhodes (CCR) DEA technique is one of the most basic Data Envelopment Analysis techniques, and was originally developed by Charnes et al. (1978). The CCR Data Envelopment Analysis technique computes the overall technical efficiency of the health posts based on the constant returns to scale assumption and then, defines the efficiency frontier of the health posts (Kengil et al., 2010).

Accordingly, consider that there are 'n' number of health posts and each health post utilises ‘m’ quantities of inputs and produces 's' quantities of outputs. Therefore, to obtain the maximum possible estimate of the technical efficiency of the i^{th} health post, an output-oriented under CRS specification DEA, which is known as CCR DEA model (Charnes et al., 1978; Jacobs et al., 2006; Shahabinejad et al., 2013; Yu, 2011), is given by:

$$Max\ (\theta_i) = \frac{\sum_{s=1}^{S} U_s x Y_{s,i}}{\sum_{m=1}^{M} V_m x X m_{,i}}$$

$$\text{Subject to: } \frac{\sum_{s=1}^{S} U_s x Y_{s,i}}{\sum_{m=1}^{M} V_m x X_{m,i}} \leq 1; \quad i = 1, 2, 3, ., ., ., ., I \qquad [4.17]$$

$V_m, U_s \geq 0$, s = 1,…,…, S; m = 1,…,…, M

The use of the constraint in equation [4.17] is to restrict the efficient health posts to have an efficient estimate of 100 percent, for which a health post is compared with (Yu, 2011).

Where:

- Y_s represents the quantity of outputs (s) being produced by the i^{th} health post;
- X_m represents the quantity of inputs (m) being utilised by the i^{th} health post;
- U_s stands for the weights attached to outputs (s);
- V_m stands for the weights given to inputs (m); and
- θ_i is the technical efficiency level of the i^{th} health post.

4.6.2.2. The BCC DEA efficiency estimation technique

The CCR Data Envelopment Analysis technique is based on the assumption that all health posts are operating at CRS (optimal scale size), but in practice, all health posts could not operate at optimal scale size due to the imperfect competition, human resource constraints, and financial constraints, among others (Coelli, 1996; Jacobs & Baladi, 1996). Therefore, the primary drawback of an output-oriented version of CCR DEA technique is that it results in an infinite number of optimal solutions (Jacobs et al., 2006; Simwaka, 2011) [17]. In response to these and to capture the magnitude of scale effect, Banker-Charnes-Cooper (BCC) developed a Data Envelopment Analysis technique based on the variable returns to scale assumption as an extension of BCC Data Envelopment Analysis technique (Banker et al., 1984). The BCC Data Envelopment Analysis technique thus considers that the productivity at the most productive scale size may be unattainable for the other scale sizes at which a given health post is operating. Therefore, the BCC Data Envelopment Analysis technique estimates the pure technical efficiency of a health post at a given scale of operation. It takes into account the decreasing, constant, and increasing returns to scale at some point on the efficient frontier (Cooper et al., 2006). Although the choice of either input or output-orientation version is not as it is in the econometrics estimation technique, however, some health posts might have a fixed amount of inputs being employed and asked to produce as many outputs as possible.

Thus, an output-oriented BCC Data Envelopment Analysis technique could be the most appropriate (Coelli, 1996). Therefore, the present analysis was carried out based on an output-oriented version of the BCC Data Envelopment Analysis technique, which is an extension of an output-oriented version of the CCR Data Envelopment Analysis technique by adding a convexity constraint ($\sum_{i=1}^{h} U_i \, I_{iN} = 1$) to the system[18]. The main difference between BCC and CCR Data Envelopment Analysis techniques is that the former is based on the constant returns to scale assumption while the later considers the variable returns to scale assumption (Kengil et al., 2010; Kontodimopoulos & Klein, 2005) and the addition of a convexity constraint to the system of the later technique (Taptuk, 2012). The CCR Data Envelopment Analysis technique just emphasises the efficiency (productivity) irrespective of

[17] Let (u^*, v^*) represents the optimal pair values computed from the CRS DEA model, and $(\rho u^*, \rho v^*)$ will also be another optimal pair values solution, where $\rho > 0$.

[18] According to Taptuk (2012) the output-oriented efficiency frontier represents all combinations of outputs that are attainable by the production unit. Whilst an input-oriented model refers to the minimum usage of inputs to produce given output level, an output-oriented model denotes maximum amount of outputs given input level. Furthermore, since input and output-oriented DEA techniques are estimating the same frontier, the set of efficient firms will be the same, whilst there might be slight differences in efficiency levels of inefficient firms.

the scale size of the health posts under analysis while the BCC Data Envelopment Analysis computes both the scale of the size operation as well as the relative efficiency (productivity). Thus, the BCC Data Envelopment Analysis technique is more appropriate when all health posts are not operating at optimal scale size (Jacobs et al., 2006).

Thus, let us assume that there is a set of 'n' health posts used as Decision-Making units (DMUs), N= 1, 2, 3, … n and each health post employs 'h' multiple inputs, I = (I_1 , I_2 , I_3,… I_h) to produce 'y' multiple outputs, O = (O_1, O_2, O_3,… O_y) as indicated in Figure 4.1. The i^{th} health post, i ε N, is expressed in terms of vectors of inputs being used and outputs being produced by $HP_i = (I_i, O_i)$. Note that, $I_i = (I_{1i}, I_{2i}, I_{3i},\ldots I_{hi})$; and $O_i = (O_{1i}, O_{2i}, O_{3i},\ldots O_{yi})$.

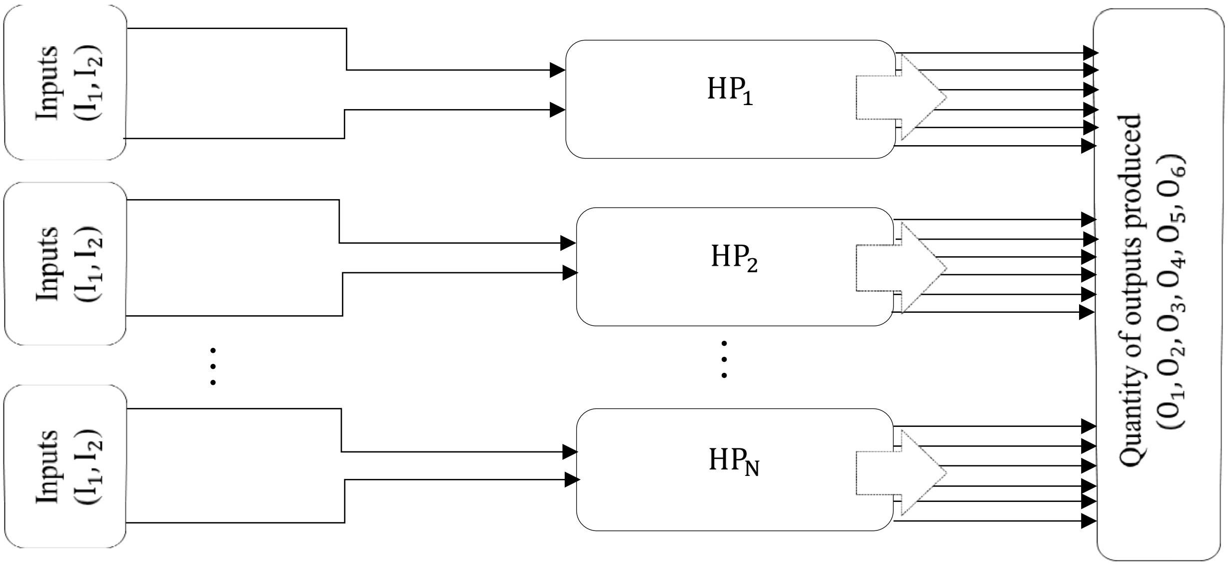

Figure 4. 1: The production of efficiency using multiple inputs and output variables

Therefore, following the works of Giuffrida and Gravelle (1999); Kirigia et al. (2011); Ray (2004); Shahabinejad et al. (2013); Sherman and Zhu (2006); Soares de Mello *et al.* (2013), the technical efficiency estimates of the $\boldsymbol{i^{th}}$ health post based on an output-oriented version of the BCC DEA technique and given 'h' quantities of inputs and 'y' quantities of outputs can be stated using a the linear programming problem as follows:

$$\left.\begin{array}{l} Max\ (\theta_i) = \dfrac{\sum_{i=1}^{y} Y_{in} W_i}{\sum_{i=1}^{h} I_{in} U_i} \\ \text{Subject to: } \left(\dfrac{\sum_{i=1}^{y} Y_{iN}\ W_i}{\sum_{i=1}^{h} I_{iN} U_i}\right) \leq 1; \quad N = 1, 2, 3, ., ., ., ., n \\ (\sum_{i=1}^{y} W_i\, Y_{in}\,);\ U_i, and\ W_i\ > 0;\ \forall i,\ \forall o \end{array}\right\} \quad [4.18]$$

Where:

- θ_i represents for the technical efficiency estimates of the i^{th} health post;

- I_{in} stands for the quantity of the i^{th} inputs being utilised by the n^{th} health post;
- I_{iN} stands for the quantity of the i^{th} inputs being utilised by N^{th} health post;
- Y_{in} represents the quantity of the i^{th} outputs being produced by n^{th} health post;
- Y_{iN} represents the quantity of the i^{th} outputs being produced by N^{th} health post;
- W_i stands for weight attached to the i^{th} outputs; and
- U_i stands for weight to attached the i^{th} input[19].

This involves finding the values of 'O' and 'I', such that the i^{th} health post's technical efficiency measure is maximised, subject to the constraint that measures all the technical efficiency estimates, and must be less than or equal to one. One of the critical problems with this specific ratio formulation is that it has an infinite number of solutions[20]. To avoid the problem of having infinite solutions and a valuable interpretation equation [4.18], (the maximisation problem) has to be reduced into the formulation of the linear programming problem by imposing the constraint $\sum_{i=1}^{h} U_i \, I_{iN} = 1$ (Coelli, 1996).

Therefore, alternatively, the BCC Data Envelopment Analysis technique can be expressed by:

$$\left.\begin{aligned} & Max\ (\theta_i) = \textstyle\sum_{i=1}^{y} W_i Y_{in} \\ \text{Subject to: } & \textstyle\sum_{i=1}^{h} U_i \, I_{iN} = 1, \\ & -\textstyle\sum_{i=1}^{y} W_i Y_{iN} \le 0; \\ & (\textstyle\sum_{i=1}^{y} W_i Y_{in} - \sum_{i=1}^{h} U_i \, I_{in}) \le 0 \end{aligned}\right] \begin{aligned} & \text{is convexity constraint} \\ & N = 1, 2, 3 \ldots n \\ & \text{, the non-negative constraints } U_i \text{ and } W_o > 0;\ \forall i, o. \end{aligned} \quad [4.19]$$

The weights (attached to outputs and inputs, U_i and W_o) are unique to each health post in order that the computed technical efficiency level to be bounded between zero and unity ($0 < \theta_i^* \le 1$ or $]0,]$) depending on the distance between the efficiency frontier and the health posts. Since the weights attached to both the input and output variables are not known ahead, then they are computed by the Data Envelopment Analysis technique from the efficient frontier by comparing a specific health post with the other peers, which produces alike outputs by employing alike inputs (Coelli, 1996).

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[19] Using DEA weights of input (U_i) and outputs (W_o) are calculated for each health post based on the input and output variables that they used and produced. The DEA technique looks for values for output and input weights (W_o, and U_i) that maximizes the efficiency level of the i^{th} health post, subject to constraints (Jacobs et al., 2006). The weights can take any non-negative value, and in general, a different set of weights is calculated for every health post in the system. Thus, output and input weights (W_o and U_i) are a central feature of DEA model. These are selected to put health post in the 'best possible light', meaning that no other set of weights could give a larger efficiency level (Jacobs et al., 2006).

[20] Example, (U^*, W^*,) is a solution, (δU^*, δW^*,) is then another solution etc.

The value of θ_i^* is the technical efficiency level of the i^{th} health post satisfying the condition $0 < \theta_i^* \leq 1$. The interpretation of the estimated results of the θ_i^* obtained from the first-stage of the BCC-DEA analysis is summarised as follows:

- When the value of θ_i^* equal to one (θ_i^*=1), it means that the health posts are on the efficient frontier point, operating at an optimal scale or relatively technical efficient health posts.
- When the value of θ_i^* is less than one (θ_i^*<1), it means that the health posts are technical inefficient (Charnes et al., 1978; Farrell, 1957; Jacobs et al., 2006; Kumar & Gulati, 2008).

Thus, Data Envelopment Analysis technique computes all possible sets of weights which satisfy all constraints and chooses those which give the most favourable view of the units (health post), that is the highest efficiency score (Charnes et al., 1978). To obtain the technical efficiency level (θ_i^*) for each health post, the linear programming problem should be solved "N" times, once for each health post in the sample and then the value of θ_i^* is computed for each health post in the system in turn (Coelli et al., 1998). The basic difference between the CCR and BCC techniques is the treatment of returns to scale. The output technical efficiency (based on output-oriented context), with which each health post functions, is computed based on the ratio of the actual outputs being produced by health posts to its maximum possible output being produced by those health posts developing the efficiency frontier (Sav, 2012) [21].

Thus, following the works of Laura (1998); Theodoridis and Psychoudakis (2008), the technical efficiency (TE) of the i^{th} health post denoted by TE_i, can be computed as follows:

$$TE_i = \frac{1}{\theta_i^*}, \qquad 0 < TE_i \leq 1 \qquad [4.20]$$

Where:

- $\theta_i^*$is the optimal value for the i^{th} health post, which is computed by the VRS DEA or BCC DEA technique using linear programming approach, equation [4.20]

As illustrated in Figure 4.1, the technical efficiency estimates, therefore, vary in the range between zero and unity ($0 < TE_i \leq 1$) with the value of one representing a technically efficient health post functioning on the efficiency frontier, while a value of less than one

[21] The output technical efficiency of a health post is a measure of how much the health post could increase its outputs, keeping its inputs consumption constant Laura (1998).

being an inefficient health post functioning below the efficiency frontier. Although the CRS Data Envelopment Analysis technique has a limitation in providing multi-optimal solutions, computation was executed on the same data under both constant and variable returns to scale Data Envelopment Analysis techniques in order to compute the scale efficiency (SE) of the health posts as the ratio of the computed technical efficiency estimates under the CRS Data Envelopment Analysis technique to VRS Data Envelopment Analysis technique (Jacobs et al., 2006; Sav, 2012) [22]. By inserting, therefore a convexity constraint to the CRS Data Envelopment Analysis technique, the BCC Data Envelopment Analysis technique can estimate the technical efficiency levels (equation 4.19). The technique efficiency levels estimated by the BCC Data Envelopment Analysis technique are at a higher level than the corresponding technical efficiency levels estimated by CCR Data Envelopment Analysis technique (Coelli, 1996; Parkin & Hollingsworth, 1997; Sav, 2012).

4.6.2.3. Scale efficiency and returns to scale

According to Coelli (1996), the technical efficiency levels computed from an output-oriented CRS Data Envelopment Analysis estimation technique are divided into two components (the scale inefficiency and the pure technical inefficiency). To compute the scale efficiency estimates of a health post, both the CCR and BCC output-oriented version of the Data Envelopment Analysis estimation techniques were executed on the same data. Note that when there is a difference between the two technical efficiency levels computed under the CCR and BCC output-oriented version of the Data Envelopment Analysis techniques for a specific health post, it then shows that the health post has scale inefficiency (Coelli, 1996). When using the radial technique, the scale efficiency can be obtained by computing the technical efficiency estimates derived under the assumptions of CRS (${TE_i}^{CRS}$) and that of VRS (${TE_i}^{VRS}$) (Jacobs et al., 2006).

Thus, following the works of Jacobs et al. (2006); Sav (2012); Theodoridis and Psychoudakis (2008), among others, the scale efficiency of the i^{th} health post, denoted by SE_i, can be computed as a ratio of the technical efficiency estimates of the i^{th} health post using the an output-oriented CRS Data Envelopment Analysis technique (${TE_i}^{CRS}$) to an output-oriented VRS Data Envelopment Analysis technique (${TE_i}^{VRS}$) as follows:

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[22] Similarly, the scale efficiency of a health post is a measure of how close the health post is to functioning at optimal size and how far a health post (an observation) is away from the efficiency frontier. It is also measured by how much more the health post could increase its output, if it were operating at optimal scale size (Laura, 1998).

$SE_i = \frac{TE_i^{CRS}}{TE_i^{VRS}} = \frac{TE_i^{CCR}}{TE_i^{BCC}}$ $0 < SE_i < 1$ [4.21]

If the value of the SE_i equals to unity ($SE_i = 1$), then the health post is scale efficient (operating at optimal scale size). Whereas if the value of the SE_i is less than one ($SE_i < 1$), the health post is scale inefficient.

Now, what does return to scale indicate?

The return to scale shows how many outputs are being produced by the health post in response to changes in inputs (scale size) being consumed by the health posts (Jacobs et al., 2006). Therefore, the inappropriate scale size (inputs) of the health post could result in scale inefficiency. The returns to scale could have three possible forms (Pindyck & Rubinfeld, 1998). These are:

i) The increasing returns-to-scale (IRS), which means the scale size of the health post is very small (output production increases by a larger proportion than each of the inputs being consumed).
ii) The decreasing returns-to-scale (DRS), means the scale size of operation of the health post is very large (output production augments by a smaller proportion).
iii) The constant returns to scale (CRS) when all inputs being consumed are doubled and yields double outputs.

A scale inefficient health post can operate at the scale of either increasing or decreasing returns (Theodoridis & Psychoudakis, 2008), thus, the scale efficiency level does not indicate whether a health post is operating at the scale of increasing or decreasing returns to scale (Jacobs et al., 2006). In order to indicate whether a health post is operating at increasing, or decreasing returns to scale, a non-increasing return to scale, (NIRS constraint ($\sum_{i=1}^{h} U_i \, I_{iN} \leq 1$) has to be imposed by replacing the convexity constraint" ($\sum_{i=1}^{h} U_i \, I_{iN} = 1$) into equation [4.19] (Jacobs et al., 2006).

Therefore, the scale inefficiency whereby a health post is operating either at increasing or decreasing returns to scale can then be computed by comparing the technical efficiency estimates of the health post under convexity constraint (TE_o^{VRS}) to its technical efficiency estimates under the NIRS constraint (TE_o^{NIRS}).

- A value of $\frac{TE_o^{CRS}}{TE_o^{VRS}} = \frac{TE_o{}^{CCR}}{TE_o{}^{BCC}} < 1$, and $TE_{CRS} = TE_{NIRS}$ (or $TE_o^{VRS} \neq TE_o^{NIRS}$), indicates the health post is operating at IRS,

- A value of $\frac{TE_o^{CRS}}{TE_o^{VRS}} = 1$, that is $TE_{CRS} = TE_{VRS}$, indicates that the type of scale inefficiency that health post operates at CRS, and
- A value of $\frac{TE_o^{CRS}}{TE_o^{VRS}} < 1$, but $TE_{CRS} < TE_{NIRS}$ (or $TE_o^{VRS} = TE_o^{NIRS}$), indicates the health post is operating at DRS (Coelli et al., 1998; Madau, 2012).

4.6.2.4. Productivity changes or growth analysis of health posts

In order to evaluate whether, and the extent to which, productivity (the technical efficiency changes) of the Ethiopian health extension programme changed over the two-time periods examined (2013 and 2014), the present study adopted an output-oriented DEA-based Malmquist productivity index (MPI) developed by Fare et al. (1989) [23]. There are three indices of productivity growth or changes estimation techniques commonly employed in the efficiency measurement literature, namely the Fisher (1992); Malmquist (1953); and Tornqvist (1936) indices). The Malmquist productivity index was chosen over the other two indices (Fisher and Tornqvist productivity indices) in the present study, because the Malmquist index does not require price information on the input and output variables to be considered in the study. It can then further be decomposed into two parts, the efficiency change, and technical change. Finally, unlike the other two indices, the Malmquist index does not make any assumptions on the functional form on how the input and output variables are related to developing the efficiency frontier (Grifell-Tatje & Lovell, 1996).

The Malmquist productivity index can be defined using distance functions to estimate the efficiency and technical changes. This function permits us to explain a multiple inputs and outputs production technology, without requiring that a behavioural objective be defined (Coelli et al., 1998). It is then developed by computing the radial distance of the observed inputs and outputs employed in periods,'t-1' and 't', compared to a reference technology. The distance function can be either input-or output-oriented; however, the index varies according to the type of orientations that it considers. The output-oriented distance functions should be defined properly before defining the index based on the two time-periods, 't-1' and 't' production technologies. Thus, the technical efficiency of the i^{th}health post at time-period 't-1' relative to at time-period 't' production technology is defined by the distance function as follows:

[23] The output-oriented productivity measures focus on the maximum level of outputs that could be produced using a given level of inputs and a given production technology relative to the observed level of outputs (Coelli et al., 1998)

$D_0^t(Y_i^{t-1}, I_i^{t-1}) = min\{\emptyset | (I_i^{t-1}, Y_i^{t-1}/\emptyset) \in P^t\}$ [4.22]

Equally, the efficiency of the i^{th}health post at time 't' relative to at time-period 't-1' is defined by the distance function as follows:

$D_0^{t-1}(Y_i^t, I_i^t) = min\{\emptyset | (I_i^t, Y_i^t/\emptyset) \in P^{t-1}\}$ [4.23]

That is, given the output level (Y_i) and input level (I_i), $D_0(Y_i, I_i)$ is the largest number Y_i to deflate I_i under the condition that the deflated inputs $I_i/\emptyset$ can still produce output, Y_i. The input level (I_i) is then divided by a number $\emptyset$ to yield F ($I_i/\emptyset$) $=Y_i$. Then, the next is to use the deflation functions to define the Malmquist index of the health posts under analysis.

Where:

- P^{t-1} is the production technology at time-period 't-1',
- P^t is the production technology at time-period 't',
- D_0 is the output deflation function, and $\emptyset$ is the value of the distance function.

The Malmquist productivity index should be defined using the time periods't-1' and 't' production technologies, therefore it is defined as the geometric mean of the two indices, measuring the productivity or change in efficiency from one-time period 't-1' to the next time period 't' (Coelli et al., 1998). There are two techniques in computing productivity differences among the health posts. These are input-based and output-based productivity indices. The former assumes the health posts use the same inputs and compare their outputs, while the latter compares the inputs being used to produce the same level of outputs. Generally, however, the two techniques yield different estimates (Yu, 2011). Accordingly to the work of Worthington (2004); Hollingsworth and Wildman (2002); Hollingsworth et al. (1999); Coelli et al., (1998) and Fare et al. (1994), among others, the current study adopted an output-based DEA-based Malmquist productivity index that assumes the health posts use the same inputs and compare their outputs being produced. The analysis uses an output distance function, which was initially developed by Shephard (1970) to estimate how much a health post's outputs can be proportionately increased given the observed levels of its inputs. The scale effect on the Malmquist index was computed by multiplying the technological change, the pure efficiency changes, and the scale efficiency change (Fare et al., 1994).

The objective of computing Malmquist productivity index is to measure the productivity variation and decomposition of this productive change into technological change and technical change (Fare et al., 1994). An output-oriented DEA-based Malmquist productivity index ($MPI_o^{t-1,t}$), that a health post transforms its inputs being consumed (I_i^t)

into its outputs being produced (Y_i^t), the geometric average of distance ratios, between periods, 't-1' and 't', is computed as:

$$MPI_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = \sqrt{MPI_o^{t-1}[(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)\text{x}MPI_o^t[(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)]}$$

$$= \sqrt{\left[\left(\frac{D_0^{t-1}(Y_i^t,\ I_i^t)}{D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})}\right)\left(\frac{D_0^t(Y_i^t,\ I_i^t)}{D_0^t(Y_i^{t-1},\ I_i^{t-1})}\right)\right]} \quad [4.24]$$

It is common to observe some degree of inefficiency in most health posts while they operate. Therefore, it is realistic and more practical to assume that $D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1}) \leq 1$ and $D_0^t(Y_i^t,\ I_i^t) \leq 1$. Accordingly, in the presence of the technical inefficiency, an output-oriented Malmquist productivity index equation [4.23] can be rewritten as follows:

$$MPI_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = \sqrt{\left(\frac{D_0^t(Y_i^t,\ I_i^t)}{D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})}\right)\left[\left(\frac{D_0^{t-1}(Y_i^t,\ I_i^t)}{D_0^t(Y_i^t,\ I_i^t)}\right)\left(\frac{D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})}{D_0^t(Y_i^{t-1},\ I_i^{t-1})}\right)\right]} \quad [4.25]$$

Where:

- I_i^{t-1} and I_i^t denotes the values of inputs being consumed by the i^{th} health post in time-period 't-1' and 't', respectively.
- $Y_i^{t-1}$$and$ Y_i^t denotes the value of outputs being produced the i^{th}health post in time-period 't-1' and 't', respectively.
- $MPI_o^{t-1,t}$ represents the values of the productivity changes of the i^{th} health post in time-period 't-1' and 't', respectively.
- $\left(\frac{D_0^t(Y_i^t,\ I_i^t)}{D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})}\right)$ is an index measuring the change in output-oriented the measure of the technical efficiency between two periods 't-1' and 't', indicating whether i^{th} health post moves either far away from or nearer to the efficient frontier during the time-periods.

The index shows whether the health post approaches nearer to its efficient frontier, becomes more efficient, or moves far away from its efficient frontier (becomes less efficient with an efficiency of level of less than unity), or it remains constant (with an efficiency level of equal to unity) (Coelli et al., 1998; Hollingsworth & Wildman, 2002).

- $\left[\left(\frac{D_0^{t-1}(Y_i^t,\ I_i^t)}{D_0^t(Y_i^t,\ I_i^t)}\right)\left(\frac{D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})}{D_0^t(Y_i^{t-1},\ I_i^{t-1})}\right)\right]^{0.5}$ is an index measuring technical change, how the efficiency frontier shifted between periods, 't-1' and 't'. That is the movement of the actual efficiency frontier itself between the two-time periods, 't-1' and 't' (Coelli et al., 1998; Hollingsworth & Wildman, 2002).

- A value of $MPI_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ greater than unity, equal to unity, or less than unity shows improvement (progress), no change (stagnation), or a decline (deterioration) in productivity between periods 't-1' and 't', respectively.

Alternatively, a health post in period 't' is more efficient relative to itself in period 't-1', the relative efficiency of the health post remains constant over periods and the relative efficiency of the health post deteriorates over periods ('t-1' and 't'), respectively (Coelli et al., 1998).

To formulate the Malmquist productivity index of the i^{th} health post between periods 't-1' and 't', the four distance functions have to be computed using DEA efficiency estimation technique (Coelli et al., 1998; Mohamad, 2004). These are:

i. $D_0^{t-1}(Y_i^t,\ I_i^t)$ denotes an output-oriented distance function between period 't' health post (observation) to period 't-1' production technology.

ii. $D_0^t(Y_i^{t-1},\ I_i^{t-1})$ denotes an output-oriented distance function between period 't-1' health post (observation) to period 't' production technology.

iii. $D_0^{t-1}(Y_i^{t-1},\ I_i^{t-1})$ represents an output-oriented distance function computed using the production technology period 't-1', and

iv. $D_0^t(Y_i^t,\ I_i^t)$ represents an output-oriented distance function computed using the production technology period 't'.

a) The technical efficiency change

The technical efficiency of the health posts using multiple inputs and multiple outputs based on an output-orientation is computed by the extent to which the observed vector of output could be radially expanded to be on the efficiency frontier of the production possibility set associated with the vector of input. The $MPI_o^t(Y_i^t, I_i^t)$ and $MPI_o^{t-1}(Y_i^{t-1}, I_i^{t-1})$ are measures of the technical efficiency between periods, 't-1' and 't', respectively (Coelli et al., 1998). Thus, estimates of change in technical efficiency $(effch)$ between periods, 't-1' and 't' is computed by:

$$effch_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = \left(\frac{D_{VRS}^t(Y_i^t, I_i^t)}{D_{VRS}^{t-1}(Y_i^{t-1}, I_i^{t-1})}\right) \quad [4.26]$$

Where:

- The D_{VRS}^{t-1} and D_{VRS}^t indicate the change in technical efficiency computed based on VRS production technology between periods, 't-1' and 't', respectively.

- When $effch_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ is greater than unity shows that an increase in technical efficiency between periods, 't-1' and 't'.
- When $effch_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ is equal to unity, it indicates constant in technical efficiency between periods 't-1' and 't'), and
- When $effch_o^{t-1,t}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ is less than unity, it indicates decrease in technical efficiency while less than unity, it indicates a decrease in technical efficiency between periods 't-1' and 't'.

b) The scale efficiency change

The basic idea behind scale efficiency is that a health post can increase its level of efficiency (productivity) by altering the size of the scale it operates in such a way that a health post could operate at an optimum scale size (Coelli, 1998). Therefore, the scale efficiency changes (sech) for a given health post can be computed using an output distance function of the observed input and output combinations relative to the variable returns to scale efficiency frontier and from constant returns to scale that are generated from the observed variable returns to scale production technology.

Thus, following the works of Coelli et al. (1998); and Fare et al. (1994), an output-oriented scale efficiency changes $(sech)$ in time periods 't' is computed by:

$$sech_o^t(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = D_{CRS}^t(Y_i^t,\ I_i^t)/D_{VRS}^t(Y_i^t,\ I_i^t) \qquad [4.27]$$

Similarly, an output-oriented scale efficiency change in time-period 't-1' is computed by:

$$sech_o^{t-1}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = D_{CRS}^{t-1}(Y_i^{t-1},\ I_i^{t-1})/D_{VRS}^{t-1}(Y_i^{t-1},\ I_i^{t-1}) \qquad [4.28]$$

The scale efficiency change $(sech)$ is computed using the two-time periods,'t-1' and 't' scale efficiency measures, which is obtained from a given multiple inputs and output combinations $(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$. The $sech$ can, therefore, be computed using the scale efficiency measure as the ratio of the scale efficiency measures of equation [4.27] to equation [4.28]. Using the radial technique, the scale effect on the technological change is computed by dividing the technological change under constant returns to scale to the technological change under variable returns to scale assumptions. Similarly, the scale effect on the efficiency change could be computed by dividing the efficiency change under constant returns to scale to the efficiency change under variable returns to scale assumptions (Coelli et al., 1998; Coelli, 1996).

Therefore, an output-oriented scale efficiency change($sech$) is given as follows:

$$sech_o^{t,t-1}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t) = \left(\frac{D_{CRS}^t(Y_i^t, I_i^t)/D_{VRS}^t(Y_i^t, I_i^t)}{D_{CRS}^{t-1}(Y_i^{t-1}, I_i^{t-1})/D_{VRS}^{t-1}(Y_i^{t-1}, I_i^{t-1})}\right) \quad [4.29]$$

Where:

- $D_{CRS}^t(Y_i^t,\ I_i^t)/D_{VRS}^t(Y_i^t,\ I_i^t)$ measures the estimates of the scale efficiency computed at time-period ‘t’ while $D_{CRS}^{t-1}(Y_i^{t-1},\ I_i^{t-1})/D_{VRS}^{t-1}(Y_i^{t-1},\ I_i^{t-1})$ is a measure of the scale efficiency computed at time-period 't-1' for the health posts.
- A value of $sech_o^{t,t-1}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ greater than unity indicates that a given health post is the most scale efficient (operating at optimal scale size) and that the scale efficiency of the health post is improving.
- A value of $sech_o^{t,t-1}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ less than unity indicates that a give health post is not operating at optimal scale size and the scale efficiency of the health post is deteriorating.
- A value of $sech_o^{t,t-1}(Y_i^{t-1}, Y_i^t, I_i^{t-1}, I_i^t)$ equals unity indicates that there is no change in the scale efficiency of the health post between the time periods, 't-1' and 't'.

Therefore, there are many studies, and the majority of them employed the Data Envelopment Analysis technique and its alternatives in various disciplines such as in health science, social science, engineering, and others (Jacobs et al., 2006; Sav, 2012; Shahabinejad et al., 2013; Theodoridis & Psychoudakis, 2008). Currently, economists employ the parametric (SFA) and non-parametric (DEA) techniques to measure the productive performance of the healthcare institutions (Worthington, 2004). Accordingly, the healthcare efficiency studies (Burgess & Wilson, 1998; Rollins et al., 2001) applied the Data Envelopment Analysis technique to measure the technical and scale efficiency of the healthcare institutions. Similarly, in many other non-healthcare institutions (service-based industries), the efficiency measurement studies (Madau, 2012; Rollins et al., 2001; Shahabinejad et al., 2013) employed both the non-parametric and parametric techniques to measure the technical, scale efficiency and productivity changes. Thus, following the works of most empirical previous healthcare efficiency measurement studies mentioned above, the present study employed the Data Envelopment Analysis technique and DEA-based Malmquist productivity index in a similar fashion to those of earlier empirical studies.

4.6.3. Models for identifying the determinant factors influencing the variations in technical efficiency estimates among the health posts

When looking at examining the technical efficiency variations among the health posts as a continuation of the first-stage DEA analysis, many previous health-related, as well as non-health related, empirical studies applied a variety of regression analysis methods in their second-stage regression analysis to estimate the impact of the factors affecting the variation in the technical efficiency estimates of the health units or health posts. Some of the studies that include a binary (probit or logit) regression model in their subsequent second-stage regression analyses are Dutta et al. (2014); Hernández & San Sebastián (2014); San Sebastián & Lemma (2010); and Ravangard et al. (2014), among others. On the other hand, some other studies also employed a Tobit regression model in their second-stage analysis (De et al., 2012; Dutta et al., 2014; McDonald, 2008; and Xenos et al., 2016, among others). Moreover, there are some other studies that also employed ordinary least square (Dutta et al., 2014; McDonald, 2008).

Most importantly, there are also some studies that applied a combination of the above-mentioned regression analysis models. For example, McDonald (2008) employed both the ordinary least square and Tobit regression models in their second-stage regression analysis. An empirical analysis by Hoff (2007) indicated that although a Tobit regression model is the most appreciated and successful model in the second-stage regression analysis, however, ordinary least square model can be used replacing the Tobit regression model as subsequent in the second-stage regression analysis. Therefore, following the works of Butta, *et al*., 2014; Hoff (2007); and McDonald (2008), among others the present study employed two different regression estimation techniques to examine the variations in technical inefficiency estimates among the health posts as second-stage regression models to ascertain how sensitive and robust the results are. These are the Tobit and ordinary least square regression models.

4.6.3.1. The Tobit regression model

A number of studies examined the determinant factors affecting the variations in technical efficiency estimates of healthcare organisations (programmes). Therefore, to identify the determinant factors affecting the variations in technical efficiency estimates among the health posts used as decision-making units, several studies employed different measures of regression models in their subsequent second-stage regression analysis (Fizel & Nunnikhoven, 1992; McDonald, 2008; Rajiv et al., 2008; and Xenos et al., 2016, among others). Therefore, as part of the second-stage Data Envelopment Analysis technique, the computed technical efficiency estimates (see subsection 4.6.2.2, equation [4.19]) were regressed as the dependent variable to examine the technical efficiency variations among the health posts. In most Data Envelopment Analysis literature, the effect of these variables is usually analysed using a Tobit regression model since they considered the estimates of efficiency levels to be bounded between zero and unity (McDonald, 2008). Thus, the estimates of the technical efficiency obtained from the first-stage of the DEA analysis, equation [4.19] are used as the dependent variable and then are regressed on the independent variables (contextual variables) in the second-stage regression analysis in order to identify the factors that drive the technical inefficiency differences among the health posts.

Following the works of Cheng et al. (2015); Green (1994); and Xenos et al. (2016), among others, the Tobit regression model was applied to explain the disparities in the technical efficiency estimates of the health posts. For computation purposes, Green (1994) suggested a left censoring point at zero and thus, using the transformed technical efficiency estimates based on variable returns to scale assumption as the dependent variable (for computation purpose) was estimated as follows:

$$DEA_{Ineff} = \left(\frac{1}{\theta_i^*}\right) - 1 = \frac{1}{\theta_i^*} - \frac{\theta_i^*}{\theta_i^*} = \left(\frac{1-\theta_i^*}{\theta_i^*}\right) \qquad [4.30]$$

Therefore, the Tobit regression model can be expressed as follows:

$$\left.\begin{array}{ll} Y_i^* = \alpha_0 + \alpha_i X_i + \varepsilon_i \; ; & \varepsilon_i \sim N(0, \delta^2) \\ Y_i = Y_i^* \; if \; Y_i^* > 0 \; ; & \\ Y_i = 0 \; if \; Y_i^* \; if \; Y_i^* \leq 0; & i = 1, 2, 3, \ldots n \end{array}\right. \qquad [4.31]$$

Where:

- Y_i^* represents possibly censored version of Y_i;
- X_i denotes vector of independent variables;
- α_0 and α_i represent constant term and vector of regression parameters, respectively;
- $\frac{1}{\theta_i^*}(= TE_i)$ is the technical efficiency level of the i^{th} health post;
- θ_i^* denotes technical efficiency of the i^{th}health post; and ε_i is the random error term

Thus, the estimated empirical Tobit regression model is given as follows:

$$DEA_{Ineff} = \alpha_{0i} + \alpha_{1i}PSHEW + \alpha_{2i}RTHEW + \alpha_{3i}DVHP + \alpha_{4i}YWHEW + \alpha_{5i}RPHEW + \alpha_{6i}AHEW + \alpha_{7i}MRHEW + \alpha_{8i}MIHEW + \alpha_{9i}SSHEW + \alpha_{10i}RRHEW + \alpha_{11i}RLHWE + \alpha_{12i}ABME + \varepsilon_i \qquad [4.32]$$

Where:

- $DEA_{Ineff}(=Y_i)$ represents the observed technical inefficiency levels of health posts.

The technical efficiency estimates computed from the first-stage of Data Envelopment Analysis technique analyses are truncated to lie between zero (totally inefficient) and unity (100 percent efficient). Hence, to explain the sources of differences in technical efficiency scores across the sample health posts, Tobit regression model was also employed.

4.6.3.2. The ordinary least square method

As note earlier, an alternative but complementary technique is to use an ordinary least square regression method as subsequent second-stage regression analysis to examine the determinant factors affecting the variations in technical inefficiency among the health posts. There are some studies, which were employed the ordinary least square regression method to identify the factors affecting technical efficiency disparities among the health posts (Burgess & Wilson, 1998; Vitaliano & Toren, 1996). Non-healthcare efficiency measurements studies also employed an ordinary least square method in their second-stage regression analysis (McDonald, 2008). The ordinary least square is likely to provide valuable insights into the factors that affect the technical inefficiency differentials among the health posts. The use of a two-step procedure involving Data Envelopment Analysis estimation technique followed by ordinary least square method could result in consistent estimators of the regression coefficients. Furthermore, McDonald (2008) and Dutta et al. (2014) indicated that while applying ordinary least square method in the second-stage regression analysis, the use of Data Envelopment Analysis estimation technique followed by ordinary least square regression model is a consistent estimator. The independent variables used in second-stage ordinary least square regression analysis should be independent of (uncorrelated to) the input variables employed in the first-stage of Data Envelopment Analysis while estimating the technical efficiency levels; otherwise, estimates from the second-stage ordinary least square regression method would be biased and inconsistent (Banker & Natarajan, 2008; Worthington, 2004).

Thus, following the works of Long (1997); Rajiv et al. (2008); McDonald, 2008 among others, a two-step procedure involving Data Envelopment Analysis measurement technique followed by using the ordinary least square regression model based on the transformed technical efficiency estimates as the dependent variables obtained from equation [4.30] was estimated by:

$$DEA_{Ineff} = \alpha_{0i} + \alpha_{1i}PSHEW + \alpha_{2i}RTHEW + \alpha_{3i}DVHP + \alpha_{4i}YWHEW + \alpha_{5i}RPHEW + \alpha_{6i}AHEW + \alpha_{7i}MRHEW + \alpha_{8i}MIHEW + \alpha_{9i}SSHEW + \alpha_{10i}RRHEW + \alpha_{11i}RLHWE + \alpha_{12i}ABME + \varepsilon_i \qquad [4.33]$$

Where:

- DEA_{Ineff} represents the transformed technical inefficiency of the i^{th} heah post;
- x_i represents the vector of independent variables;
- α_{1j} through α_{13j} represents the regression coefficient estimates (parameters);
- α_0 stands for the regression intercept; and ε stands for the disturbance term.

Note that, the subscripts 'i' indicates the number of observations from 'N' random observations, health posts.

4.6.4. A binary logistic regression model: Determinant factors affecting the health extension programme beneficiary households' graduation

Taking into account the fact that the outcome variable of interest is dichotomous in nature, the use of linear regression, ordinary least square method is not appropriate as it yields biased estimates as it assumes a linear relationship between an outcome variable and the explanatory variables (covariates). The expected value of the outcome variable that is given by $E(HEP_i \mid C_i)$ where HEP_i represents the outcome variable of interest (i.e. the health extension programme graduates versus the non-graduates) and C_i is the value of the explanatory variable, which can take a negative or a positive value. Also, in an ordinary least square regression method, the basic assumption is that the error term should normally be distributed with an expected mean of zero (E($\varepsilon_i|C_i$)=0) for all observations and a constant variance (Var($\varepsilon_i \mid C_i$)=E($\varepsilon_i^2|C_i$)=δ_ε^2). This does not hold true when the outcome variable is a binary (Hosmer & Lemeshow, 2000; Wooldridge, 2002). The ordinary least square method also assumes constant marginal effects of explanatory variables on the outcome variable. Thus, when the dependent variable is a binary outcome, making use of a binary choice model is an appropriate analytical tool to analyse the obtained data (Wooldridge, 2002).

The utilisation of either logit or probit regression model is a matter of preference (Mulugeta, 2011). However, despite the similarity the between two models, a logistic regression model has two primarily applied merits over the probit model. First, it is extremely flexible and has an easily employed function (computation of parameter estimates is simple) and second, it is easy to interpret parameter estimates meaningfully (Fox, 2010; Hosmer & Lemeshow, 2000). This study, however, utilises the logistic regression model following the works of Agresti and Kateri (2011); Gujarati (2004); Menard (2002); O'Connell (2006);

Wooldridge (2002); Hosmer and Lemeshow (2000); and Wooldridge (2002) to examine the major graduation determinants of the health extension programme beneficiary households. Assume there are 'N' independent sample observations with HEP_i representing the binary outcome variable, which has two categories denoted by 1 and 0. Therefore, in a logistic regression model, the dependent variable (HEP_i) follows a Bernoulli probability function, which takes a value of 1 for the health extension programme beneficiary households (or the HEP graduates, HEP_i =1) and 0 for the non-graduate (or the non-graduates, HEP_i =0).

The overall model specification for a binary choice model is given by:

$$\pi = \Pr(HEP_i{=}1|c_k) = \Pr(c_k) = G(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ldots + \alpha_k c_k) = G(c\alpha) \qquad [4.34]$$

Where:

- π $(0 \leq \pi \leq 1)$ is the probability of the outcome of interest (graduating);
- $G(.)$ is the normal or logistic commutative distribution function (CDF);
- $c_i = (c_1, c_{2,} \ldots c_k)$ is the vector of explanatory variables for the i^{th} observation and;
- α_k denote the vector of unknown parameters.

Since the logit model is non-linear, equation [4.34] enables us to estimate the marginal effect of a particular predictor (c_k). Therefore, based on equation [4.34], the conditional probability of the logistic regression equation for a health extension programme graduate household (y_{ij} =1) is given as follows:

$$\Pr(y_{ij}=1) = \Pr(HEP_i{=}1|c_k) = \Pr(c_k) = \left(\frac{\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ldots + \alpha_k c_k)}{1 + \exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ldots + \alpha_k c_k)}\right) \qquad [4.35]$$

Equation [4.35] can be rewritten as follows:

$$\Pr(y_{ij}=1) = \Pr(HEP_i{=}1|c_k) = \Pr(c_k) = \left(\frac{exp^{\alpha_0 + \sum_{i=1}^{n}\alpha_k c_k}}{1 + exp^{\alpha_0 + \sum_{i=1}^{n}\alpha_k c_k}}\right) \qquad [4.36]$$

Against the probability of the non-graduate households, that is given by:

$$1 - \Pr(HEP_i{=}1|c_k) = 1 - \Pr(c_k) = 1\text{-} \left(\frac{\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ldots + \alpha_k c_k)}{1 + \exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ldots + \alpha_k c_k)}\right) \qquad [4.37]$$

Similarly, equation [4.37] can be rewritten as follows:

$$1 - \Pr(HEP_i{=}1|c_k) = 1 - \Pr(c_k) = 1\text{-} \left(\frac{exp^{\alpha_0 + \sum_{i=1}^{n}\alpha_k c_k}}{1 + exp^{\alpha_0 + \sum_{i=1}^{n}\alpha_k c_k}}\right) \qquad [4.38]$$

Using some of the algebraic techniques, equation [4.38], can also be rewritten as follows:

$$1 - \Pr(HEP_i{=}1|c_k) = 1 - \Pr(c_k) = \frac{1}{1 + exp^{\alpha_0 + \sum_{i=1}^{n}\alpha_k c_k}} \qquad [4.39]$$

In the model estimation, the first task is to transform the explanatory variables and to determine the regression coefficients of these explanatory variables. In the basic logistic regression model analysis, the task begins with logit transformation of the dependent variable using an estimation technique known as maximum likelihood estimation (MLE) (Fox, 2010; Menard, 2002). The transformation is performed using the odds ratio[24]. Thus, to compute the odds ratio, equation [4.36] should be divided by equation [4.38] as follows:

$$\left(\frac{\Pr(c_k)}{1-\Pr(c_k)}\right) = \frac{\left(\frac{\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)}{\left(\frac{1}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)} = \exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + \ . \ . \ . \ + \alpha_k c_k) \quad [4.40]$$

Since from equation [4.37], $\Pr(y_{ij}=1) = \Pr(HEP_i=1|c_k) = \Pr(c_k) = \left(\frac{v}{1+v}\right)$

Where:

- v= $exp^{\alpha_0 + \sum_{i=1}^{n} \alpha_k c_k}$

Hence, the odds = $\left(\frac{\Pr(c_k)}{1-\Pr(c_k)}\right) = \frac{\left(\frac{\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)}{\left(\frac{1}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)} = \frac{v}{1+v} = \frac{1}{1-\frac{v}{1+v}} = \text{v}$ [4.41]

Where:

- $(\frac{\Pr(c_k)}{1-\Pr(c_k)})$ is the odds of being a health extension programme graduate against being a non-graduate household.
- The left-hand side of equation [4.41] is the value of the ratio of probabilities $(\frac{\Pr(c_k)}{1-\Pr(c_k)})$ while the right-hand side represents the nonlinear function of the explanatory variables.
- The α_0 and α_k, respectively denote the intercept and the vector of unknown parameters.

An alternative logistic regression can be formed by transforming equation [4.41] or the logit transformation by taking its natural $\log(ln)$. Therefore, the logarithmic transformation of the estimated logistic regression model can be rewritten as follows:

$$In\left(\frac{\Pr(c_k)}{1-\Pr(c_k)}\right) = In\left\{\frac{\left(\frac{\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)}{\left(\frac{1}{1+\exp(\alpha_0 + \alpha_1 c_1 + \alpha_2 c_2 + ... + \alpha_k c_k)}\right)}\right\}, \text{ for } 0 \leq \Pr(c_k) \leq 1 \quad [4.42]$$

Thus, the logarithmically transformed the logit regression model, equation [4.42] can be rewritten as a linear combination of the explanatory variables as follows:

[24] Because it is not very intuitive to interpret based on their coefficient estimates of logistic regression analysis as they are in log-odds scale or units. Explaining the effects on odds-ratio scale is much easier to understand than explaining the effects on the log-odds scale in logistic regression analysis (Long & Freese, 2006).

$$Logit = In\left(\frac{\Pr(c_k)}{1-\Pr(c_k)}\right) = \alpha_{0i} + \alpha_{i1}c_{i1} + \alpha_{i2}c_{i2} + \alpha_{i3}c_{i3} + \alpha_{i4}c_{i4} + \alpha_{i5}c_{i5} + \alpha_{i6}c_{i6} + \alpha_{i7}c_{i7} + \alpha_{i8}c_{i8} + \alpha_{i9}c_{i9} + \alpha_{i10}c_{i10} + \alpha_{i11}c_{i11} + \alpha_{i12}c_{i12} + \alpha_{i13}c_{i13} + \alpha_{i14}c_{i14} + \alpha_{i15}c_{i15} + \alpha_{i16}c_{i16} \quad [4.43]$$

Where:

- $\text{In}\left(\frac{\Pr(ck)}{1-\Pr(ck)}\right)$ is the logit regression model, the left-hand-side of equations [4.42 -4.43], which is simply called the log odds or logit.

The rationale behind the use of logarithmic transformation of the logistic regression, the logit model, equation [4.43] is that it has many of the required properties of ordinary least square, for instance, the linearity in parameters. Also, depending on the value of the explanatory variables, the values of the logit model can be continuous ranging from -∞ and +∞. The maximum likelihood estimation technique was employed to estimate the vector of unknown parameters (α_0 and α_k). It is the most preferred and applied techniques of likelihood estimation for nonlinear regression models (Hosmer & Lemeshow, 2000; Kleinbaum & Klein, 2002).

The Hosmer and Lemeshow (H-L) test

The Hosmer and Lemeshow (H-L) test was employed to assess whether the fitted regression model sufficiently explains the observed outcome variable in the data (Hosmer & Lemeshow, 2000). Hosmer and Lemesbow (1980) formulated model fit tests in which the sample observations are grouped into 'g' subgroups and then, a Chi-squared (labelled χ^2_{HL}) test is estimated. Explicitly, the Hosmer and Lemeshow statistic is computed by dividing the observations in the sample into decile groups to which they are partitioned into ordered subgroups of equal size (g=10) according to their computed predicted probabilities ($\Pr(y_{ij}=1|c_k)$). And then, the Hosmer and Lemeshow Chi-squared (χ^2_{HL}) value is estimated based on the observed and expected frequencies. This is a χ^2_{HL} test for which many researchers do not want to obtain a statistically significant value (Hosmer & Lemeshow, 1980; Hosmer & Lemeshow, 2000). Therefore, each of these sample observations (categories) is further divided into two target groups (the health extension programme graduates versus non-graduates). The value of the probability for the target groups is then computed from the χ^2_{HL} distribution with g-2 degree of freedom to test the fit of the model, logistic regression model in the present context.

Thus, following the works of Agresti and Kateri (2011); Hosmer et al. (1997); Hosmer and Lemesbow (1980) to determine the goodness-of-fit of the model, the Hosmer-Lemeshow's χ^2_{HL} the goodness-of-fit test statistic for the logistic regression model was computed as follows:

$$\chi^2_{HL} = \sum_{j=1}^{10}\left(\frac{\left(\sum_j y_{ij} - \sum_j \hat{\pi}_{ij}\right)^2}{\left(\sum_j \hat{\pi}_{ij}\right)\left[1 - \left(\sum_j \hat{\pi}_{ij}\right)/n_i\right]}\right) \quad [4.44]$$

Where:

- y_{ij} is the dichotomous outcome variable of the i^{th}observation in the j^{th} subgroup,
- $\hat{\pi}_{ij}$ the expected probability of the i^{th}observation in the j^{th} subgroup,
- $n_i$is the number of sample observations in the j^{th} subgroup, and $\chi^2_{HL}$is the estimate of Chi-squared.

A statistically nonsignificant Chi-squared test value (χ^2_{HL}) shows that the estimates of the logistic regression model fits the data with an acceptable level and is correctly specified while a significant test value of the Chi-squared test value indicates the model, or the logistic regression model is not correctly specified. The test for goodness of fit for this logistic regression model was computed using estat gof, g(10) table stata command's (see Appendix C, Table C-4). Thus, the estimated value of the goodness of fit test was significant with a Chi-squared p-value of > 0.2123, indicating the model is a good fir mode, correctly specified to analyse the data adequately.

The Wald-test statistic

A Wald-test was also employed to test the statistical significance of an individual unknown parameter in the logistic regression model. It computes a Z-statistics indicating whether the predicted data significantly differs from the observed data or not. Therefore, following Hosmer and Lemesbow (1980), the Wald-test statistic was computed by dividing the estimate of the maximum likelihood of the regression coefficient, $\hat{\alpha}_J$ to its standard error as follows:

The Wald-test statistic, $Z = \frac{\hat{\alpha}_J}{\widehat{se}(\alpha_{J)}}$ [4.45]

4.7. Conclusion

The multiple analytical econometric models detailed in this chapter will assist to comprehensively address the stated specific research objectives of this study as indicated in Chapter One. The study employed cross-sectional secondary data, which were obtained from the Ethiopian Demographic and Health Survey, 2016 as well as 2013 and 2014 from the regional health bureaus under the stewardship of the Federal Ministry of Health, Ethiopia. To examine the determinant factors affecting the inter-regional differentials in under-five child mortality, this study employed an extended nonlinear Oaxaca-Blinder decomposition technique.

In addition, based on a two-year panel data, the present study also evaluated the technical efficiency and productivity changes of the health extension programme using health posts as decision-making units by employing the most commonly applied efficiency measurement technique known as Data Envelopment Analysis. In addition, to examine the variations in the technical efficiency among health posts, the study employed both the Tobit and ordinary least square regression models. Finally, a logistic regression model was applied to identify the major determinant factors influencing the health extension programme beneficiary households’ graduation in rural settings of Ethiopia.

CHAPTER FIVE

RESULTS OF RESEARCH FINDINGS

5.1. Introduction

This chapter examines three specific research objectives; the determinant factors affecting the inter-regional differentials in under-five child mortality, an evaluation of the efficiency and productivity changes of the Ethiopian community-based health extension programme using health posts as decision-making units, and identifying the determinant factors influencing the health extension programme beneficiary households' graduation in rural settings of Ethiopia. Despite the overall remarkable rate of reduction in under-five child mortality, the magnitude of mortality rate disparities varied significantly among the regions and over time in Ethiopia, masking the problem. While the majority of previous studies focused on factors influencing infant or under-five child mortality rates in Ethiopia (Amouzou et al., 2014; Dejene & Girma, 2013; Regassa, 2012; Tesfa & Jibat, 2014, among others), much less is known about the determinant factors affecting the inter-regional variations in under-five mortality rate in rural settings in Ethiopia at the national level.

The improvement in child mortality is considered to be the outcome of a combination of various healthcare facilities, such as the use of immunisation, mother's level of health knowledge, accessibility of healthcare services, use of improved latrines and safe drinking water (UNICEF, 2014). In Ethiopia, as in many other countries, these healthcare services are delivered by the community-based health extension programme. Measuring the efficiency of the health extension programme is very important to gain insight into the success of the programme, as well as to implement policy measures to improve the potential output level within the context of limited resource inputs. Although Ethiopia's health extension programme is one of the biggest community-based health worker programmes in the world (Perry et al., 2013), there is very limited available literature that explores the efficiency of the health extension programme both at regional and national levels. Furthermore, the overall national throughput rate of graduating the health extension programme beneficiary households as model households was 7.2 percent, with considerable disparities across regions of the country, indicating the need for improving the throughput rate of health extension programme beneficiary graduates as model households (FMoH, 2014a). These could enhance access to and utilisation of basic healthcare services to distant and underserved rural communities and thus, ensure the universal healthcare coverage of the country. This, in turn, would significantly reduce the variations in under-five child mortality among the Ethiopian regional states.

This chapter is outlined as follows: Section 5.2 presents findings of the determinant factors affecting the inter-regional differentials in under-five child mortality. Section 5.3 provides an analysis of the results of the efficiency and productivity changes of the health posts along with the findings of the key determinate factors affecting the variations in the technical efficiency estimates among these health posts. Section 5.4 reports the major findings of determinant factors affecting the health extension programme beneficiary households' graduation. Section 5.5 concludes the key findings of the study.

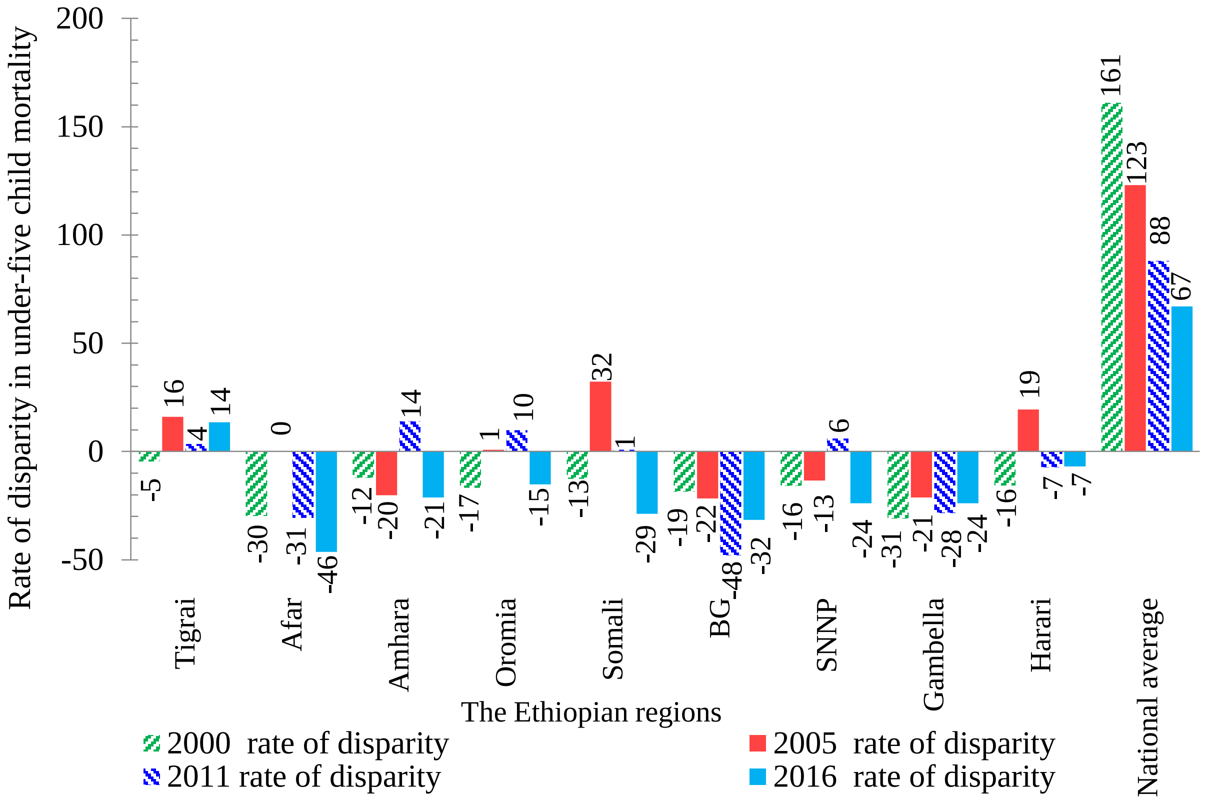
5.2. Study results for the determinant factors affecting the inter-regional differentials in under-five child mortality

5.2.1. The rate of disparity differences in under-five child mortality among regions

Although the average rate of the Ethiopian under-five child mortality was significantly reduced at the national level, there was a substantial variation among the regions in the rate of reduction in under-five child mortality and during certain time periods. The rates of disparity in the under-five child mortality between a region and the national average was computed by subtracting the respective regional rate of under-five child mortality from the national average rates and then, multiply this by 100. The percentage rates of disparities in the under-five child mortality for each region were reported in Figure 5.1. Accordingly, a positive value of the rate of disparity in under-five child mortality indicates that the respective regional average rate of under-five child mortality was higher than the national average rate in under-five child mortality while a negative value of the average rate of disparity in under-five child mortality designates the opposite (the regional average rate of reduction in under-five child mortality was lower than the national average rate).

As indicated in Figure 5.1, the rate of disparity in under-five child mortality varied significantly among regions and over periods. For example, in 2000, the negative values of the average rates of disparity indicated that the under-five child mortality rates of all regions were higher than the national average rates, with significant variations in rates of reduction across regions. The lowest rate of reduction in under-five child mortality was found in the Gambella region followed by the Afar region, with an average rate of disparity of 31 and 30 percent, respectively compared to the national average rate. In 2005, four regions, namely the Benshangul-Gumuz, Gambella, Amhara, and SNNP regions reduced their under-five child mortality rate to less than the national average rate, with differences in the rates of disparity in under-five child mortality (123 deaths per live thousand).

On the contrary, in the Somali region, the under-five child mortality was reduced by 32 percent more than the national average rate. The Harari region also reduced its under-five child mortality by 19 percent more than the national average rate, while the rate in the Tigrai region was reduced by 16 percent more than the national average rate in under-five child mortality. The Oromia region reduced its under-five child mortality rate by 1 percent more than the national average rate in 2005. Similarly, in 2011, six regions namely, Amhara, Oromia, SNNP, and Tigrai regions reduced their under-five child mortality rates more than the national average rate, with differences in the rates of disparities in under-five child mortality reduction. Moreover, in 2016, Tigrai was the only region found to reduce its rate of under-five child mortality by more than the national average rate, with 14 percent rate of disparity. This implies that in the Tigrai region, the rate of under-five child mortality (59 deaths per thousand live births) was reduced by 14 percent more than the national average rate (67 deaths per thousand live births).



Source: Own computation (EDHS; 2000; 2005; 2011; and 2016)

Figure 5. 1: The rate of disparity in under-five child mortality among regions

The descriptive analysis further indicates that the lowest rate of reduction in under-five child mortality was found in the Benshangul-Gumuz region followed by the Afar region, with an average rate of disparity of 48 and 31 percent, respectively, compared to the national average rate in 2011. These figures imply that the under-five child mortality rates in the Benshangul-Gumuz and Afar regions were reduced by 48 and 31 percent, respectively, more than the national average rate. Similarly, in 2016, the lowest rate of reduction in under-five child mortality was found in the Afar region followed by the Benshangul-Gumuz region, with an average rate of disparity of 40 and 32 percent, respectively (see Figure 5.1).

Furthermore, the results of the descriptive analysis indicated that the regions under analysis varied significantly in their average rate of under-five child mortality and characteristics. For example, the Tigrai region (59 deaths per thousand live births) had the lowest number of deaths of under-five children followed by the Harari region (72 deaths per thousand live births). Moreover, the descriptive analysis revealed that factors such as size of the child at birth, shorter birth spacing between children, mother's age at first birth, antenatal healthcare service visits, maternal educational level, household's wealth status, access to safe drinking water, use of modern contraceptives, the head of the household, and place of child delivery could be the major sources of regional differentials in under-five child mortality in rural settings of Ethiopia. This was because there were considerable differences in sample means and proportions for variables employed in the present study, and significant variations in the means and proportions among the regions. For example, the proportion of a child's birth size varied among the regions, with the lowest proportion of average birth size of a child was found in the Harari region (0.321) followed by the Gambella region (0.341), while the highest was found in Afar (0. 621) (see Appendix C, Table C-1).

Similarly, the regions also varied in the proportion of the heads of the households, with the lowest proportion of female-headed households found in the Amhara region (0.235) followed by the Somali region (0.284), while the highest proportion was found in Harari region (0.621). Moreover, the lowest proportion of child's birth spacing was found in the Tigrai region (0.126) and thus, an under-five child was more likely to die there than a child of the same cohort in the other regions. The descriptive findings also indicated that there was a considerable difference among the regions in terms of the proportion of the mother's age at the first birth of the child. Accordingly, the lowest proportion of mothers who were younger than 20 years at the first birth was found in the Tigrai region (0.236), while the highest proportion was found in the Afar region (0.455) followed by the Somali (0.436) and

Gambella (0.435) regions. Moreover, in all the regions, the highest proportion of mothers who delivered at health facilities was found in the Tigrai region. Likewise, in terms of antenatal healthcare service visits, the analysis considered whether the mother of the household was receiving or visiting a health professional, or not, at least four times during her pregnancy. Findings of the analysis indicated that there were substantial proportional differences in antenatal healthcare service visits among the regions. For example, a substantial proportion of mothers were getting antenatal healthcare services or were visiting health professionals during their pregnancy in the Tigrai region followed by Gambella region (see also Appendix C, Table C-1).

Furthermore, a mother's educational attainment was the most prominent variable, as many previous studies indicated its considerable effect on child mortality (Akuma, 2013; Assi, 2014; Gayawan et al., 2016; Hosseinpoor et al., 2006; Ikamari, 2013). The descriptive findings of this study revealed that there were substantial proportional differences among regions in mothers' educational attainment. The proportion and likelihood of deaths in the under-five children born to mothers who never completed their primary school were much higher than children of the same cohort whose mother at least completed their primary school. There was, however, a substantial difference across regions for children of mothers who never completed their primary school.

The descriptive analysis indicated that there were also considerable proportional differences in households' wealth index among the regions. Compared to the Tigrai region, the proportion of deaths of under-five children from households in the poorest third wealth index was much higher for the other regions. This implies that the proportion and likelihood of under-five child mortality in the Tigrai region were lower than in the other regions. The findings further revealed that there were significant disparities in the proportion of households who had access to safe drinking water among the regions, with the lowest proportion of households who had access to safe drinking water found in the Gambella and Afar regions. Moreover, in terms of use of modern contraceptive methods, there were differences among the regions with the lowest proportion of modern contraceptive methods users found in the Afar region (0.214) and the highest proportion found in the Tigrai region (0.736). Furthermore, the proportion of institutional delivery (at health facilities) varied among the regions, with the lowest proportion of institutional deliveries found in the Southern Nations, Nationalities, and People region (0.012) followed by the Somali region

(0.026) and Benshangul-Gumuz (0.027), while the highest proportion was found in the Tigrai region (0.216) (see also Appendix C, Table C-1). In summary, across the regions, there were considerable variations in the magnitude of effect of under-five child mortality and the factors associated with it.

5.2.2. Characteristics associated with under-five child mortality: A count data model analysis

As stated earlier, examining the major determinant factors affecting the inter-regional differentials in under-five child mortality were among the three specific research objectives of this study. The first step of the analysis was, therefore, to test for structural differences in the determinants of under-five child mortality and to evaluate the strength of their relationships across each region under analysis. Thus, a separate count data model regression was computed for each region, and pooled (at an aggregate level) to establish whether the levels of determinant factors varied across regions, and it also examined the strength of association of these determinants to under-five child mortality[25]. Thus, using the likelihood-ratio tests, the two different models (Poisson and negative binomial regression models) were tested against each other. Based on the estimation of the likelihood-ratio test, the separate and pooled Poisson regression estimates were rejected. This is because results of regression analysis indicated that the dependent variable suffered from over-dispersion (i.e. the conditional variance exceeded conditional mean) (see Appendix C, Table C-2). Most importantly, the descriptive summary of statistics also consolidated and supported estimates of the likelihood-ratio test, and indicated remarkable descriptive statistical differences between the regional comparisons for most of the regressed variables.

Furthermore, the results of the computed life-table indicated that there were considerable variations in estimates of rural under-five child mortality rates among the regions. Accordingly, the highest mortality was found in the Gambella (81 deaths per thousand births) followed by the Afar region (77 deaths per thousand births), while the lowest rate in under-five child mortality was observed in the Tigrai region with 51 deaths per thousand births. Moreover, the under-five child mortality for the Benshangul-Gumuz region was about 74 deaths per thousand births (see Appendix C, Table C-3).

[25] A determinant factor of under-five child mortality can be technically defined as a factor (variable) that would vary the levels of the population of mortality when its own value has been changed (Farah & Preston, 1982).

The estimated negative binomial regression analysis for each region, as well as the pooled analysis (the national level) is reported in Appendix C, Table C-4. The findings of the negative binomial regression analysis indicated that there were substantial differences in estimated coefficients of the proximate, socio-economic and environmental factors in under-five child mortality across regions. The separate regional regression analysis indicated that there were substantial differences in the effects of the regressed determinants on child mortality. Although much of the regressed variables showed mixed patterns of statistical levels of significance across the regions, the direction of association of most of the variables with regards to under-five child mortality was as expected, and was supported by many previous studies (Akuma, 2013; Goli et al., 2015; Houweling & Kunst, 2010; Masuy-Stroobant, 2001; Negera et al., 2013, among others)[26].

The second step of the analysis was then to decompose the aggregate and independent effect of these determinants across the regional comparisons. The sizable heterogeneity in the estimated coefficients of these variables (characteristics) for each regional comparison indicates that a non-linear regression based detailed Oaxaca-Blinder decomposition analysis is an appropriate approach in this context involving a separate regression for each region. A more detailed understanding of the independent and aggregate effects of these determinants could be achieved by decomposing their impact into components gap (explained and unexplained) using the recently developed detailed Oaxaca-Blinder decomposition technique (Powers et al., 2011).

5.2.3. The results of a detailed decomposition analysis

The results of a detailed decomposition analysis indicated that there were considerable regional differences in the components gap, the individual covariates effect, and the coefficients effects across the regional grouping[27]. Firstly, the results of the detailed decomposition analysis for each regional comparison were analysed, followed by findings of

[26] The specific objective of this chapter is not to examine the determinants of under-five child mortality rate rather it is to examine the determinants of inter-regional differentials in under-five child mortality rate and therefore these findings are presented and discussed in this chapter.

[27] Characteristics effect is that part of the group difference in the under-five child mortality rate attributable to explained component part due to observed characteristics. Whereas, coefficients effect is that part of the group differences in the under-five child mortality rate attributable to unexplained component part due to the effect of these characteristics.

the aggregate decomposition analysis as reported in Tables 5.1 to 5.4[28]. Furthermore, the findings of the aggregate impact of the proximate, socio-economic, and environmental factors as well as the covariates effect, coefficients effect, and aggregates effect on the regional differentials in under-five child mortality were also analysed, as illustrated in Figure 5.2 and Figure 5.3 as well as in Tables 5.1 to 5.4.

The results of the detailed decomposition analysis provided adequate evidence on the positive and negative effects of the explained components of the regional gaps in under-five children mortality. The results of the detailed decomposition analysis, which are the explained components of the regional gaps are presented in Table 5.1 - Table 5.4. The first column of Table 5.1 - Table 5.4 reported the covariates while the next three columns of Table 5.1 - Table 5.4 presented the relative contribution of individual covariate estimates (characteristics effect) along with their Standard Errors (SE) and their relative percentage contribution (share) of the comparison regions. Similarly, the last three columns of Table 5.1 - Table 5.4 indicated the relative contribution of individual covariate estimates along with their corresponding standard errors, and their relative percentage contribution (share) of the other comparison regions. The detail relative contributions of individual covariates as well as both the explained and unexplained components of the regional gaps are presented in Appendix C, Table C-5 to Table C-12.

The findings of the detailed decomposition analysis indicated that the magnitude of differences due to the difference in characteristics or covariates effect, coefficients effect, and the aggregate effect, varied substantially across regional comparisons. Thus, this section presented the findings of the detailed decomposition analysis that explored the relative individual contribution of the factors in reducing (explaining) or widening the regional differentials in under-five child mortality followed by results of the aggregate contribution of the socio-economic, proximate, and environmental factors in explaining or widening the regional gaps in under-five child mortality for the regional grouping[29]. In addition, findings of the aggregate decomposition analysis, such as the overall covariates effect, coefficients

[28] The present study analysis focused on the explained part of the components gap (covariates effect) because influencing the behavioural responses to the characteristics (captured by coefficient effects) is more complicated (Jann, 2008; O'Donnell et al., 2009; Oaxaca & Ransom, 1999).

[29] The relative contribution of individual covariates was expressed by taking the total gaps in under-five child mortality equivalent to 100 percent. Hence, a positive contribution (value) of the covariates indicate that the covariate is widening the gap in under-five child mortality between groups of comparison regions while the opposite holds true for a negative contribution (value) of the covariate.

effect, and aggregates (total gap or raw differences) effect of the regional comparisons were also analysed.

A) The Tigrai versus the Benshangul-Gumuz region (Tigrai-BG region)

As illustrated in Table 5.1, the detailed decomposition analysis revealed that the differences in observed characteristics (characteristics or covariates effect) explained only 37 percent of the gap in under-five child mortality between the Tigrai and Benshangul-Gumuz region[30]. The remaining unexplained 63 percent of the components gap in under-five child mortality between the two regions was attributable to differences in return of these characteristics (coefficients effect). This implies that the significant variations in under-five child mortality between the two regions remain largely unexplained.

Furthermore, results of the detailed decomposition analysis revealed that the relative contribution of individual decomposed covariates varied substantially in their magnitudes of effect and level of significance, while explaining the regional gaps in under-five child mortality. For example, the proportional regional differences in under-five child mortality largely reduced by the following mothers who were younger than 20 years at the first birth (38 percent), mothers who completed at least primary education (24 percent), children from a household in the poorest third wealth index (18 percent), shorter birth spacing between children (14 percent), children of larger household size (12 percent), father who completed at least a primary education level (10 percent), mothers who attended more than four antenatal healthcare service visits (8 percent), age of the child at death (3 percent), and being a male child (3 percent). In contrast to this, the proportional regional differences in under-five child mortality were widened by children whose birth size was less than the average (36 percent) and children of birth order of four or higher (12 percent) (see Table 5.1).

Most importantly, the significant negative contribution of the male under-five child (2.52percent) indicated that females of the same cohort were in a more disadvantageous situation in terms of mortality in the two comparison regions. Moreover, the negative contribution of the age of the child at death (2.93 percent) indicated that children of the Benshangul-Gumuz region were dying at a relatively younger age than children of the same cohort in the Tigrai region (see also Appendix C of Table C-5).

[30] Note that throughout the present study the characteristics effect and covariates effect are used interchangeably.

Thus, the proportional differences between the Tigrai and the Benshangul-Gumuz regions in age of the child, gender of the child, child's birth order, size of the child at birth, child's birth spacing, mother's age at first birth, antenatal healthcare service visits, parent's educational level, and household size were the determinant factors affecting the regional differentials in the under-five child mortality rate. Moreover, female under-five children of the Benshangul-Gumuz region were in a more disadvantageous situation in terms of mortality and children of the Benshangul-Gumuz region were dying at a relatively younger age.

Table 5. 1: Results of detailed Oaxaca-Blinder decomposition analysis for the Tigrai[RC]-BG and the Tigrai-Harari region

	Tigrai-BG region			Tigrai-Harari region		
Detailed Decomposition:	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Child's age	.00729***	.0147	-2.93	.01568	.0023	.62
Child's age squared	-.00002	.0006	-.01	-.01131	.1638	-5.15
Gender of the child =Male	-.00629***	.0008	-2.52	-.00096	.0010	-4.93
Child's birth order>4	.03102**	.0001	12.46	.41744 ***	.0433	17.01
Birth size < average	.09008***	.0217	36.17	.12902*	.0748	-3.45
Birth size = average	.023452	.02810	14.71	-.05695	.0444	-10.55
Multiple birth	.00031	.0009	.13	.00048	.0069	12.85
Short birth spacing	-.00406***	.0032	-13.63	-.03354	.0468	-9.29
Mother's age at birth <20	-.02061***	.0051	-38.27	.27147	.1402	5.05
Mother's age at birth >35	.0286	.0235	11.49	.16758***	.0569	8.45
Contraceptive use	.0017	.0014	.68	-.09187*	.0478	-15.68
Antenatal visits	-.02022*	.0113	-8.12	-.0455 ** *	.0109	-9.86
Mother's education	.05982** *	.0118	-24.02	.06339 *	.0379	-6.34
Mother's work status	-.03027	.0051	-12.15	.00232	.0335	11.93
Female-head household	-.01571	.0289	-6.31	-.02046	.0570	-4.29
Age of household head	-.03664	.0514	-6.27	.07445	1.069	8.72
Father's education	-.00133**	.0065	-9.53	.01849	.0555	9.39
Poorest third	-.04535**	.0211	-18.21	.00913 ***	.0004	-9.61
Middle third	.00972	.0068	3.91	-.00188	.0270	-9.67
Household size	-.00203***	.0066	-11.82	-.00913***	.0018	-4.22
Toilet facility	-.00039	.0007	-.16	-.00133	.0183	-6.51

Detailed Decomposition:	Tigrai-BG region Estimates	SE	Share[a]	Tigrai-Harari region Estimates	SE	Share[a]
Electricity facility	.00768	.0007	3.08	.16025***	.0613	-9.42
Place of child delivery	-.00850	.0048	-3.41	-.00780	.0385	-3.43
Safe drinking water	.00522	.0074	2.09	.01719	.0367	5.08
Aggregate decomposition						
Explained gap	.0924***	.0299	37.12	.09173	.00871	41.57
Unexplained gap	.1566***	.0464	62.88	.11118	.09559	58.43
Total gap[31]	.2491	.3544	100.00	.01945	.03619	100.00

Source: Own computation (EDHS, 2016)

Notes[32]: i) [a] The contribution of each covariate as a percentage of the total explained gaps

ii) The relative contributions of individual covariates can be positive (>0 percent) or negative (<0 percent). The positive contribution (4th and 7th columns) of the covariates shows that particular covariate contributes to widening the regional differentials in under-five child mortality rate while the negative contribution of a covariate designates the opposite (reducing or diminishing the regional gaps).

iii) **RC** represents the reference category and thus, in this study, Tigrai region was used as reference category

iv) (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

B) The Tigrai versus the Harari region (Tigrai-Harari region)

When looking at the Tigrai-Harari region in Table 5.1, the differences in the observable characteristics (covariates effect) accounted for 42 percent of the explained gaps between the Tigrai and the Harari regions in under-five child mortality. While the remaining 58 percent remained unexplained due to the differences in returns of these characteristics (coefficients effect). Findings of the decomposition analysis indicated that there were considerable differences in the relative contribution of individual decomposed covariates in terms of their level of significance and magnitudes of effect in explaining the Tigrai-Harari regional differentials in under-five child mortality. For example, the proportional differences regional differences in under-five child mortality were reduced by mothers who used modern

[31] In decomposition analysis, the raw difference in under-five child mortality across regions can be stated in terms of the overall components (explained and unexplained components) as a sum of weighted sums of the specific contributions of the individual explanatory variables (Powers & Yun, 2009).

[32] The information displayed under the notes in Table 5.1 also applies to the remaining Table 5.2 to Table 5.4

contraceptives (16 percent), women who received at least four antenatal healthcare service (10 percent), children of a household in the poorest third wealth index (10 percent), children of a household with access to electricity (9 percent), mothers who completed at least primary education (6 percent), children of a larger household size (4 percent), and children whose birth size was less than the average (3 percent) reduced significantly the regional gaps in child under-five child mortality. In contrast to this, the proportional regional differences in the under-five child mortality were widened by children of birth order of four or higher (17 percent) and mothers whose age at the first birth was greater than, or equal to 35 years (8 percent).

Findings further revealed that the negative relative contribution of the male under-five child (4.93 percent) indicated that females of the same cohort were in a more disadvantageous situation in terms of mortality in the two regions. In contrast this, the positive relative contribution of the age of the child at death (0.62 percent) indicated that children of the Tigrai region were dying at a relatively younger age than children of the same cohort in the Harari region **(**see also Appendix C, Table C-6).

Overall, the proportional regional differences in child's birth order, size of the child at birth, mother's age at first birth, mother's use of modern contraceptive, mother's education level, antenatal healthcare services, household size, household's access to electricity, and households' wealth status were the major determinant factors affecting the regional differentials in under-five child mortality. Moreover, female children of the Harari region were in a more disadvantageous situation in terms of mortality and the under-five children of the Harari region were dying at a relatively older age than children of the same cohort in the Tigrai region (See Table 5.1).

C) The Tigrai versus the Amhara region (Tigrai-Amhara region)

Look at the Tigrai and Amhara region as indicated in Table 5.2. Approximately 31 percent of the Tigrai-Amhara regional difference in under-five child mortality was explained by the differences in the distribution of determinants of under-five child mortality (covariates effect). The remaining unexplained major part of 69 percent of the components gap in under-five child mortality between the two regions was attributable to differences in return of these characteristics (coefficients effect).

The findings of the decomposition analysis indicated that the relative contribution of individual covariates varied significantly in explaining, or widening the regional differentials in under-five child mortality. For example, the proportional regional differences in under-five child mortality were reduced by mothers who completed at least primary education (13 percent), children born at home (12 percent), and children of a larger household size (10 percent). Most importantly, child's birth spacing played an increasingly important role in reducing the regional gaps in under-five child mortality. Thus, shorter birth spacing between children reduced significantly the regional gaps in under-five child mortality by 34 percent. In contrast to this, the proportional regional differences in under-five child mortality were widened by children of a household in the poorest third wealth index (24 percent), mothers who received four or higher antenatal healthcare services (9 percent), and children of birth order of four or higher (9 percent) (see also Appendix C, Table C-7).

Findings of the decomposition analysis further indicated that the negative relative contribution of a male under-five child (-0.50 percent) indicated that females of the same cohort were in a more disadvantageous situation in terms of mortality in the Tigrai and Amhara regions. In contrast to this, the positive contribution of the age of the child at death (3.64 percent) revealed that children of the Tigrai region were dying at a relatively younger age than children of the same cohort in Amhara region (see Table 5.2).

Thus, the proportional differences in a child's birth order, child's birth spacing, antenatal healthcare services, mother's educational attainment, household's wealth status, household size, and place of child delivery were the major determinant factors affecting the Tigrai-Amhara regional differentials in under-five child mortality. Moreover, female under-five children of the Amhara region were in a more disadvantageous situation in terms of mortality and children of the Amhara region were dying at a relatively older age.

Table 5. 2: Results of detailed Oaxaca-Blinder decomposition analysis for the Tigrai-Amhara and the Tigrai-Oromia region

	Tigrai-Amhara region			**Tigrai-Oromia region**		
Detailed Decomposition:	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Child's age	.00052	(.0014)	3.64	.00589	.2281	-14.27
Child's age squared	.00133	(.0063)	6.84	.11205	.1787	7.47
Gender of the child =Male	-.00035	(.0199)	-.50	-.00016	.0063	.39
Child's birth order>4	.00168***	(.0002)	8.62	.08548	.1921	3.44
Birth size < average	-.009203	(.1887)	-14.73	1.1348***	.1212	-11.49
Birth size = average	-.000838	(.0026)	-4.30	.00004	.0001	5.65

Detailed Decomposition:	Tigrai-Amhara region Estimates	SE	Share[a]	Tigrai-Oromia region Estimates	SE	Share[a]
Multiple birth	.000556	(.0012)	2.85	.02895	.0477	-9.56
Short birth spacing	-.00657***	(.0014)	-33.75	.44607***	.0359	-23.02
Mother's age at birth <20	.000685	(.0007)	3.51	.00187	.0012	-22.85
Mother's age at birth >35	.005045	(.0089)	25.92	-.01787	.0452	43.31
Contraceptive use	.001794	(.0015)	9.21	.00068	.0057	9.32
Antenatal visits	.001660*	(.0009)	8.53	-.21740***	.0198	26.39
Mother's education	-.03535***	(.0095)	-13.07	-.22877**	.1074	-13.77
Mother's work status	.001855	(.0027)	9.52	.00308	.1193	-7.46
Female-head household	-.000576	(.0086)	-2.95	-.00094	.0019	12.88
Age of household head	-.002869	(.0023)	-14.74	-.00307	.0208	-4.53
Father's education	-.001668	(.0274)	-8.57	-.08249	.1405	13.27
Poorest third	.000864**	(.0004)	24.43	-.04047	.2 807	-15.43
Middle third	.066438	(.2415)	-6.27	-.14386	.2190	9.85
Household size	-.001945***	(.0006)	-9.99	.27993*	.1436	7.80
Toilet facility	-.000612	(.0015)	-3.14	-.11036	.3408	19.69
Electricity facility	-.000624	(.0063)	-3.20	-.00045	.0174	10.79
Place of child delivery	.000526***	(.0001)	-12.14	2.04272***	.4014	-36.81
Safe drinking water	-.000746	(.0009)	4.83	-.00323	.1254	13.58
Aggregate decomposition						
Explained gap	.00414	.0059	31.13	.01899***	.00255	46.04
Unexplained gap	.01532	.0271	68.87	.02226	.03719	53.96
Total gap	.01946	.0384	100.00	.04126	.026191	100.00

Source: Own computation (EDHS, 2016)

Note: (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

D) The Tigrai versus the Oromia region (Tigrai-Oromia region)

Of the regions being compared to the benchmark of the Tigrai region, the Oromia region looks like an exception in the explained part due to differences in distributions of the observable covariates or characteristics (covariates or characteristics effect), which was substantially larger than in the case of the other regional comparisons. The covariates effect played a significant role in explaining the differences in under-five child mortality between the Tigrai and Oromia region. Thus, covariates effect constituted 46 percent of the explained regional gaps, while the coefficients effect accounted for over 54 percent of the unexplained part of the components gap.

Results of the decomposition analysis further indicated that the proportional regional differences in), children born at home (37 percent), shorter birth spacing between children (23 percent), and size of the child at birth less than average (11 percent) reduced the regional gaps in under-five child mortality. Moreover, parental education level, mainly the mother's education attainment, played a significant role in reducing the regional gaps in the under-five child mortality rate. Thus, mothers who had completed at least primary education contributed to a 14 percent in reducing the regional gaps in under-five child mortality. In contrast to this, the proportional regional differences in under-five child mortality were widened by mothers who received four or more antenatal healthcare service (26 percent), and children of households in the poorest third wealth status (24 percent) widened the Tigrai-Oromia regional differentials (see also Appendix C, Table C-8).

Furthermore, findings of the analysis revealed that the negative relative contribution of the male under-five children (0.50 percent) indicated that females of the same cohort were in a more disadvantageous situation in terms of mortality in the Tigrai and Oromia regions. The positive contribution of the age of the child at death (4 percent) indicated that children of the Oromia regions were dying at a relatively older age than children of the same cohort in the Tigrai region.

Overall, antenatal healthcare services, the child's birth order, the child's birth spacing, household's wealth status, household size, mother's educational attainment, and child's birth place were the most important determinant factors affecting the Tigrai-Amhara regional differentials in under-five child mortality. Moreover, male children of the Oromia region were in a more disadvantageous situation in terms of mortality and thus, under-five children of the Oromia region were dying at a relatively older age than children of the same cohort in the Tigrai region (See Table 5.2).

E) The Tigrai versus the Somali region (Tigrai-Somali region)

As indicated in Table 5.3, 44 percent of the components gaps was explained due to differences in distribution of the observable covariates (covariates effect), while 56 percent remained unexplained gap (coefficients effect) between the Tigrai and Somali region. Findings of the detailed decomposition analysis identified potential determinant factors that played an increasingly important role in reducing the regional gaps in under-five child mortality. Accordingly, the proportional regional differences in under-five child mortality were reduced by the proportion of children born at home (30 percent), children whose birth size was less than the average (20 percent), shorter birth spacing between children (18 percent), and mothers who attended more than four antenatal healthcare service visits (11 percent). In contrast to this, children of a multiple birth (20 percent) and children of a larger household size (18 percent) were the other potential determinant factors that widened the regional differentials in under-five child mortality.

The decomposition analysis further revealed that the positive relative contribution of the male under-five child (2.79 percent) indicated that males of the same cohort were in a more disadvantageous situation in terms of mortality in the two regions. Moreover, the positive contribution of the age of the child at death (13.45 percent) indicated that children of the Somali region were dying at a relatively older age than children of the same cohort in the Tigrai region **(**see also Appendix C, Table C-9).

In summary, household size, antenatal healthcare services, place of child delivery, the child's birth size, child's multiple births, and the child's birth spacing were the determinant factors affecting the regional differentials in under-five child mortality. Moreover, male children of the Somali region were in a more disadvantageous situation in terms of mortality and children of the Somali region were dying at a relatively older age than children of the same cohort in the Tigrai region (See Table 5.3).

Table 5. 3: Results of detailed Oaxaca-Blinder decomposition analysis for the Tigrai-Somali region and the Tigrai-Afar region

	Tigrai-Somali region			**Tigrai-Afar region**		
Detailed Decomposition:	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Child's age	-.05155	.0615	13.45	-.06610	.0435	-3.06
Child's age squared	-.06163	.0568	16.04	.09254	.1013	2.32
Gender of the child =Male	-.00304	.0051	2.79	-.07682	.1196	4.10
Child's birth order>4	-.00861	.0177	2.24	.00529	.1623	-6.22
Birth size < average	.450205***	.0434	-19.63	.02784	.0116	-17.64
Birth size = average	.00218	.0042	-2.56	-.04639	.1937	6.34
Multiple birth	.08416**	.0394	19.76	-1.7280	.4844	-.13
Short birth spacing	-.07001*	.0422	-18.48	-3.60573	6.3699	17.68

Detailed Decomposition:	Tigrai-Somali region			Tigrai-Afar region		
	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Mother's age at birth <20	-.01463	.0146	3.82	-.08114*	.0461	-21.71
Mother's age at birth >35	.00340	.0049	-.82	.05727	.0395	-3.95
Contraceptive use	.00376	.0270	-8.98	.13252	.1361	9.79
Antenatal visits	-.04520***	.0101	-10.85	.47684***	.0402	-18.81
Mother's education	-.00018	.0096	14.04	-.06583***	.03427	-19.58
Mother's work status	-.00613	.0158	13.69	-.02946	.0448	3.59
Female-head household	.00138	.0058	-5.34	-.09773	.0594	-2.28
Age of household head	-.02040	.0121	15.32	-.00029	.0519	-15.12
Father's education	-.00035	.0022	1.09	-.06564	.0399	7.37
Poorest third	.00273	.0199	-.74	-.00454	.0029	9.58
Middle third	.00424	.0173	-12.45	-.00014	.0003	-13.97
Household size	-.07099***	.0179	18.02	.02116	.0616	-5.02
Toilet facility	-.00164	.0138	-.42	.02015	.0438	-2.62
Electricity facility	.00169	.0041	-1.47	-.00992	.1601	-.33
Place of child delivery	.21882*	.1306	-29.58	-.03394	.0357	-6.06
Safe drinking water	-.00527	.0192	13.42	-.00377	.0110	4.24
Aggregate decomposition						
Explained gap	-.23733**	.0895	43.85	-.03472**	.0184	41.04
Unexplained gap	-.14635	.1298	56.15	-.0499	.0434	58.96
Total gap	-.38368***	.0884	100.00	-.08459**	.0366	100.00

Source: Own computation (EDHS, 2016)
Note: (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

F) The Tigrai versus the Afar region (Tigrai-Afar region)

When looking at the Tigrai and Afar region, as indicated in Table 5.3, the covariates effect accounted for 41 percent of the explained gap in under-five child mortality, while the coefficients effect accounted for 59 percent of the components gap between the Tigrai-Afar region. Findings of the detailed decomposition analysis further indicated that there were considerable differences in the relative contribution of individual covariates in reducing or widening the regional disparities in under-five child mortality. Among the potential determinant factors, mothers who were younger than 20 years at the first birth (22 percent), mother who had completed at least primary education (10 percent), and mother who had had four or more antenatal healthcare service visits (19 percent) reduced the regional gaps in under-five child mortality.

Furthermore, findings revealed that the positive relative contribution of the male under-five children (4.1 percent) indicated that males of the same cohort were in a more disadvantageous situation in terms of mortality in the two regions. In contrast to this, the negative contribution of the age of the child at death (3.06 percent) showed that children of the Afar region were dying at a relatively younger age than children of the same cohort in the Tigrai region **(**see also Appendix C, Table C-10).

In summary, mother's age at first birth (less than 20 years), antenatal healthcare services, and mother's educational attainment were the major determinant factors influencing the Tigrai-Somali regional differentials in under-five child mortality. Moreover, male children of the Afar region were in a more disadvantageous situation in terms of mortality and children of the Afar region were dying at a relatively younger age (See Table 5.3).

G) The Tigrai versus the SNNP region (Tigrai-SNNP region)

The SNNP region looks like an exception in that its unexplained gaps (coefficients effect) accounted for the largest 69 percent of the components gap, while the remaining 31 percent of the regional gap remained unexplained gaps (coefficients effect). Results of the decomposition analysis further indicated that maternal antenatal healthcare service played an important role in explaining the Tigrai-SNNP regional gaps in under-five child mortality. Accordingly, mothers who had had at least four or more antenatal healthcare service visits reduced the regional gaps in under-five child mortality by about 22 percent. Moreover, the proportional regional differences in children born at home (17 percent) and children of households in the poorest third wealth status (14 percent) reduced the regional gaps in under-five child mortality **(**see also Appendix C, Table C-11).

Findings further revealed that the positive relative contribution of the male under-five children (5.27 percent) indicated that males of the same cohort were in a more disadvantageous situation in terms of mortality in the two regions. In contrast to this, the negative contribution of the age of the child at death (6.81 percent) indicated that children of the Southern Nations, Nationalities, and People region were dying at a relatively younger age than children of the same cohort in Tigrai region. In general, antenatal healthcare services, households' wealth status, and place of child delivery were the major determinant factors affecting the regional differentials in under-five child mortality. Moreover, male children of the Southern Nations, Nationalities, and People region were in a more disadvantageous situation in terms of mortality and children of this region were dying at a younger age (See Table 5.4).

Table 5. 4: The results of detailed Oaxaca-Blinder decomposition analysis for the Tigrai-SNNP region and the Tigrai-Gambella region

	Tigrai-SNNP region			**Tigrai-Gambella region**		
Detailed Decomposition:	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Child's age	.009895	.03702	-6.81	-.003820	.00436	7.75
Child's age squared	.013149	.03146	2.42	-.001847	.00178	3.74
Gender of the child =Male	.042895	.03867	5.27	-.001230	.00227	2.44
Child's birth order>4	-.011836	.04369	32.42	.156431**	.06107	-23.68
Birth size < average	-.006443	.04268	-8.42	-.001197	.00245	12.42
Birth size = average	.059058	.04779	-11.95	.001539	.00229	-3.12
Multiple birth	.000144	.00469	-.21	-.003904	.00245	7.91
Short birth spacing	-6.95913	23.019	19.82	-.015156*	.00891	-30.73
Mother's age at birth <20	.005687	.08045	-9.07	-.006511	.00705	13.23
Mother's age at birth >35	-.000301	.00974	29.51	.004053	.00862	-5.31
Contraceptive use	.067751	.04198	-4.64	.000650	.00437	-1.31
Antenatal visits	.12219***	.03267	-21.62	-.029137	.03200	59.02
Mother's education	.092288	.07639	13.61	.000373	.00364	-6.75
Mother's work status	.078168	.09457	-6.64	.004175	.01546	-8.46
Female-head household	.002193	.00149	9.28	.007649	.02739	-15.51
Age of household head	.004971	.03305	-32.64	.011072	.06695	22.45
Father's education	-.087541	.12999	-5.58	-.071629***	.02188	-26.72
Poorest third	-.06539***	.01344	-13.77	.005087	.02033	-10.31
Middle third	-.000264	.00041	8.99	.003243	.01927	-6.57
Household size	.075981	.06570	3.54	-.073835	.02331	49.72
Toilet facility	-.050992	.12831	-2.96	.000131	.00208	-.26
Electricity facility	-.098967	.08133	9.04	-.005235	.01022	10.61
Place of child delivery	-.06379***	.01432	-17.13	.003852**	.00153	-27.12
Safe drinking water	-.003775	.12251	6.41	-.007259	.02173	14.71

	Tigrai-SNNP region			Tigrai-Gambella region		
Detailed Decomposition:	Estimates	SE	Share[a]	Estimates	SE	Share[a]
Aggregate decomposition						
Explained gap	.040941	.02509	30.54	.20308***	.04115	35.75
Unexplained gap	.017895	.03887	69.46	.06764	.11451	64.25
Total gap	.05884**	.02755	100.00	.04932	.07791	100.00

Source: Own computation (EDHS, 2016)
Note: (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

H) The Tigrai versus the Gambella region (Tigrai-Gambella region)

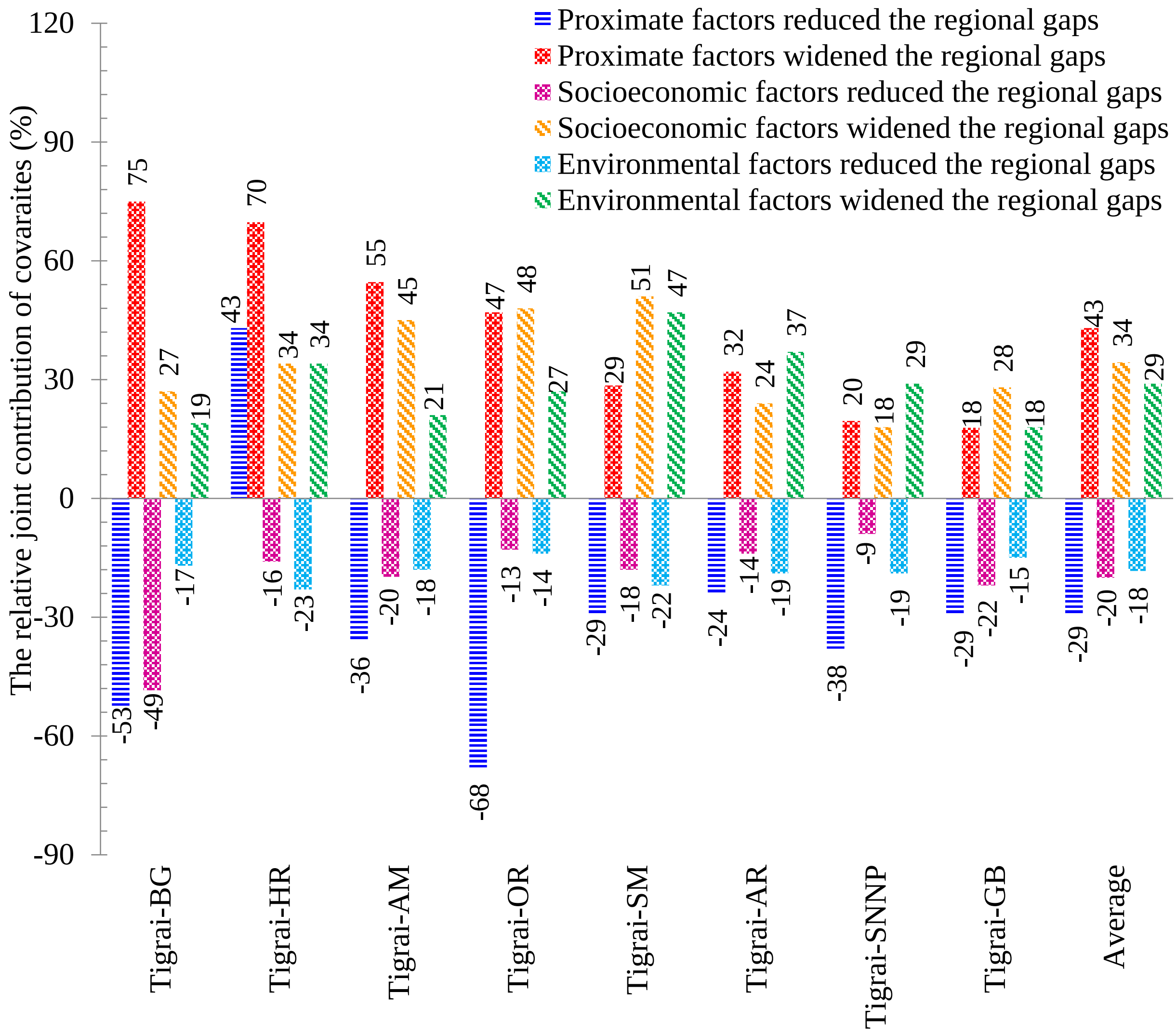
As indicated in Table 5.4, about 36 percent of the Tigrai-Gambella regional disparities in under-five child mortality was significantly explained by differences in the observable characteristics of the two regions (characteristics effect) while the remaining, 64 percent of the components gap remained unexplained due to differences in returns of these characteristics (coefficients effect). Results of the decomposition analysis further revealed that the relative contribution of individual determinant factors varied significantly in explaining or widening the regional disparities in under-five child mortality. For example, among the major determinant factors, the proportional differences in shorter birth spacing between children (31 percent), father who had completed at least primary education (27 percent), children born at home (27 percent), and children of birth order of four or higher (24 percent) reduced the regional gaps in under-five child mortality **(**see also Appendix C, Table C-12).

Findings of the decomposition analysis further indicated that the positive relative contribution of the male under-five children (2.44 percent) indicated that males of the same cohort were in a more disadvantageous situation in terms of mortality in the two regions. Moreover, the positive contribution of the age of the child at death (7.75 percent) showed that children of the Gambella region were dying relatively at an older age than children of the same cohort in the Tigrai region (See Table 5.4). In summary, the child's birth order, the child's birth spacing, parental educational attainment, and place of child delivery were the determinant factors affecting the regional disparities in under-five child mortality. Moreover, male children of the Gambella region were in a more disadvantageous situation in terms of mortality and children of the Gambella region were dying at a relatively older age.

5.2.4. Results of aggregate decomposition analysis

The study also analysed the aggregate decomposition analysis of the joint effects of the determinant factors or covariates (proximate, socio-economic, and environmental factors), covariates effect, coefficients effect, and aggregate effect for the regional differentials in under-five child mortality. Figure 5.2 and Figure 5.3 report the findings of the aggregate decomposition analysis of the joint effects of the covariates, covariates effect, coefficients effect, and aggregate effect for the regional grouping. On average, about 38.2 percent of the explained regional gaps (covariates effect) were attributed to the proximate, socio-economic, and environmental factors, while the largest 61.8 percent of the components gaps remained unexplained gaps (coefficients effect).

When taking a look at the aggregate effect of the decomposed factors, on average, the proximate (29 percent), socio-economic (20 percent), and environmental factors (18 percent) jointly reduced the regional gaps in under-five child mortality. In contrast to this, on average, the proximate (43 percent), socio-economic (34 percent), and environmental factors (29 percent) widened the regional variations in under-five child mortality. The major contributor to reducing the regional differentials in under-five child mortality was attributed to the aggregate effect of the proximate factors, which accounted for 29 percent of the regional gaps, while they also widened 43 percent of the regional gaps in under-five child mortality. The socio-economic factors altogether reduced the highest, 9 percent of the Tigrai-SNNP regional gaps and the lowest 49 percent of the Tigrai-BG regional differentials in under-five child mortality. They also widened the lowest 18 percent of the Tigrai-SNNP regional gaps and the highest 51 percent of the Tigrai-Somali regional gaps in under-five child mortality (see Figure 5.2). Similarly, the proximate factors altogether reduced the lowest 24 percent in the Tigrai-Afar regional gaps and the highest 68 percent of the Tigrai-Oromia regional gap in under-five child mortality. They also widened the lowest about 18 percent of the Tigrai-Gambella regional gaps (Tigrai-GB) and the highest 75 percent of the Tigrai-BG regional gaps in under-five child mortality. Moreover, on average, the environmental factors also reduced the lowest 14 percent of the Tigrai-Oromia regional gaps and the highest 23 percent of the Tigrai-Harari regional gaps in under-five child mortality. They also widened the lowest 18 percent of the Tigrai-Gambella the regional gaps and the highest 47 percent of the Tigrai-Somali regional gaps in under-five child mortality rate, with a different in the magnitude in the magnitudes of effect and mixed sign of estimates across the regional comparisons (see Figure 5.2).



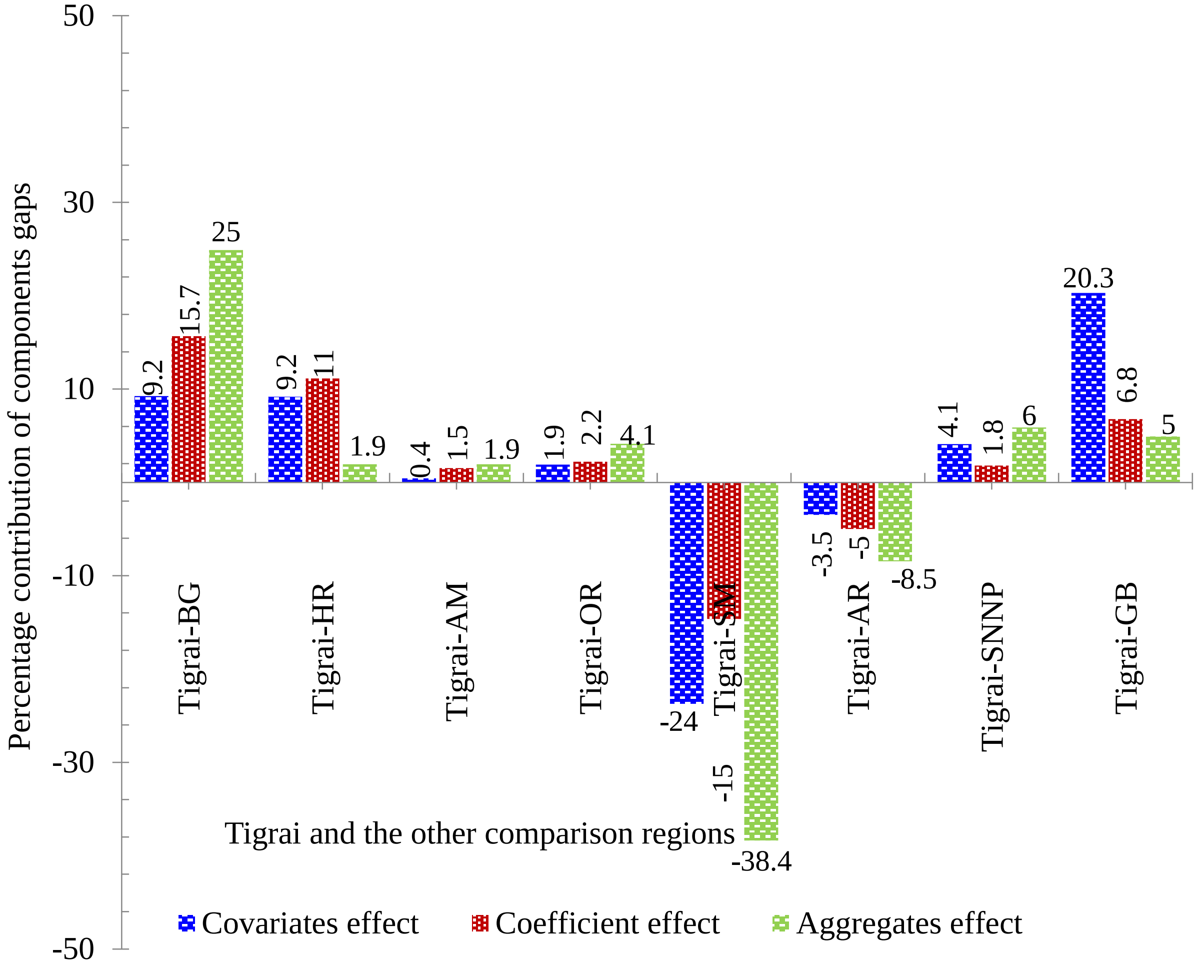
Source: Own computation (EDHS, 2016)

Figure 5. 2: The relative joint contribution of covariates between comparison regions

The results of the decomposition analysis further revealed that the contribution of the coefficients effect outweighs that of the covariates effect in explaining the regional differentials in under-five child mortality. As indicated earlier in Tables 5.1 to 5.4, on average, 61.8 percent of the regional gaps in under-five child mortality were unexplained gaps (coefficients effect), ranging from the lowest 54 percent (for the Tigrai-Oromia region) to the highest 69 percent (for the Tigrai-SNNP region). The remaining 38.2 percent of the regional gaps were explained gaps (covariates effect), ranging from the smallest 30 percent (for the Tigrai-SNNP region) to the highest 46 percent (for the Tigrai-Oromia region), with significant estimates of variations across the regional comparisons. Of the regions being compared with the Tigrai region was as a benchmark, the Southern Nations, Nationalities, and People region looks like an exception in that its covariates effect (30 percent) and coefficients effect (69 percent), respectively were significantly smaller and larger than in the case of the other comparison regions. This implies that relatively, the Tigrai region was advantaged in endowments of the decomposed covariates.

The aggregate magnitudes of both the explained and unexplained components gap could not indicate the relative magnitudes effect of the individual covariates on the regional gaps in under-five child mortality. A regional differential with the smallest (highest) explained gap (covariates effect) does not imply that the individual covariate has an insubstantial (substantial) effect on the explained regional gap in under-five child mortality. For example, as indicated in Figure 5.2, the results of the decomposition analysis indicated that 37 percent of the Tigrai and Benshangul-Gumuz regional gap was explained by the differences in the distribution of the decomposed characteristics. However, the mother's age at first birth alone contributed substantially to 38 percent of the regional gap, which is more than the explained aggregate regional gap (37 percent). Similarly, for the Tigrai-Gambella regions, about 36 percent of the components gap was an explained gap, but this also did not imply that all individual covariates had substantial effects in reducing or widening the regional gaps. For example, households with access to a modern toilet (0.26 percent) and mothers who used modern contraceptives (1.31 percent) had insubstantial effects in reducing the regional differentials. In contrast to this, for example, a children with short birth spacing between children (31 percent), children born at home (27 percent), and children of a birth order of four or higher (24 percent) all were factor that has substantial effects on reducing the regional gap in under-five child mortality (see Table 5.8).

The findings of the decomposition analysis further indicated that there were significant variations in the covariates effect, coefficients effect, and aggregate effect (total gaps or raw difference) across the regional comparisons. For the purpose of this study, and to make the analysis more understandable, the estimates of the covariates effect, coefficients effect, and aggregates effect were expressed as percentage and reported in Figure 5.3. The results of the decomposition analysis revealed that the lowest covariates effect of 24 percent was observed in the Tigrai-Somali region, while the highest 20 percent of the covariates effect was observed in the Tigrai-Gambella region.



Source: Own computation (EDHS, 2016)

Figure 5. 3: Aggregate decomposition gaps in under-five mortality among regions

The findings of the decomposition analysis further indicated that the lowest -15 percent of the aggregate coefficients effect was found in the Tigrai-Somali region, while the highest 16 percent of the aggregate coefficients effect was found in the Tigrai-BG region. Moreover, findings of the decomposition analysis revealed that the aggregate effect of 38 percent implied that the Somali region was performing a little better than the Tigrai region in reducing under-five child mortality, given the relative individual covariates' coefficients effect difference between the two regions. Results further revealed that the lowest aggregate effect of 38 percent was found in the Tigrai-Somali region, while the highest aggregate effect of 25 percent was observed in the Tigrai-BG region[33]. Except for the Tigrai-Somali and Tigrai-Afar region, in all other regions, there was a positive covariates effect, coefficients effect, and aggregate effect, with a different in the magnitude in the levels of effects and significance levels. Moreover, except for the Tigrai-Afar, Tigrai-Somali, and Tigrai-SNNP

[33] The aggregate effect (the total gap or raw difference) is the sum of the covariates and coefficients effects.

regions, the aggregate effect of the other regional comparisons was not significant (see also Tables 5.1 to 5.4).

As indicated in Figure 5.3, the positive significant covariates effect suggested that the regional gaps would be a little wider, given the covariates differences among the regions, while a negative significant covariates effect indicated that the second comparison region was performing relatively better than the Tigrai region. Accordingly, the Tigrai region was performing a little better than the other comparison regions in reducing the under-five child mortality except for the Somali and Afar region. Most importantly, results revealed that the regions being compared with the Tigrai region, the Somali and Afar regions were exceptions in that their covariates effect, coefficients effect, and aggregates effect were substantially smaller than those of the other regions (see also Tables 5.1 to 5.4).

5.3. The results of the Data Envelopment Analysis

5.3.1. Descriptive statistics of the DEA analysis: Input and output variables

A two-stage output-oriented DEA technique was employed to measure the efficiency and productivity changes of health posts for the period 2013 to 2014. Given that the time period under consideration was short, a variable returns to scale Data Envelopment Analysis technique was better suited to capture the overall efficiency of the sample health posts. This study employed 1,552 sample health posts with two input variables and six output variables to evaluate the efficiency and productivity changes of the health posts. Table 5.5 provides the descriptive statistics of the sample health posts.

On average, two female health extension workers per health post were performing their duties as per the national guideline to provide basic healthcare services to their respective communities. Although a significant variation was observed across regions of the country, an average of 42 health development armies per health post was found to perform their duties to assist their respective health extension workers. Compared to the year2013, on average, the quantities of inputs being utilised by almost all health posts increased in 2014. Accordingly, in 2014, the number of health extension workers increased by about 10.63 percent compared to those in 2013, while the number of health development armies increased by about 44.67 percent in 2014 compared to the number of the health development armies in 2013 (see Table 5.5).

Table 5. 5: Descriptive statistics of input and outputs considered in the DEA analysis

Variables	2013 Mean	2013 Range	2014 Mean	2014 Range	Change (2014-2013)
Inputs**:** Number of					
○ HEWs	1.82 (0.44)	[1, 3]	2.02 (0.41)	[1, 4]	10.63
○ HDAs	29.13 (13.41)	[5, 87]	42.144 (14.24)	[10, 98]	44.67
Output**:** Number of					
▪ HEP beneficiary graduates	143.71 (57.1)	[17, 446]	246.59 (246.59)	[21, 598]	71.59
▪ Households visited by HEWs	198.42(140.1)	[13, 935]	289.73 (289.73)	[55, 1139]	46.02
▪ Health education provided by HEWs	28.80 (14.13)	[2, 87]	22.06 (22.06)	[14, 46]	-23.39
▪ Child delivery by HEWs	24.94 (13.20)	[2, 89]	48.07 (48.07)	[4, 176]	92.72
▪ Child delivery by HDAs	17.33 (12.34)	[0, 81]	32.17 (32.17)	[3, 92]	85.61
▪ Under-five fully immunised children	20.89 (5.06)	[10, 30]	41.59 (41.59)	[2, 68]	99.03

Source: Own computation (RHB, 2013/14)

Note: Values in parenthesis are standard deviation; HDAs=Health Development Armies; HEWs=Health Extension Workers; and HEP= Health Extension Programme

As indicated in Table 5.5, there was a notable change in output provision in almost all outputs except for the output known as health education sessions, which was provided by health extension workers. The highest change of 99.03 percent was observed for an output of fully immunised children, with an annual average of 21 and 42 percent in 2013 and 2014, respectively. This was followed by a 92.72 percent increase in child delivery by a health extension worker, with an annual average of 25 and 48 percent in 2013 and 2014, respectively. But, a substantial change of reduction of 23.39 percent was observed in the health education sessions, with an annual average of 29 and 22 percent in 2013 and 2014, respectively. Findings further indicated that about 72 percent of households were graduated as model households, which were trained by the health extension workers in 2014. The rural households who had access to basic healthcare services were visited by health extension workers in order for the households to utilise and acquire skills on basic healthcare services. Moreover, the findings indicated that about 46 percent of households were visited by health extension worker, with annual average visits of 198 and 289 in 2013 and 2014, respectively. In addition, the number of children under-five years of age who were delivered at the health posts by the health development armies increased from 17 percent in 2013 to about 32 percent in 2014, with an annual average change of 86 percent (see Table 5.5).

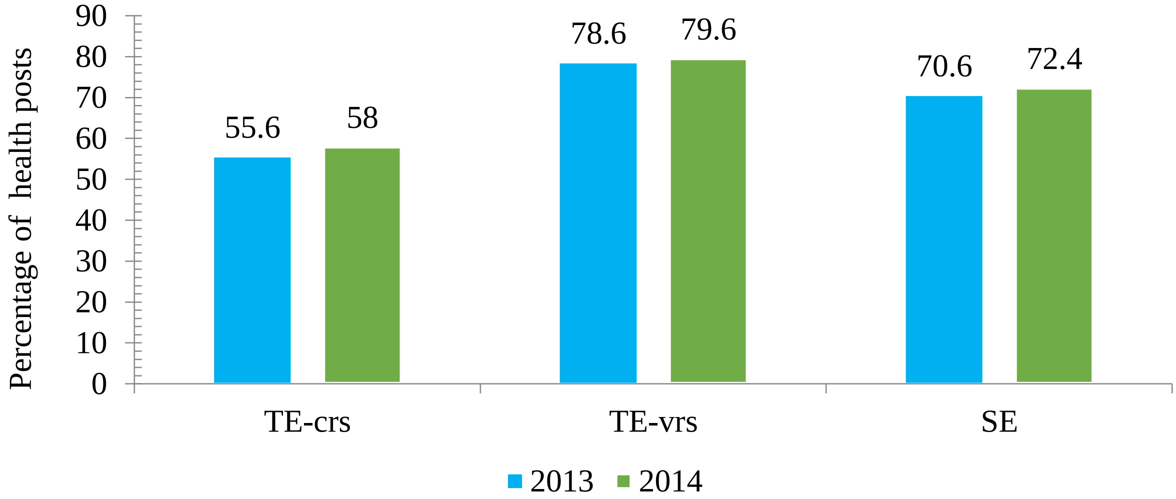
5.3.2. Empirical results of the DEA Analysis

The technical efficiency estimates of the sample health posts were computed using an output-oriented Data Envelopment Analysis technique based on constant and variable returns to scale assumptions. In addition, the analysis was made by determining by how much the levels of the technically inefficient health posts could be improved as a proportional increase in outputs, while keeping their present levels of inputs consumption constant. An analysis was also made on whether the levels of the technically inefficient health posts could be improved as a proportional reduction in their input consumption, while producing the same levels of outputs. The results of the relative technical and scale efficiency estimates (TE_{CRS}, TE_{VRS} and SE) of the sample health posts are presented in Table 5.6 to Table 5.8.

5.3.2.1. Estimates of the relative technical efficiency

As illustrated in Figure 5.4, the findings of the DEA analysis indicated that there was a substantial difference in technical and scale efficiency levels among the sample health posts, and over the study periods. In 2013, the average relative technical efficiency estimate of the sample health posts was 55.6 and 78.6 percent, respectively under constant and variable returns to scale assumptions, while for 2014, the mean technical efficiency level of the sample health posts was 58 and 79.6 percent under constant and variable to returns scale assumptions, respectively. These figures indicated that, on average, the sample health post could potentially produce at least 42 and 20.4 percent more outputs than those that were being produced (provided), while holding its current levels of input consumption fixed. Similarly, in 2013, the highest average technical efficiency estimates of the Tigrai regional health posts were 63.4 and 80.3 percent, while in 2014, they were 67.5 and 84.1 percent under constant and variable to returns scale assumptions, respectively. In contrast to this, in 2013, the lowest average technical efficiency estimate of the Harari regional health posts was 31.7 and 50.1 percent, while in 2014, it was 48.2 and 68.2 percent under constant and variable returns to scale assumptions, respectively (see Table 5.7 and Table 5.8).

Despite the level of differences in the technical efficiency estimates, the average technical efficiency level of the sample health post was higher by about 4.14 and 1.26 percent under constant and variable returns to scale assumptions, respectively in 2014 than it was in 2013. Furthermore, in 2014, the results of the DEA analysis indicated that the technical and overall efficiency levels of the sample health posts ranged from 0.273 to 1.00 and from 0.511 to 1.00 under constant and variable to returns scale assumptions, respectively. These figures suggested that the technically inefficient health posts given the existing production technology could potentially, on average, enhance their output provision by 72.7 and 48.9 percent under constant and variable returns to scale assumptions, respectively without requiring any additional quantities of inputs being consumed. That is, the sample health post had the scope of producing 3.66 and 1.96 times as much output from the same levels of input being consumed under constant and variable to returns scale assumptions, respectively.



Source: Own computation (RHB, 2013/14)

Notes: i) TE-crs and TE-vrs denote the technical efficiency under CRS and VRS, respectively

ii) SE: represents scale efficiency

Figure 5. 4: Average technical and scale efficiencies of health posts

As indicated in Table 5.6 and Table 5.8, the findings of the DEA analysis further indicated that the mean technical and scale efficiency estimates among the technically inefficient health posts varied significantly across the regions and during the study periods. This implies that there was potential room for those technically inefficient health posts to improve their overall technical efficiency estimates significantly by utilising the available levels of input in an efficient manner. Furthermore, between 2013 and 2014, the results of the

DEA analysis showed that the number of technically efficient health posts declined by about 29.23 and 45.5 percent under the constant and variable returns to scale assumptions, respectively. Similarly, the overall number of scale efficient health posts reduced by about 138.5 percent [0.376, 1.00] between the study periods. Moreover, the overall technical efficiency levels of the technically inefficient health posts ranged between 51.1 percent (in the Southern Nations, Nationalities, and People region) and 99.8 percent (in the Amhara region), with an average technical efficiency level of 78.3 percent. These figures indicated that the health posts of the SNNP and Amhara regions could potentially expand their output production by about 48.9 and 0.2 percent, respectively, with the current levels of input held fixed to operate at their optimal scale size of operation.

Table 5. 6: Summary of technical and scale efficiency estimates of the technically inefficient health posts

Statistics	Technical efficiency		Scale efficiency	
	CRS	VRS	CRS	VRS
Mean 2014	0.568 [0.273, 0.998]	0.783 [0.511, 0.998]	0.716 [0.376,1.00]	0.724 [0.376, 1.00]
Overall annual mean efficiency				
2013	0.539 [0.209,0.996]	0.766 [0.467,0.999]	0.695 [0.385,1.000]	0.697 [0.377,1.000]
2014	0.568 [0.273,0.998]	0.783 [0.511, 0.998]	0.716 [0.376,1.00]	0.713 [0.376,1.00]

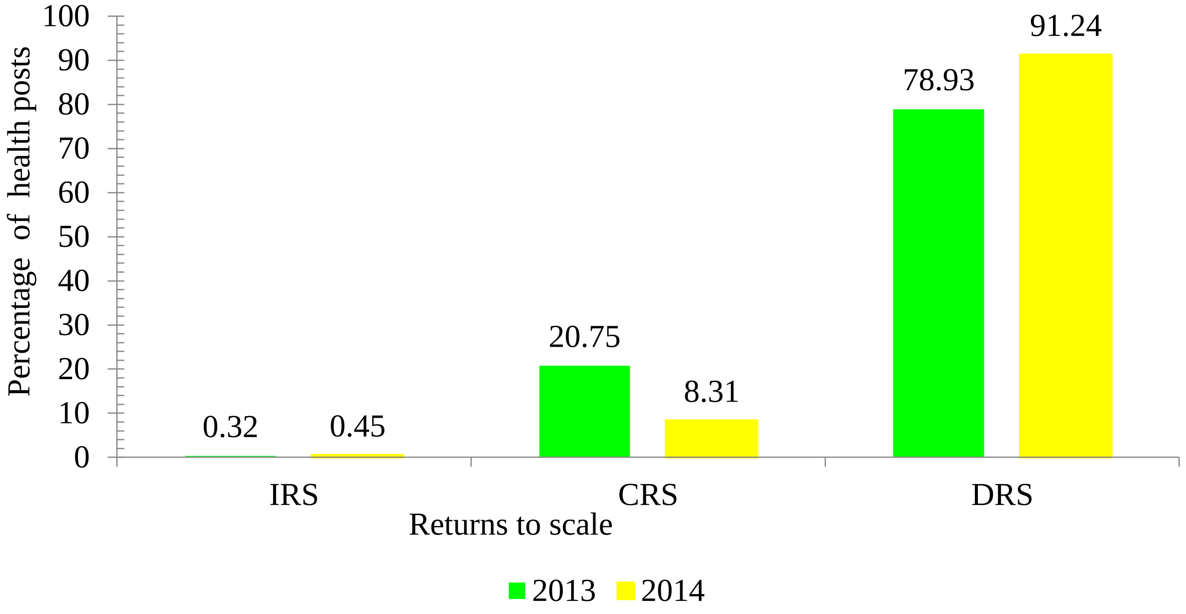
Sources: Own computation (RHB, 2013/14)

Note: i) Figures in brackets are the range in estimates of technical and scale efficiency
ii) CRS and VRS respectively represent constant and variable returns to scale

However, in 2013, only 3.67 and 8.25 percent of the sample health posts were technically efficient under the constant and variable returns to scale assumptions, respectively. While in 2014, only 2.84 and 5.67 percent of the sample health posts were defined as technically efficient under the constant and variable returns to scale assumptions, respectively, indicating that there was room for improvement in the technical efficiency estimates of the health posts. Findings further indicated that the average technical efficiency levels of the technically inefficient health posts were 53.9 and 76.6 percent, as well as 56.8 and 78.3 percent in 2013 and 2014 under the constant and variable returns to scale assumptions, respectively (see Table 5.6).

As illustrated in Table 5.7, the proportion of the technically efficient and inefficient sample health posts varies significantly across regions and during the study periods. For example, out of the total proportional sample health posts in the Tigrai region about 8.69 and 19.88 percent, in the Oromia about 3.83 and 7.15 percent, in the Amhara about 1.87 and 2.49 percent, and in the SNNP about 0.38 and 1.5 percent of the health posts were technically efficient under the constant and variable returns to scale assumptions, respectively. The Tigrai regional health posts had average technical efficiency estimates of 84.1 and 67.5 percent, implying that the health posts could potentially, on average, produce additional outputs about 16 and 33 percent using the current level of inputs under the constant and variable returns to scale assumptions, respectively. The Oromia regional health posts had 60.6 and 81.6 percent, suggesting the health posts could potentially, on average, produce additional outputs 39.4 and 18.4 percent under the constant and variable returns to scale assumptions, respectively, while using the same level of inputs. Furthermore, the Amhara regional health posts had had average technical efficiency estimates of 58.1 and 77.8 percent, implying that using the present level of inputs; they could potentially, on average, produce additional outputs 41.9 and 22.2 percent under the constant and variable returns to scale assumptions, respectively. The SNNP regional health posts had had average technical efficiency estimates of 51.5 and 75.5 percent, implying that they, on average, could potentially produce additional outputs about 48.5 and 24.5 percent under the constant and variable returns to scale assumptions, respectively, while using the same levels of inputs. Moreover, the highest mean technical efficiency level for the Tigrai regional health posts indicated that relatively they consumed their available inputs in a most efficient way. Hence, the Tigrai region attained the highest rank since this region had health posts, with the highest average technical efficiency levels under both scale assumptions. Whereas, the Harari regional health posts relatively had the highest input wastage, which was attributed to their optimal scale size with 48.2 and 68.1 percent of mean technical efficiency levels under the constant and variable returns to scale assumptions, respectively. Besides, the health posts of this region were, on average, operating below the national mean technical and scale efficiency levels of the sample health posts. On the other hand, the Amhara and the SNNP regional health posts were operating close to the national mean technical efficiency level of the sample health posts (see Table 5.7 and 5.8).

As reported in Figure 5.5 and Table 5.7, findings of the DEA analysis revealed that the proportion of sample health posts, which were operating at decreasing, constant, and increasing returns to scale, varied considerably across the regions and over the study periods. For example, the results of the efficiency analysis indicated that about 20.75 and 8.31 percent of the overall sample health posts were operating at their constant returns to scale (optimal scale size) in 2013 and 2014, respectively. Similarly, in 2013 and 2014, about 78.93 and 91.24 percent of the sample regional health posts were operating at the stage of decreasing returns to scale, respectively. Over the same periods, the sample regional health posts could potentially increase their current levels of technical efficiency estimates by persistently increasing their scale size of operation on the efficient frontier. Over the same periods, fewer than one percent (0.32 and 0.45 percent) of the sample health posts were operating at increasing returns to scale. Furthermore, in 2014, the results of the DEA analysis indicated that, on average, the largest 18.63 percent of the Tigrai regional health posts were scale efficient and were operating at their optimal scale size followed by 9.98 percent of the Oromia regional health posts. Moreover, about 7.48 percent of the Amhara region's proportional health posts, 6.69 of the Gambella region's proportional health posts, 5.26 percent of the SNNP region's proportional health posts, and 2.32 percent of the Benshangul-Gumuz region's proportional health posts were operating at their optimal scale size. In contrast to this, none of the Harari region's proportional health posts was found operating at their optimal scale size.



Source: Own computation (RHB, 2013/14). Notes: IRS, CRS, and DRS, respectively indicate increasing, constant, and decreasing returns to scale

Figure 5. 5: Proportion of health posts under various returns to scale

The results of the DEA analysis further indicated that the 100 percent of the Harari regional sample health posts were operating at supra-optimal scale size followed by Benshangul-Gumuz regional sample health posts (97.77 percent), while about 80.13 percent of the Tigrai regional health posts were operating at decreasing returns to scale (see Figure 5.4 and Table 5.7). In contrast to this, a very small sample of the regional health posts was operating at increasing returns to scale and therefore, this implies that these health posts could increase their technical efficiency levels by reducing their current scale size of operation. For example, about 1.24 percent of the Tigrai regional health posts, 0.62 percent of the Amhara regional health posts, 0.38 percent of the SNNP regional health posts, and about 0.33 percent of the Oromia regional health posts were operating at decreasing returns to scale (sub-optimal scale size operation) (see Table 5.7).

Table 5. 7: Percentage of technical and scale efficient health posts, by region

		Technically efficient HPs		Scale efficient	HPs operating at:		
Regions	Rank	TE_{CRS}	TE_{VRS}	Health posts	DRS	CRS	IRS
Tigrai	1	8.69 (0.675)	19.88 (0.841)	18.63 (0.797)	80.13	18.63	1.24
Amhara	3	1.87 (0.581)	2.49 (0.778)	7.48 (0.744)	91.90	7.48	0.62
Oromia	2	3.83 (0.606)	7.15 (0.816)	9.98 (0.737)	89.52	10.15	0.33
SNNP	4	0.38 (0.515)	1.50 (0.755)	5.26 (0.681)	94.36	5.26	0.38
Gambella	5	0.00 (0.522)	0.00 (0.841)	6.69 (0.617)	92.31	7.69	0.00
BG	6	0.00 (0.510)	0.00 (0.775)	2.32 (0.657)	97.77	2.23	0.00
Harari	7	0.00 (0.482)	4.54 (0.681)	0.00 (0.707)	100.00	0.00	0.00
2013		3.67 (0.556)	8.25 (0.786)	20.75 (0.706)	78.93	20.75	0.32
2014		2.84 (0.580)	5.67 (0.796)	8.70 (0.724)	91.24	8.31	0.45

Source: Own computation (RHB, 2013/14)

Note: i) Values in parentheses are average technical and scale efficiency levels
ii) TE_{CRS} and TE_{VRS}, respectively represent technical efficiency based on constant and variable returns to scale assumptions
iii) DRS, CRS, and IRS represent decreasing, constant, and increasing returns to scale, respectively.

As indicated in Table 5.8, the findings of the DEA analysis further indicated that the average scale and technical efficiency levels of the sample health posts varied considerably across regions and over the study periods. For example, in 2013, the Tigrai regional health posts had an average technical efficiency level of 63.4 and 80.3 percent under the constant and variable returns to scale assumptions, respectively. Similarly, in 2014, they had an average technical efficiency level of 67.5 and 84.1 percent under the constant and variable returns to scale assumptions, respectively. The health posts with the relatively highest mean scale and technical efficiency levels were found in the Tigrai region, with mean scale efficiency estimates of 78.6 and 79.7 percent in 2013 and 2014, respectively. Similarly, the Amhara regional health posts had a mean technical efficiency level of 57.1 and 77.1 percent in 2013, and 58.1 and 77.8 percent in 2014 under the constant and variable returns to scale assumptions, respectively. Over the same periods, they had a mean scale efficiency estimate of 74 and 74.4 percent. Whereas, the Harari regional health posts had the lowest mean technical efficiency levels, with average technical efficiency estimates of 31.7 and 50.1 percent in 2013, and 48.2 and 68.1 percent in 2014, under the constant and variable returns to scale assumptions, respectively. Moreover, in 2013 and 2014, the Harari regional health posts had an average scale efficiency estimate of 62.6 percent and 70.7 percent, respectively.

Table 5. 8: Average technical and scale efficiency estimates of health posts by region

	2013			2014		
Region	TE_{CRS}	TE_{VRS}	SE	TE_{CRS}	TE_{VRS}	SE
Tigrai	0.634	0.803	0.786	0.675	0.841	0.797
Amhara	0.571	0.771	0.740	0.581	0.778	0.744
Oromia	0.597	0.802	0.744	0.606	0.816	0.737
SNNP	0.484	0.757	0.637	0.515	0.755	0.681
Gambella	0.481	0.868	0.554	0.522	0.840	0.617
BG	0.451	0.801	0.561	0.510	0.775	0.657
Harari	0.317	0.501	0.628	0.482	0.681	0.707
Mean	0.556	0.786	0.706	0.580	0.796	0.724

Source: Own computation (RHB, 2013/14)

Note: i) TE_{CRS} and TE_{VRS}, respectively denote technical efficiency under constant and variable returns to scale assumptions. ii) SE: represents scale efficiency

5.3.2.2. Estimates of scale efficiency and returns to scale

Due to the presence of scale efficiency, the technical efficiency estimates of the sample health posts used as the decision-making units under constant returns to scale assumption are lower than those of the technical efficiency estimates under the variable returns to scale assumption (Coelli, 1996). To provide further insight into the impact of the Ethiopian health extension programme on efficiency, separate scale efficiency estimates and types of returns to scale for each regional health post were performed and identified. Therefore, the effect of each health post's scale on its technical efficiency estimates was computed in three steps. In the first step, the overall technical efficiency estimate of each health post was computed under the constant returns to scale assumption. In the second step, the technical efficiency estimate of each health post was also computed under the variable returns to scale assumption. Finally, in the third step, the scale efficiency (SE) was computed by dividing the overall technical efficiency estimates (TE_{CRS}) to a pure technical efficiency estimate (TE_{VRS}) based on an output-oriented measure of technical efficiency (SE $= TE_{CRS}/TE_{VRS}$). The ratio of unity (100 percent) indicates that the health post was scale efficient, which implies that the health post was operating at optimal scale size for that specific input-output combination. Whereas a ratio of less than unity (<100 percent) indicates the opposite, which means that the health posts were scale inefficient.

As displayed in Table 5.6, findings of the analysis revealed that the scale efficiency estimates of the sample health posts varied substantially across regions and over the study periods. Moreover, the scale efficiency levels for the technically efficient and inefficient health posts also varied significantly across regions and over the study periods. For example, in 2013, about 20.75 percent of the overall sample health posts were scale efficient, with an overall average scale efficiency estimate of 70.6 percent, while in 2014; only 8.7 percent of the health posts were scale efficient, with an overall average scale efficiency level of 72.4 percent. In 2013, the overall mean scale efficiency for the technically inefficient health posts was 69.5 and 69.7 percent under the constant and variable returns to scale assumptions, respectively, indicating that, on average, they could potentially reduce their scale size by 30.5 and 30.3 percent maintaining their current levels of output production, respectively. While in 2014, the overall mean scale efficiency level for the technically inefficient health posts was 71.6 and 71.3 percent under the constant and variable returns to scale assumptions, respectively. These figures signify that, on average, a scale inefficient health post could potentially reduce its scale size by 28.4 and 28.7 percent without affecting its output provision to operate at its most productive scale size, respectively.

Over the two study periods, there was an improvement in the average scale efficiency level of the sample health posts, with significant variations in magnitudes of changes. For example, the overall national average scale efficiency level of the health posts was improved by 2.5 percent over the two periods. Moreover, as indicated in Table 5.7, about 20.75 percent of the health posts were scale efficient operating at an optimal scale size in 2013 and therefore, this implies that they could potentially increase their levels of technical efficiency by increasing their scale size. Whereas in 2014, about 8.7 percent of the health posts were operating at optimal scale size, suggesting that they could potentially increase their technical efficiency levels by increasing their scale size of the operation.

As reported in Figure 5.5, Table 5.7, and Table 5.8, in 2013, overall a sample health post had a mean scale efficiency of 70.6 percent, while in 2014, the overall average scale efficiency estimate of the health post was 72.4 percent. These figures suggest that, on average, the scale inefficient health posts could continue producing their current level of outputs by reducing their scale size of operation by 29.4 and 27.6 percent in 2013 and 2014, respectively. The actual scale of production of the sample health post was deviated from the optimal scale size of operation, on average, by about 29.4 in 2013 and 27.6 percent in 2014. These figures imply that an average scale inefficient health post achieved 70.6 and 72.4 percent of its optimal scale efficiency in 2013 and 2014, respectively. Most importantly, in 2014 the findings the of DEA analysis indicated that the majority of the sample health posts (91.24 percent) were operating at decreasing returns to scale (supra-optima scale size), which is the major form of scale inefficiency in the present study, while the remaining 8.31 and 0.45 percent of them were operating at constant returns to scale (optimal scale size) and increasing returns to scale (sub-optimal scale size), respectively.

In 2013, most of the sample health posts (78.93 percent) were also operating at decreasing returns to scale, while the remaining 20.75 and 0.32 percent of them were operating at constant and increasing returns to scale, respectively. The DEA analysis further indicated that there were regional differentials in scale efficient health posts. For example, in 2014, in the Tigrai region, about 18.63 percent of its proportional sample health posts were scale efficient and were operating at an optimal scale size, while the remaining 80.13 and 1.24 percent of them were operating at decreasing and increasing returns to scale, respectively. This region consistently had more technical and scale efficient health posts, and took the lead with a mean scale efficiency level of 79.7 percent, indicating the health posts had the scope to additionally increase their outputs provision by about 20.3 percent by downsizing their scale size. Likewise, about 9.98 percent of the Oromia regional health posts were scale efficient and were operating at their optimal scale size, with an average scale efficiency estimate of 73.7 percent. In the Amhara region, about 7.48 percent of the health posts were scale efficient and were operating at their optimal scale size, with an average scale efficiency estimate of 74.4 percent. Moreover, nearly 6.69 and 5.26 percent of the Gambella and the SNNP regional health posts were scale efficient and were operating at their optimal scale size, with average scale efficiency estimates of 61.7 and 68.1 percent, respectively. Most importantly, though the average scale efficiency level of the sample health posts was about 72.4 percent in 2014, none of the Harari regional health posts was scale efficient followed by the Benshangul-Gumuz region, with only 2.32 percent of its health posts found to be scale efficient. The number of scale efficient health posts varied across regions and over the study periods. For example, the number of scale efficient sample health posts was reduced from 20.75 percent in 2013 to 8.7 percent in 2014. On the other hand, the average scale efficiency estimates of the sample health posts was increased from 70.6 percent in 2013 to 72.4 percent in 2014, with an annual rate of increase 2.5 percent. Moreover, at national level, the number of health posts operating below their optimal scale size was increased from 78.93 percent in 2013 to 91.24 percent in 2014, with an annual average rate of increase 13.5 percent. This figure indicates a potential to downsize their scale size to operate at the efficient frontier. Furthermore, results of decomposition analysis indicated that across regions and over the study periods, very few health posts were operating at increasing returns to scale (see Table 5.7).

5.3.2.3. Improving universal healthcare services coverage

The Data Envelopment Analysis technique further computed the annual average quantities of output gains and input savings needed to make the technically inefficient health posts technically efficient. The estimates of quantities of output gains and input savings could deliver a wealth of information relating to the areas in which the technically inefficient health posts need to improve their levels of technical inefficiency estimates to achieve the efficiency frontier. Table 5.9 provides a summary of annual average potential quantities of output gains (additions) and input savings (reductions) estimates of the DEA analysis needed to make the technically inefficient health posts technically efficient. The potential improvement shows the areas of improvement for input savings and output gains needed by the technically inefficient health posts to reach the efficiency frontier (Worthington, 2000).

The technically inefficient health posts could potentially improve their technical efficiency by either reducing their inputs being currently consumed or increasing their outputs being currently produced or at the same time by increasing their present level of outputs being produced. Findings also showed that there were significant differences in the quantities of inputs needing to be reduced (input savings) and the quantities of outputs needing to be added (output gains) to the technically inefficient health posts across the technically inefficient health posts and over the study periods needed to make them technically efficient. The findings of the DEA analysis further indicated that the average number of health extension workers needing to be reduced by the Harari regional technically inefficient health posts was 0.25 percent followed by 4.92 percent of the Tigrai regional technically inefficient health posts to make them produce at the efficiency frontier were at a minimum level in 2013. Moreover, the average number of health development armies needing to be reduced by the Amhara regional technically inefficient health posts (4.02 percent) followed by Tigrai regional technically inefficient health posts (7.45 percent) to make them technically efficient were at a minimum level in 2013. In 2014, the smallest average number of health extension workers needing to be reduced by the SNNP regional technically inefficient health post was 1.72 percent followed by the Benshangul-Gumuz regional technically inefficient health post (2.48 percent). Similarly, the average number of health development armies needing to be reduced by Amhara regional technical inefficient health post was 10.86 percent followed by 12.32 percent of the Tigrai regional technically inefficient health post to make them produce at efficient frontier were at the minimum level. These figures indicate that the regional technically inefficient health posts could be made technically efficient by reducing their current levels of inputs being wasted or by improving (rising) their current level of outputs being produced (see Table 5.9).

The results of the DEA analysis further indicated that the quantities of inputs being saved (input savings) and outputs gains (output additions) needed to make the technically inefficient health post technically efficient varied substantially across regions of the country and over the study periods (see Table 5.9). Therefore, the proportional reductions in the level of inputs alone would not make the technically inefficient health posts technically efficient, unless they simultaneously augmented their current levels of outputs production (Kumar and Gulati, 2008). Concurrently, the technically inefficient health posts needed potentially to produce more outputs, while reducing the level of inputs being consumed. For example, in 2013, the Tigrai regional technically inefficient health post could possibly have raised its current level of outputs. Thus, to make it produce at the most productive scale size point, the technically inefficient health post should have increased the health extension programme beneficiary graduates by 36 percent, 40 percent of households had to be visited by the health extension workers, 51 percent of health education sessions needed to be provided by health extension workers, 52 percent of children needed to be delivered by health extension workers, 74 percent of children needed to be delivered by health development armies, and 35 percent of children needed to be fully immunised. At the same time, an average technically inefficient health post in the Tigrai region could possibly have reduced its health extension workers and health development armies' employment by about 5.49 and 7.45 percent, respectively. Whereas in 2014, an average technically inefficient health post in the Tigrai region could possibly have raised its current level of outputs being produced. Therefore, to make it produce at efficiency frontier, it should have increased the health extension programme beneficiary graduates by 40 percent, 32 percent of households needed to be visited by health extension workers, 29 percent of health education sessions needed to be provided by health extension workers, 63 percent of children needed to be delivered by health extension workers, 53 percent of children needed to be delivered by health development armies, and 35 percent of children needed to be fully immunised.

In 2013, for the technically inefficient health post in the Amhara region, to operate at the efficient frontier, it could on average, potentially produce an additional 44 percent of programme beneficiary graduates, 46 percent of households need to be visited by the health extension workers, 85 percent of health education sessions should be provided by health extension workers, 82 percent of children need to be delivered by health extension workers, 63 percent of children need to be delivered by health development armies, and 42 percent of children need be fully immunised. At the same time, it could possibly reduce its inputs of health extension workers and health development armies' employment by about 5 and 4 percent, respectively. Moreover, in 2014 an Amhara regional technically inefficient health post could potentially increase its outputs by 42 percent of programme beneficiary graduates, 54 percent households need to be visited by the health extension workers, 43 percent of health education sessions must to be provided by health extension workers, 49 percent of children need to be delivered by health extension workers, 33 percent of children need to be delivered by health development armies, and 30 percent of under-five children need to be fully immunised. Simultaneously, it could possibly reduce its health extension workers and health development armies' employment by about 6 and 11 percent, respectively.

Table 5. 9: The average input savings and output gains needed to make the inefficient health posts technically efficient

		Potential improvements in percentage, 2013							
		Output gains (Output addition)						Input savings	
Regions	TE	O_1	O_2	O_3	O_4	O_5	O_6	I_1	I_2
Tigrai	0.78	36.23	40.27	51.19	52.33	74.06	34.66	-5.49	-7.45
Amhara	0.73	44.11	46.23	84.86	81.89	63.07	41.50	-4.92	-4.02
Oromia	0.78	43.30	105.3	44.33	59.57	55.64	34.13	-7.23	-15.33
SNNP	0.75	66.01	88.09	79.51	137.95	125.8	40.63	-14.27	-21.59
Gambella	0.87	73.29	177.26	31.63	158.21	258.0	15.23	-19.89	-29.71
BG	0.80	75.39	224.9	35.92	142.38	243.73	26.20	-13.58	-13.49
Harari	0.50	104.85	143.57	117.75	562.81	83.86	100.83	-0.25	-17.43
Mean	0.77	51.87	98.36	59.12	96.26	68.31	36.43	-8.83	-13.92
		Potential improvements in percentage, 2014							
		Output gains (Output addition)						Input savings	
Regions	TE	O_1	O_2	O_3	O_4	O_5	O_6	I_1	I_2
Tigrai	0.80	40.03	31.68	28.83	63.10	52.82	35.01	-6.50	-12.32
Amhara	0.77	42.17	53.80	42.89	49.14	33.11	30.06	-5.99	-10.86
Oromia	0.80	37.31	59.68	28.96	36.92	26.93	25.81	-2.80	-21.94
SNNP	0.75	42.13	49.29	44.91	58.80	36.35	34.26	-1.71	-21.58
Gambella	0.84	29.21	70.38	19.09	47.18	25.87	19.09	-6.09	-40.48
BG	0.78	36.25	77.32	29.32	68.01	31.48	29.06	-2.48	-22.41
Harari	0.67	63.96	121.98	49.61	162.74	50.52	52.99	-5.20	-33.89
Mean	0.78	43.81	54.77	34.04	48.09	32.22	29.17	-4.00	-20.44

Source: Own computation (RHB, 2013/14)

Note: i) TE represents the technical efficiency estimates under the VRS assumption

ii) O_1, O_2, O_3, O_4, O_5, and O_6 represent the number of (not rounded): the HEP beneficiary graduates, rural households visited by HEWs, health education sessions provided by HEWs, child delivery by HEWs, child delivery by HDAs, and under-five fully immunised children, respectively (output gains)

iii) I_1 and I_2 denote the number of HEWs and HDAs (both measured in number) need to be reduced (input savings)

Overall, at the national level, for example in 2013, an average technically inefficient health post could possibly augment its current levels of outputs by about 52 percent of programme beneficiary graduates, 98 percent of rural households needed to be visited by health extension workers, 59 percent of health education sessions needed to be provided by health extension workers, 96 percent of children need to be delivered by health extension workers, 68 percent of children needed to be delivered by health development armies, and 36 percent of children needed to be fully immunised. At the same time, it needed to reduce its present levels of inputs being employed, the number of health extension workers and health development armies' employment by about 9 and 14 percent, respectively, to be a technically efficient health post. Similarly, in 2014 an average technically inefficient health post could possibly increase its current levels of outputs being produced by 44 percent of programme beneficiary graduates, 55 percent of rural households had to be visited by health extension workers, 34 health education sessions needed to be provided by health extension workers, 48 of children needed to be delivered by health extension workers, 32 percent of children needed to be delivered by health development armies, and 29 percent of children needed to be fully immunised. Concurrently, it needed to reduce its current levels of inputs being employed, the number of health extension workers and health development armies' employment by about 4 and 20 percent, respectively, to operate at the efficient frontier. Therefore, the reduction in inputs (input savings) and the simultaneous increases in outputs (output additions) by the technically inefficient health posts could lead to a considerable increase in healthcare services output provision both at the regional and national levels by increasing access to and utilisation of the basic healthcare services to the large and underserved population of the country (see also Appendix C, Tables C-13 to C-14).

5.3.3. Estimates of the Malmquist Productivity Analysis

Estimates of productivity changes or growth for the sample health posts were also examined using an output-oriented DEA technique-based Malmquist productivity index between the two study time periods (2013 to 2014). The efficiency change reflects to what extent a health post improves or worsens its efficiency level, while the technological change reflects the change of the efficiency frontiers between the two-time periods (2013 to 2014) (Coelli et al., 2005). Table 5.10 provides summary statistics of the Malmquist productivity index analysis of the sample health posts, along with its sources of growth (productivity change components). This productivity change or growth was decomposed into five component measures of efficiency changes. These are:

i) Technical efficiency change ($effch$) reported in the 2nd column of Table 5.10.
ii) Technological efficiency change ($techch$) provided in the 3rd column of Table 5.10.

iii) Pure technical efficiency change ($pech$) presented in the 4th column of Table 5.10.

iv) Scale efficiency change ($sech$) provided in the 5th column of Table 5.10, and

v) Total factor productivity change ($tfpch$) reported in the 6th column of Table 5.10.

Table 5. 10: Malmquist Productivity index summary of annual means

Region	Technical efficiency change ($effch$)	Technological change ($techch$)	Pure efficiency change ($pech$)	Scale efficiency change ($sech$)	Total factor productivity change ($tfpch$)
Tigrai	0.962	1.232	1.00	0.962	1.193
Amhara	0.894	1.242	1.00	0.894	1.110
Oromia	0.889	1.182	1.00	0.889	1.045
SNNP	0.895	1.338	1.00	0.895	1.195
Gambella	0.955	1.440	1.00	0.955	1.386
BG	0.902	1.372	1.00	0.902	1.236
Harari	0.780	1.415	1.00	0.780	1.094
Mean	0.868	1.229	1.00	0.868	1.067
>1.00	18.82	83.76	0.00	18.82	60.12
=1.00	7.02	0.20	100	7.02	0.19
<1.00	74.16	16.04	0.00	74.16	39.69

Sources: Own computation (RHB, 2013/14)

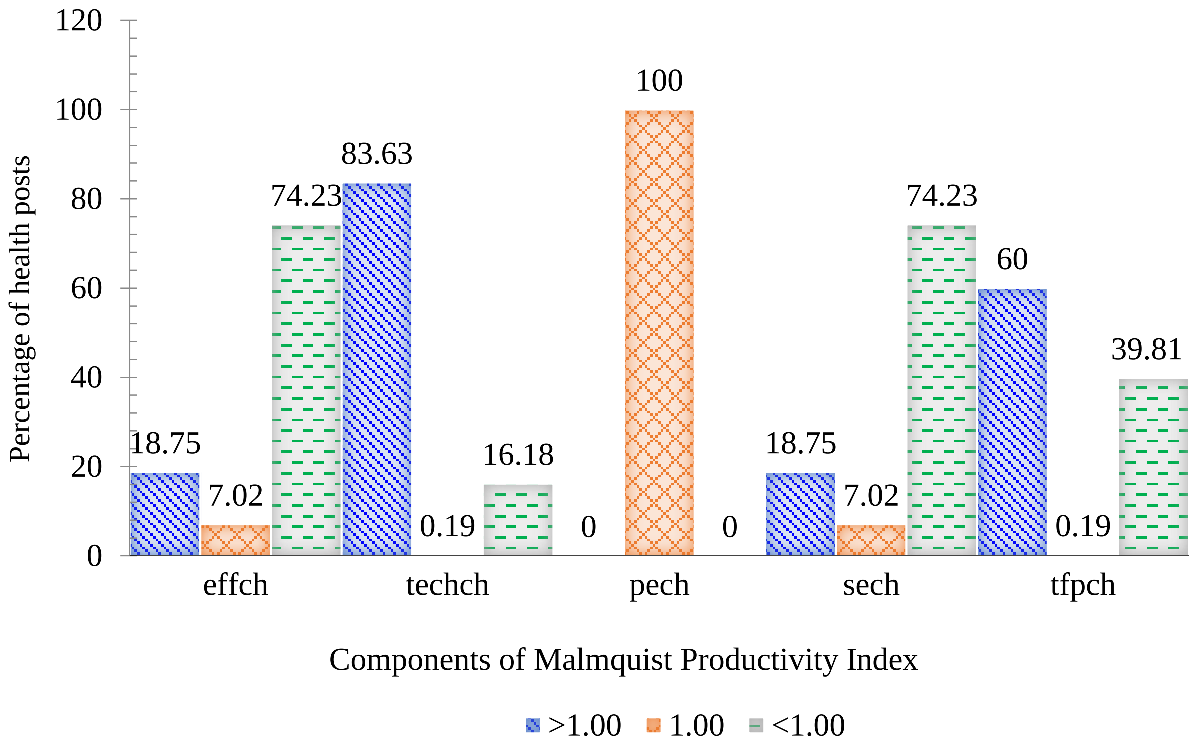
Note: i) effch = $pech * sech$; tfpch = $effch * techch$

ii) All Malmquist index averages are in geometric means; an index estimates of greater than unity indicates improvement (productivity changes); an index estimate of equal to unity indicates stagnation (no productivity changes), and an index estimate of less than unitysignifies reduction (productivity losses).

5.3.3.1. Estimates of technical efficiency changes

As indicated in Table 5.10, the technical efficiency change provides a measure of contribution to the productivity change, indicating the occurrence of the technical efficiency change between the two study periods. Findings of the Malmquist analysis revealed that none of the regional health posts experienced technical efficiency changes of greater than unity. Moreover, the overall average technical efficiency change of the sample health posts was 0.868, implying that on average, the technical efficiency change regressed by 13.2 percent over the course of the two time periods analysed. As illustrated in Figure 5.6, the percentage share of the health posts to the different components of the Malmquist productivity index indicated that about 18.82 percent of the sample health posts experienced technical progress, with technical efficiency level of greater than unity. In contrast, very few health posts (7.02 percent) experienced technical stagnation, with technical efficiency estimates equal to unity. This means that the scale of production of these health posts did not contribute to their productivity growth change over the two study periods.

As indicated in Figure 5.6, the Malmquist productivity analysis further revealed that about 74.16 percent of the health posts had a technical efficiency index of less than unity, suggesting that the scale of production of these health posts contributed negatively to the productivity change. Findings of the Malmquist productivity analysis further indicated that the sample health posts were maintaining their constant productivity, with an average annual productivity growth rate of pure technical efficiency equal to unity. To put it differently, the average pure efficiency change of the sample of the health posts was equal to unity. Therefore, none of the sample health posts attained an index of pure efficiency change of greater than unity, implying that the production scale of these health posts did not contribute to the overall productivity growth (change) because the technical efficiency change of the health posts remained unchanged over the course of the two years under examination.



Source: Own computation (RHB, 2013/14)

Figure 5. 6: Health posts' share of the components of the Malmquist index

5.3.3.2. Estimates of scale efficiency changes

As reported in Table 5.10, the results of the Malmquist productivity analysis revealed that none of the health posts under scrutiny attained a scale efficiency change index of greater than unity. Results further indicated that, on average, the scale efficiency changes of the sample health posts remained less than unity, with an average index of 0.868. This figure signifies that, on average, the scale of production of the health posts slightly decreased the efficiency change by 13.2 percent and therefore, contributed negatively to the overall productivity growth of the sample health posts. About 74.16 percent of the health posts had an estimated scale efficiency index of less than unity, implying that the scale production of these health posts contributed negatively to the overall productivity change. Moreover, about 18.82 percent of the health posts had scale efficiency index estimates of greater than unity, indicating that the scale production of these health posts contributed positively to the overall productivity of the health posts. While a very small number of sample health posts (7.02 percent) experienced technical stagnation, with technical efficiency level equal to unity, it signified that the scale of production of these health posts did not contribute to the overall productivity change of the sample health posts.

5.3.3.3. The technological and total factor productivity changes

As indicated in Figure 5.6 and Table 5.10, the findings of Malmquist productivity analysis indicated that the overall sample health posts, on average, achieved their productivity growth, with an increasing productivity index of 6.7 percent. This productivity growth was mainly as a result of the technological efficiency changes (technological progress). Despite the efficiency improvement (productivity growth), the technical efficiency estimates were decreased, which accounted for a 13.2 percent reduction in the overall productivity change. The average change in technical efficiency estimate was 0.868, much less than the average change in the technological efficiency estimate of 1.229, implying that there was an inefficient use of the available inputs by the technically inefficient health posts. Analysis of the Malmquist productivity further revealed that there was a 22.9 percent in technological improvement for the sample health posts over the course time periods. Moreover, about 83.76 percent of the sample health posts had a technological change index of greater than unity, implying that this productivity change attributed largely to technological progress, whereas the remaining 16.04 percent of the health posts had a technological change index of less than unity, which indicated that they contributed negatively to the overall productivity change during the study periods.

The findings of the Malmquist productivity analysis revealed that the overall total factor productivity change of the health posts increased at a mean annual increase of 6.7 percent due to the slight change in the technological efficiency change. The Oromia regional health posts had the lowest total factor productivity changes of 5.1 percent, while the highest total factor productivity change of 38.6 percent was found in the Gambella regional health posts. The findings further indicated that about 60 percent of the health posts had a total factor productivity of greater than unity, indicating that, on average, their overall productivity was increased by 6.7 percent. This was the net outcome of a concurrent progress of 22.9 percent in the technological efficiency change, but a reduction of 13.2 percent in the technical efficiency change of the sample health posts. This means that most of the gains in the productivity change were exclusively due to the slight average increase in the technological progress of 22.9 percent (see Table 5.10). The findings of the productivity analysis further indicated that the regional health posts increased their productivity during the study time periods, with an index of greater than unity. For example, the Gambella regional health posts achieved their productivity growth, with an estimated average annual productivity growth rate of 37.52 percent, while the Oromia regional health posts recorded the lowest productivity growth of 5.08 percent. Analysis of the Malmquist productivity further revealed that there were considerable variations in the productivity index of changes for sample health posts across the regions. For example, the average index of changes in the technical and scale efficiency changes of the Tigrai regional health posts reduced by 3.8 percent each. In contrast to this, these health posts have improved their technological progress and total factor productivity, with an average annual productivity growth rate of 23.2 and 19.3 percent, respectively.

The results of the productivity analysis revealed that, on average, the Gambella regional health posts had the highest total factor productivity change of 38.6 percent over the two study periods. Moreover, they also improved their technological changes by about 44 percent. Most importantly, results of the Malmquist productivity analysis indicated that there was productivity loss in the technical efficiency and scale efficiency changes among the regional health posts. For example, the Tigrai regional health posts experienced the smallest reduction in technical efficiency change (3.8 percent) contributing to a small reduction in the overall productivity, followed by the Gambella regional health posts, with a 4.5 percent technical efficiency change. In contrast to this, the highest loss in productivity was observed in the Harari regional health posts, with an average estimated technical efficiency change of

22 percent. Thus, the Harari regional health posts experienced the largest decrease in the technical efficiency change, contributing a significant reduction in the overall productivity in terms of having health posts, with the highest average rate of technical efficiency regress (22 percent) (see Table 5.10).

5.3.3.4. Sources of productivity improvement (gain or loss)

As indicated in Table 5.10, almost 74.16 percent of the sample health posts have achieved an estimated annual productivity growth rate, with scale efficiency change of less than unity. The overall productivity change of the sample health posts increased their productivity at an annual productivity growth of 6.7 percent, indicating an increase in the output being produced for the given levels of input being employed or consumed. This improvement in the overall productivity was mainly due to the technological efficiency changes (technological progress).

To identify the major source of productivity improvement, the productivity change was decomposed into the technological change (frontier shift effect) and the efficiency change (catching-up effect). Consecutively, to identify the major source of the efficiency change (improvement), the efficiency change was further decomposed into the scale and technical efficiency changes. The values of the technical efficiency changes and the technological efficiency change should be compared to each other in order to find out the major source of productivity improvement. Therefore, if the value of the technological efficiency change outweighs that of the technical efficiency change, the productivity gains (improvements) are mainly the result of gains (improvements) in the technological efficiency change (technological progress) (as a major source of improvement in productivity) or vice versa (Charnes et al., 1978; Worthington, 2004).

As indicated in Table 5.10, results of the productivity analysis revealed that, on average, the sample health posts have experienced an approximate 6.7 percent productivity increase during the two study periods. The most important source of this improvement in productivity growth was attributed to the average technological progress of 22.9 percent, which contributed positively to the overall productivity growth of the sample health posts. Alternatively, the improvement in productivity for this study was the net outcome of the improvement in the technological efficiency change (as a major source of efficiency change) since the mean estimates of changes in the technological efficiency outweighed that of the mean estimates of the technical efficiency change. In contrast to this, the changes in the technical efficiency meant a reduction in the productivity growth for the health posts. The loss (reduction) in the overall productivity change was largely attributed to the technical efficiency regress.

5.3.3.5. How to identify the major sources of the efficiency change

To identify the most important source of efficiency change or efficiency improvement, one must compare the values of the scale efficiency change $(sech)$ to the pure technical efficiency change$(pech)$. Note that the overall technical efficiency change $(effch)$ is the product of the scale efficiency change $(sech)$ and the pure technical efficiency change$(pech)$, so that $effch = (pech) * (sech)$. Therefore, by comparing the values of the index of productivity changes in the scale efficiency $(sech)$ to the pure technical efficiency$(pech)$, the major source of efficiency change in the productivity could be easily ascertained. If the value of the $pech$ outweighs (greater than) that of the value of the $sech$, the major source of change in the efficiency is largely due to the improvement in the pure technical efficiency or vice versa. The increased technical efficiency changes could arise when the value of technical efficiency is greater than unity, while the technological efficiency change progress could arise when the value of the technological efficiency change is greater than unity. Similarly, the reduction in the technical efficiency changes could arise when the value of technical efficiency is less than unity, while the technological efficiency change regress could arise when the value of the technological efficiency change is less than unity (Charnes et al., 1978; Worthington, 2004).

In this study, the sample health posts have experienced approximately a 6.7 percent productivity increase during the two study periods. Therefore, neither the pure technical efficiency changes nor the scale efficiency change was the most important source of efficiency change, but rather the scale efficiency change contributed negatively to the overall productivity changes. Alternatively, the average reduction in the scale efficiency of 13.2 percent was made for the overall loss in the productivity of the sample health posts. The contribution of the pure technical efficiency change (as a major source of efficiency change) was stagnant in the productivity improvement since the mean estimates of the change in pure technical efficiency remained unchanged (unity). The findings of the productivity analysis further revealed that, on average, the sample health posts experienced nearly a 6.7 percent productivity change increase during the study periods. Furthermore, results of Malmquist productivity analysis indicated that the efficiency frontier moved a bit to a higher level. This could imply that there would be a possibility of increasing the basic healthcare services outputs provision from the health extension programme over time. Results also revealed that the overall efficiency changes of the Malmquist productivity of the health posts varied across regions. This could signify the possibility of improving the efficiency of the health extension programme mainly by improving the efficiency of the technically inefficient health posts in order to provide additional healthcare services at the efficiency frontier.

In summary, findings of the DEA analysis indicated that the average productivity growth of the sample health posts was 6.7 percent during the two study periods, with significant variations among the regions. This productivity improvement was mainly due to technological change (22.9 percent). Most of the sample health posts were relatively technically inefficient. The overall estimated technical efficiency of the health posts varied among the sample health posts and over the two study periods. Identifying the factors affecting the variations in the technical efficiency estimates among the sample health posts could substantially improve the technical efficiency of the health extension programme and therefore, need to be rigorously examined. Thus, the following sub-section 5.3.4, examines the factors affecting the variations in the technical efficiency estimates among the sample health posts.

5.3.4. The results of the second-stage regression analysis: Determinant factors influencing the technical inefficiency variations among the health posts

As explained earlier and indicated in Table 5.6 to Table 5.8, the results of the DEA analysis revealed that there was a significant variation in the mean technical and scale efficiency estimates among the sample health posts, implying that mainly inputs were not efficiently utilised. Findings further indicated that the technical and scale efficiency estimates varied significantly among the sample health posts. The variations in the technical efficiency among the sample health posts should be accompanied by an examination of the determinant factors affecting these variations in the technical efficiency estimates, using second-stage regression analysis. Hence, to gain basic insights and provide information for policy-making, the sources of technical efficiency estimate variations among the sample health posts need to be examined.

Thus, the transformed technical inefficiency estimates of the health posts obtained from the first-stage DEA analysis (see sub-section 4.6.2.2, equation [4.19]) were used as the dependent variable in the second-stage regression analysis and were regressed against the independent variables to estimate their impact on the variations in the technical inefficiency estimates of the sample health posts.

In the present study, before performing the Tobit and ordinary least square regression analysis as the second-stage regression analysis, the multicollinearity test was carried out using the Variable Inflation Factor, VIF[34]. A value of VIF>10 indicates a sign of the potential of multicollinearity problems while a value of VIF<10 indicates the opposite (Gujarati, 2004). Hence, the age of the health extension workers (AGHEW) and a dummy variable indicating the availability of basic medical equipment at the health post (ABME) were dropped due to collinearity (see Appendix C, Table C-15). Moreover, the heteroscedasticity test was also conducted using the Breusch-Pagan-Godfrey test to examine the existence of heteroscedasticity for the error term (ε) (Gujarati, 2004). Accordingly, the computed χ^2 value (2.7413) was less than the critical χ^2 value (3.3401) at the 5 percent level of significance based on the χ^2 table, indicating the absence of heteroscedasticity in the regression analysis (Var $(\varepsilon_i|X_i = E(\varepsilon_i^2|X_i) = \delta_\varepsilon^2 =$ constant). In addition, model specification and normality tests were conducted and therefore, estimates indicated that both models were well specified.

As explained earlier, an ordinary least square regression analysis was employed as an alternative estimation technique to ascertain how sensitive and robust the results were. The interpretation and discussions of the second-stage regression analysis were made based on the findings of the Tobit regression analysis even though the estimates of both regression models (the Tobit and ordinary least square regression models) were similar, except that they differed in their magnitudes effect and level of significance. Table 5.11 reported the results of the second-stage regression analysis on the determinant factors affecting the variations in technical efficiency estimates among the sample health posts. The findings of the regression analysis revealed that the travel distance of the household to the nearest health post positively affected the variations in the technical inefficiency estimates of the sample health posts. The closer the average travel distance between the nearest health posts and the household's residence, the more it enabled the health extension workers to provide more basic healthcare services to their respective community, and in turn, the better would be the technical

[34] The VIF computes the effect of collinearity among the included explanatory variables in the regression model. It is a scaled form of the multiple correlation coefficient ($R_{X_i}^2$) between the explanatory variable, X_i and the remaining variables. $VIF_i = \frac{1}{1-R_{X_i}^2}$.

efficiency level of the technically inefficient health post, if all other factors remained constant.

Table 5. 11: Determinant factors affecting the technical inefficiency variations among health posts: A second-stage regression analysis

	Tobit analysis		ols analysis	
Variables	Coefficient	p-value	Coefficient	p-value
Percentage of population served by HEW (PSHEW)	-.000512 (.000462)	0.256	-.000052 (.000206)	0.803
In-service refresher training given to HEW (RTHEW)	-.00135 (.0241)	0.960	-.002843 (.010474)	0.786
Average distance of rural households' residence to the nearest HP (DVHP)	.0427** (.0168)	0.013	.03393** (.01669)	0.042
Years of working as HEW (YWHEW)	-.00183 (.00416)	0.651	-.00056 (.016409)	0.757
Performance reward_dummy (RPHEW)	-.0540 (0.0370)	0.144	-.02276 (.035434)	0.166
$AGHEW^2$	.0000123 (.0000639)	0.868	.00078** (.000343)	0.023
Monthly income of HEW (MIHEW)	-.000012 (.0000152)	0.492	-.00002 (.000015)	0.312
Supportive supervision_dummy (SSHEW)	.0716** (.0347)	0.038	.065202** (.032894)	0.048
Reference region (RRHEW=Tigrai)				
Region_Amhara	.250*** (.0462)	0.000	.24299*** (.044244)	0.000
Region _Oromia	.185*** (.0424)	0.000	.17813*** (.040168)	0.000
Region _SNNP	.477*** (.0495)	0.000	.4721*** (.0479926)	0.000
Region_Gambella	.394*** (.0641)	0.000	.3778*** (.063602)	0.000
Region _Benshangul-Gumuz	.417*** (.0509)	0.000	.40062*** (.049208)	0.000

Variables	Tobit analysis		ols analysis	
	Coefficient	p-value	Coefficient	p-value
Region _Harari	.571***	0.000	.54261***	0.000
	(.122)		(.123275)	
Reference religion(RLHEW=Christian)				
Religion of HEW_Muslim	.134***	0.000	.1354***	0.000
	(.0296)		(.029305)	
Religion of HEW_Others	-.0158	0.596	.00235***	0.906
	(.0243)		(.019806)	
_cons	.492***	0.000	.86502***	0.004
	(.1129)		(.301556)	
Number of Obs.	1552		1552	
Pseudo-squared/R-squared	.080		.079	

Sources: Own computation (RHB, 2013/14); Note: i) Robust standard errors are in parentheses; ii) TEI_{VRS} stands for estimates of technical inefficiency under variable returns to scale assumption; iii) (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

Similarly, the supportive supervisory visit as a dummy variable affected the variation in the technical inefficiency estimates among the health posts. The less frequent (absent) supportive supervisory visits made to the health extension workers positively affected the variations in the technical inefficiency estimate of the health post. A health extension worker who was not regularly supervised at least twice a month was found to positively affect the variations in the technical inefficiency estimate of the health post by 7.16 percent, while holding constant for a multitude of other determinants in the model. This could imply that the fewer frequent (absent) supportive supervisory visits could make the health extension workers to be less efficient in providing basic healthcare services to their respective communities, which in turn affected the variations in technical inefficiency estimates among the sample health posts.

The health extension worker's region of residence affected the variations in the technical inefficiency estimates of the sample health posts. For example, the health extension workers who were operating in the Tigrai regional health posts were negatively affecting the technical inefficiency estimates of the proportional sample health posts compared to the health extension workers who were operating in the remaining other regional health posts under analysis. Alternatively, a health extension worker being a resident of the Tigrai region and who was working in those regional health posts contributed to the improvement of the technical efficiency estimates of that health post. As explained earlier (see Tables 5.7 and 5.8), there were significant differences in the estimates of the technical and scale efficient health posts across regions, and over the two study periods. The findings of the regression analysis imply that, on average, the Tigrai region relatively had the largest number of technically efficient health posts (19.88 percent), with an average technical efficiency estimate of 84.1 percent under the variable returns to scale assumption. Moreover, this region also had the largest number of scale efficient health posts (18.63 percent), with an average scale efficiency estimate of 79.7 percent, compared to the remaining other regional health posts under analysis. Furthermore, results of the regression analysis indicated that the religious affiliation of the health extension workers was among the key determinant factors affecting the variations in the technical inefficiency levels among the health posts. Hence, compared to a Christian health extension worker, being a Muslim health extension worker increased the technical inefficiency estimates of the sample health post by 13.4 percent, while keeping all other factors unchanged. This could imply that relatively, a Muslim health extension worker was less efficient in providing basic healthcare services to its community than a Christian health extension worker was (see also Appendix, Tables C-16 and C-17).

Overall, an output-oriented Data Envelopment Analysis technique evaluated the efficiency and productivity change (growth) of the sample health posts, with overall annual average productivity growth of 1.067 during the two study periods. This productivity improvement was mainly due to technological change (22.9 percent). The estimated technical efficiency of the sample health posts varied significantly across the regions and over the two study periods. The average households' travel distance to the nearest health posts, provision of supportive supervisory to health extension workers, health extension workers' region of residence, and religious affiliation of the health extension workers were all found to be among the major determinant factors affecting the variations in technical efficiency estimates among the sample health posts. Most importantly, most of the sample health posts were relatively technically inefficient and were operating at decreasing returns to scale, implying that the largest rural people of the country were not accessing and utilising the basic healthcare services from the health extension programme (see Tables 5,6, 5.7. 5.8, and 5.10).

Training and graduating of the health extension programme beneficiary households as model households is among the objectives of the Ethiopian health extension programme as a means of enhancing access to basic healthcare services and thereby, ensuring their utilisation by the largest rural poor people. To improve the throughput rate of the programme beneficiary graduates as model households, the present study also examines the factors affecting the health extension programme beneficiary households' graduation in rural settings of Ethiopia. Therefore, identifying the major determinant factors affecting graduation of the health extension programme beneficiary households could enhance the number of rural people who have been well equipped with basic skills and knowledge in basic healthcare services and as a result, improve their overall health status (outcome). In turn, this could minimise the observed substantial regional gaps in under-five child mortality and therefore, reduce the overall national child mortality level of the country (see Table 5.11).

5.4. Study results for determinant factors affecting graduation of the health extension programme beneficiary households

5.4.1. Descriptive statistics analysis

The results of the descriptive analysis indicated that the proportion of the overall male-headed households exceeded that of the female-headed households across all regions (both for the health extension programme beneficiary graduate and the non-graduate households). Table 5.12 presented the summary statistics that portrayed the proportional differences between the health extension programme beneficiary graduate and the non-graduate households in terms of gender as well as the households' region of residence.

As indicated in Table 5.12, about 62 percent of the sample respondents were the health extension programme graduate households, while the remaining 38 percent were non-graduate households. The descriptive analysis further indicated that the male-headed graduate households (72.49 percent) were considerably larger than the female-headed graduate households (27.51). In contrast to this, male-headed of the non-graduate households (74.65 percent) were also substantially larger than female-headed of the non-graduate households (25.35 percent) at the national level, with considerable variations across regions. The descriptive analysis further indicated that regions varied in the proportion of sample respondents both for the health extension programme beneficiary graduate households and the non-graduate households. For example, the largest 28.93 percent of the sample proportion (both the health extension programme beneficiary graduate and non-graduate households) was found in the Oromia region. Of these 28.93 percent, about 61.51 percent were the health extension programme beneficiary graduate households, while the remaining 38.49 percent were the non-graduate households, but they were programme beneficiaries.

Similarly, the Amhara region was the second largest, with a 21.61 percent proportion of sample respondents. Of these, approximately 60 percent were the health extension programme beneficiary graduate households, while the remaining 40 percent were the non-graduate households. In contrast to this, the lowest 2.67 percent proportion of the sample respondents was from the Harari region. Of these, approximately 56.47 percent were the health extension programme beneficiary graduate households, while the remaining about 43.53 percent were the non-graduate households. The second lowest percentage of the sample, 5.1 percent, was from the Tigrai region (64.42 percent of the health extension programme beneficiary graduates versus 35.58 percent of the non-graduates), followed by the Gambella region, with a 6.38 percent proportion of the sample respondents (59.8 percent of the health extension programme beneficiary graduates versus 40.2 percent of the non-graduates). Similar patterns were also recorded in the SNNP and the Benshangul-Gumuz regions. The overall average age of the sample household was 40 years; with slight variations across the regions (see Table 5.12).

Table 5. 12: Descriptive statistics analysis: Percentage of sample health extension programme graduate versus non-graduate households

Regions	HEP non-graduate households			HEP graduate households			
	Female	Male	Subtotal	Female	Male	Subtotal	Total
Tigrai	31.03	68.97	35.58	29.52	70.48	64.42	5.1
Amhara	22.55	77.45	39.8	30.05	69.95	60.2	21.61
Oromia	21.63	78.37	38.49	25.66	74.34	61.51	28.93
SNNP	32.02	67.98	36.66	25.38	74.62	63.34	19.46
BG	25.67	74.33	36.88	31.56	68.44	63.12	15.86
Gambella	29.27	70.73	40.2	22.13	77.87	59.8	6.38
Harari	21.62	78.38	43.53	27.08	72.92	56.47	2.67
National	25.35	74.65	38.25	27.51	72.49	61.75	100

Source: Own computation (RHB, 2013/14)

The overall summary statistics of the sample mean (proportion) of the explanatory variables (covariates) employed in the regression analysis were reported in Table 5.13. The descriptive analysis revealed that the average age of a mother in a health extension programme beneficiary household was 35 years, with minor variations across regions. The average arable land size of the sample households was 3.46 hectares. This average was similar across regions though considerable differences in magnitude within the regions were noted. Furthermore, the family size of the sample households varied across regions, with the smallest (4) average was found in the Tigrai region, while the largest (8) was found in the Gambella region. The descriptive analysis further indicated that, on average, the household's travel distance to the nearest health was 6.22 kilometres. The overall average length of time that the programme beneficiary households remained as programme beneficiaries before being graduated was one year and 8 months, with a range from one year to three years.

Table 5. 13: The sample means (proportions) by covariates

	Regions							
Variables	Pooled	Tigrai	Amhara	Oromia	SNNP	BG	Gambella	Harari
AgeHH	40	37	39	39	40	41	44	46
SexHH =Female	.267	.302	.271	.241	.278	.294	.25	.247
Agemam	35	35	35	35	36	35	35	36
Occuptrading	.011	.000	.009	.008	.013	.016	.020	.024
Occuplaborer	.188	.227	.204	.201	.172	.156	.152	.235
Occupcivil	.035	.054	.071	.050	.069	.060	.026	.065
Occupother	.012	1.00	.016	.012	.016	.006	.010	.024
Religion=Musilim	.342	.313	.366	.330	.338	.3412	.353	.353
Religion=other	.003	.006	.004	.002	.002	.004	.0098	.000
Landsize	3.46	3.63	3.47	3.53	3.32	3.46	3.43	3.48
HPdistance	6.22	5.87	6.15	6.24	6.22	6.28	6.44	6.48
HEPtuser	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.7
Familysize	6	4	5	6	6	7	8	7
Maritals=married	.924	.896	.896	.939	.919	.933	.951	.941
Maritals=separated	.028	.043	.028	.025	.043	.016	.019	.024
Maritals=widowed	.018	.012	.004	.018	.018	.036	.025	.024
Extensionuser (=yes)	.255	.159	.258	.235	.273	.286	.304	.188
HEWperhp	2	2	2	2	2	2	2	2
HEWprofflevelIII	.381	.423	.382	.369	.373	.373	.402	.482

Variables	Regions							
	Pooled	Tigrai	Amhara	Oromia	SNNP	BG	Gambella	Harari
HEWproffleveIIV	.315	.331	.336	.329	.302	.298	.250	.306
Mameducprime	.175	.288	.198	.184	.198	.128	.054	.059
Mameducsecon	.058	.012	.088	.064	.064	.036	.019	.024
Mameducprime	.343	.380	.356	.358	.365	.319	.221	.282
Parentaleducsecon	.102	.051	.095	.101	.095	.094	.142	.106
Offincome (1= yes)	.231	.258	.263	.239	.238	.213	.137	.118
Number of Observation	3197	163	691	925	622	507	204	85

Source: Own computation (RHB, 2013/14)

Results of the descriptive analysis revealed that the average number of health extension workers deployed to provide basic healthcare services to their respective community was two per health post. This was consistent across regions, with slight s variations across the regions. Farming was the primary occupation 94 percent of the sample households, followed by daily labourer, which accounted for 19 percent, with considerable differences across the regions. Findings further indicated that the largest proportion of the sample households consisted of Christians (65.5 percent), followed by Muslims (34.2 percent) (see Table 5.13). Most importantly, most mothers in the sample households were without any formal education. On average, approximately 76.7 percent of mothers of the sample respondents were without any formal educational background, ranging from 70 percent in the Tigrai region to 92 percent in the Harari region. About 17.5 percent of mothers of the sample respondents had primary education background, with significant proportional variations across the regions. Moreover, across regions, a very small proportion of mothers of the sample respondents were reported as having secondary or higher education background. The results of the analysis further revealed that there were proportional differences in religious followers and marital status, across regions as indicated in Table 5.13. On average, 34 percent of the sample respondents were Muslim, while the remaining the 66 percent of the sample respondents were Christians. Furthermore, at the national level, about 92 percent of sample households consisted of married couples, with a slight variation across the regions. For example, about 90 percent of the sample respondents in the Tigrai and the Amhara regions were married, while in the Gambella region; about 95 percent of the sample respondents were married. Similarly, on average, about 31.5 percent of the health extension workers were diploma holders (or level IV), while about 38.1 percent of them were certificate graduates (or level III), with substantial differences across the regions. Likewise, on average, about 31.5 percent of the health extension workers were working on a contract basis.

Overall, the proportion of male-headed households exceeded that of female-headed households (both for the health extension programme beneficiary graduate and the non-graduate households), with significant variations across the regions. There were determinant factors that strongly affected graduation of the health extension programme beneficiary households because there were considerable variations in the variables average and proportional effect for the health extension programme beneficiary graduate and the non-graduate households. Therefore, the question of which determinant factors, if any, were significantly accounted for in the graduation of the health extension programme beneficiary households was explained in the empirical statistical analysis below (see Table 5.14).

5.4.2. Empirical results of the logistic regression analysis

Table 5.14 reported the estimation results for determinant factors affecting graduation of the health extension programme beneficiary households was based on the logistic regression analysis. The first and second columns of Table 5.14 contain the lists of the variables and the estimated regression coefficients of these, respectively. A positive value of the estimated regression coefficients indicates a positive relationship between the dependent and explanatory variables, while a negative value indicates the opposite. For ease of interpretation, the results of the logistic regression analysis were explained in terms of odds ratios displayed in the third column of Table 5.14. A value of odds ratio greater than unity (Odds ratio>1) indicates the increased likelihood of the health extension programme beneficiary household being a health extension programme beneficiary graduate as a model household, while a value of odds ratio less than unity (Odds ration<1) indicates the opposite.

Therefore, as indicated in Table 5.14, the results of the regression analysis revealed that family size (Familysize) strongly affected the probability of a health extension programme beneficiary household's graduation, with odds of being a programme graduate increased by a factor of 3.11 as the family size increased, while other determinants remained fixed. Similarly, the mother's age (Agemam) also had a positive effect on the health extension programme beneficiary household's chance of being a programme graduate. Other factors being constant, for each additional year of mother's age, the odds of being a programme graduate increased by a factor of 1.012.

Although the proportion of male-headed health extension programme graduate households was considerably larger than its female-headed counterpart, the results of the regression analysis indicated that a female-headed health extension programme household (SexHH) positively affected the household's probability of being a programme beneficiary graduate. Therefore, compared to the male-headed households, there was a greater likelihood that female-headed households would graduate as model households, with the odds of being a programme graduate increasing by a factor of 1.029, with all other factors remaining constant (see Table 5.14).

Table 5. 14: Determinant factors affecting graduation of the health extension programme beneficiary households: Estimates of a logistic regression analysis

Variables	Coefficient	OR	SE	P-value	[95% Conf.	Interval]
AgeHH	-.00192	.9981	00459	.676	-.0109229	.0070808
SexHH (1=Female, used as a reference)	.028480**	1.029	.01154	.014	.0058547	.0511048
Agemam	.011625*	1.012	.00642	.070	.0242149	.0009657
Occup (1= Agriculture, used as a reference)						
Occuptrading	.305249	.3576	.37305	.413	-.4259046	1.036404
Occuplaborer	.018791	.0189	.10693	.861	-.1907818	.2283638
Occupcivil	.125789	.1334	.08571	.142	-.0422019	.2937809
Occupother	-.194765	.8230	.32872	.554	-.8390529	.4495234
Religion (1= Christian, used as a reference)						
Religion=Muslim	-.015138	.9849	.07722	.845	-.1664872	.1362119
Religion=other	1.021344	.7727	.77969	.190	-.5068218	2.549509
HPdist	-.29922**	.7414	.13789	.030	-.5694778	-.0289611
HEPtuser	1.81731**	6.155	.77377	.019	.3007437	3.333852
Familysize	1.13425***	3.109	.42084	.007	.3094194	1.959077
Maritalstatus (1= single, used as a reference)						
Maritalstatus =married	.082728	.0846	.09378	.378	-.1010729	.2665291
Maritalstatus=separated	-.376534	.6862	.30847	.222	-.9811242	.2280563
Maritalstatus=widowed	-.386175	.6796	.35472	.276	-1.081414	.3090633
Extensionuser	2.2851*	9.834	1.2004	.063	1.441694	4.561186
HEWperhp	-.036537	.9641	.09416	.698	-.2210811	.1480062

Variables	Coefficient	OR	SE	P-value	[95% Conf. Interval]	
Region (1= Tigrai, used as a reference)						
Region=Amhara	-.164203	.8486	.18537	.376	-.5275253	.1991195
Region=Oromia	-.095673	.9088	.18343	.602	-.4551789	.2638326
Region=SNNP	-.026902	.9735	.19433	.890	-.4077774	.3539741
Region=BG	-.039188	.9616	.20337	.847	-.4377821	.3594056
Region=Gambella	-.148736	.8618	.23663	.530	-.6125226	.3150495
Region=Harari	-.297643	.7426	.28834	.302	-.8627843	.2674987
HEWproflevel (1= contract, used as a reference)						
HEWproflevel III	.00093*	1.001	.00049	.056	.0000234	.0018817
HEWproflevel IV	.135943	1.146	.09072	.134	-.0418629	.3137479
Mameduc (0= no education, used as a reference)						
Mameducprime	.21514*	1.240	.12357	.082	.0270431	.4573307
Mameducsecon	.35452	1.426	.21839	.105	-.0735146	.7825527
Parentaleduc (0= no education, used as a reference)						
Parentaleducprime	-.04089	.9599	.08201	.618	-.2016395	.1198441
Parentaleducsecon	.38062**	1.463	.18517	.040	.7435463	.0176946
Offincome (1 = Yes, used as a reference)	-.85419***	.4256	.27796	.002	-1.398984	-.3094127
-cons	1.13425***	3.109	.42084	.007	.3094194	1.959077
Model summary	Statistics	P-value				
Model Chi-squared	31.41	.0000				
Pseudo R-squared	.0228					
Number of Obs.						3,197

Source: Own computation (RHB, 2013/14); Notes: OR stands for Odds Ration; SE represents the Standard Error (robust); (**), (*), and (***) denote significance at 10, 5, and 1 percent levels, respectively.

The results of the analysis further indicated that a health extension programme beneficiary household who participated and benefited from the agricultural extension programme (Extensionuser), increased the odds of being a programme graduate as a model household by a factor of 9.834, while all other factors remained constant. Moreover, the length of time that the households took to graduate from the health extension programme was the major graduation determinant of the health extension programme beneficiary households. Furthermore, the findings of the regression analysis indicated that the longer a household stays as a health extension programme beneficiary, the higher the probability of the household to be a programme graduate as a model household. Therefore, the length of time in which the household stay positively affected the household's probability of being a programme graduate as a model household. While other determinant factors remained constant, for each additional year of a household's being a programme beneficiary, the odds of being a programme graduate as model household increased by a factor of 6.2.

Similarly, findings of the regression analysis further revealed that the professional status of the health extension worker was also among the key graduation determinants of the health extension programme beneficiary households. Given that all other factors remained constant, this study's findings revealed that the programme beneficiary household which had been trained by a health extension worker with a professional certificate or professional level III (HEPproflevelIII) strongly affected the probability of graduating a programme beneficiary household, with the odds of being a programme graduate increasing by a factor of 1.001. The reason for this could be that a health extension worker with a professional certificate is well equipped with skills and knowledge in basic healthcare services, and has more experience in providing basic healthcare services for the respective households and societies when compared to a health extension worker employed on contract base (see Table 5.14).

Parental educational attainment was another significant determinant factor positively affecting the probability of graduation of the health extension programme beneficiary households. Therefore, a health extension programme beneficiary household with a mother who has a primary educational level (Maneducprime), the predicted odds of being a programme graduate as model household increased by a factor of 1.24 compared to a programme beneficiary household with a mother with no formal education, if all other determinant factors in the model remain constant. Likewise, the father's educational level or parental level of education (Parentaleducsecon) was also among the key determinant factors affecting graduation of the health extension programme beneficiary households. Therefore, in a health extension programme beneficiary household with at least parental secondary educational level, the odds of becoming a programme graduate increased by a factor of 1.463 when compared to a household where the parents had no formal parental education. The overall improvement both in mothers' and fathers' (or parental) educational level ensured the likelihood of being a programme graduate household as a model household and as a result, improve the country's overall universal healthcare services coverage (see Table 5.14).

As indicated in Table 5.14, the proportion of the health extension programme beneficiary households, with a relatively large arable land size decreased the likelihood of becoming a programme graduate household. With an increase in the average household arable land size (Landsize) by one hectare, the odds of being a health extension programme graduate as a model household decreased significantly by a factor of 0.9942, while all other factors remained constant. Furthermore, the results of the regression analysis indicated that the average households' travel distance to the nearest health post affected the household's probability of becoming a health extension programme graduate. Consequently, with a one-kilometre increase in the household's travel distance to the nearest health post (HPdist), the odds of becoming a health extension programme graduate decreased significantly by a factor 0.7414, if the effects of all other determinant factors remained constant. Furthermore, this study's findings of the regression analysis indicated that a health extension programme beneficiary household that had an off-farm income (Offincome) as a source of livelihood for its household was among the major graduation determinant factors affecting graduation of the programme beneficiary households. A health extension programme beneficiary household that had an off-farm income negatively affected the probability of the programme beneficiary household's graduation, with odds of becoming a programme graduate decreasing by a factor of 0. 426, if the effects of all other determinant factors remained constant (see also Appendix C, Table C-18 and Table C-19).

5.5. Conclusion

This chapter presents the findings on determinant factors affecting the inter-regional differentials in under-five child mortality; it evaluates the efficiency and productivity changes of the Ethiopian health extension programme, and examines the major determinant factors affecting graduation of the health extension programme beneficiary households in rural settings of Ethiopia. This study's findings indicate that the significant regional gaps in under-five child mortality are largely explained by the differences in the distribution of the proximate determinant factors such as the child's birth order, size of the child at birth, the child's birth spacing, and mother's age at first birth. In addition, the socio-economic determinant factors such as the households' economic status, mothers' level of education, and antenatal healthcare services, and environmental determinant factor such as place of child delivery were the key determinant factors affecting the inter-regional gaps in under-five child mortality.

The reduction of child and maternal mortality was the aim of the Ethiopian health extension programme and it set out to do this by providing basic healthcare services to the rural poor, and thereby, ensure the reduction of child and maternal mortality at the national level. There is limited available literature on the efficiency and productivity growth of the health extension programme, and the evaluation of the technical efficiency and productivity changes of the Ethiopian health extension programme, which uses health posts as decision-making units. It is important to improve the efficiency of the programme by means of which basic healthcare services provision could significantly be enhanced. As a result, the country's inter-regional gaps in under-five child mortality could be substantially minimised, as could the overall child mortality of the country. In turn, the overall health outcomes for the rural, poor communities in the country could be substantially improved.

This study's findings reveal that most of the sample health posts are relatively technically inefficient and are operating below their optimal scale size (decreasing return to scale). The overall productivity change, or growth, of the sample health posts was increased by about 6.7 percent due to an improvement in technological progress. Moreover, this study also examines whether the estimated relatively technical efficiency differences among the sample health posts is due to the management practices of the programme or due to other external factors. Results indicate that the supportive supervision, household's travel distance to the nearest health post, religion affiliation, and region of residence of the health extension workers are the determinant factors affecting the variations in the technical inefficiency estimates among the health posts. Furthermore training and graduating of the health extension programme beneficiary households as model households could enhance access to and utilisation of basic healthcare services, which in turn, would ensure the universal healthcare coverage of the Ethiopia. To improve the throughput rate of the programme beneficiary households, this study also examines the factors affecting graduation of the health extension programme beneficiary households. This study's findings reveal that family size, parental level of education, the age of the mother, household's participation in agricultural extension programme, profession level of health extension workers, arable land size, and households' access to an off-farm income were the major determinant factors affecting graduation of the health extension programme beneficiary households.

CHAPTER SIX

DISCUSSION OF RESEARCH FINDINGS

6.1. Introduction

This chapter discusses this study's findings analysed in Chapter Five in comparison with the other previous studies' findings. Thus, this chapter presents the discussion or explanation of the findings of determinant factors affecting the inter-regional differentials in under-five child mortality; evaluation of the efficiency and productivity changes of the health posts, and to examine determinant factors affecting influencing the health extension programme beneficiary households graduation. It also makes comparisons with the findings of other previous empirical studies to locate its contribution to the literature.

The chapter is subdivided into five sections: Section 6.2 presents the discussions pertaining to the determinant factors affecting the inter-regional differentials in under-five child mortality. Section 6.3 discusses the evaluation of the efficiency and productivity changes (growth) of health posts along with determinant factors affecting the variation in technical inefficiency estimates among the sample heath posts. Section 6.4 presents the discussion of the determinant factors affecting graduation of the Ethiopian community-based health extension programme beneficiary households. And section 6.5 concludes the chapter.

6.2. Determinant factors affecting the inter-regional differentials in child mortality

The present study addressed the research gap concerning the determinant factors affecting inter-regional differentials in under-five child mortality in rural settings of Ethiopia. The study is the first of its kind to decompose and examine the relative individual contribution of determinant factors affecting the inter-regional differentials in under-five child mortality into components gap (explained and unexplained parts) in the Ethiopian context. Results of the regression analysis revealed that there were substantial differences in the estimated coefficients of all regressed determinant factors affecting under-five child mortality, indicating substantial variations in the magnitudes of effects on the under-five child mortality across regions. These observation are consistent with the findings of other studies on the domains of determinant factors affecting the infant and the under-five child mortality (Amouzou et al., 2014; Dejene & Girma, 2013; Gizaw, 2015; Macassa et al., 2012; Negera et al., 2013; Patel & Sharma, 2013; Rashad & Sharaf, 2016; Regassa, 2012; Schell et al., 2007;

Tessema, 2008; Victora et al., 2011; Wang et al., 2012; Yibrah & Nyatanga, 2017; among others).

Most importantly, this study's findings of the detailed decomposition analysis further indicated that there were substantial variations in under-five child mortality across the Ethiopian regions. On the average, only a small part of 38.2 percent of the regional gaps in under-five child mortality was explained (covariates effect) while the largest part 61.8 percent of the regional gaps remained unexplained (coefficients effect), with substantial variations in magnitude effects across the regions. The findings of this study are consistent with other previous empirical studies in Iran (Hosseinpoor et al., 2006), Kenya (Demombynes & Trommlerová, 2016), Nepal (Goli et al., 2015), and Sri Lanka (Chaudhury et al., 2006). In contrast to the present findings, Burke et al. (2016) indicated that the explained variations in under-five child mortality accounted for 75 percent of the overall disparities in child mortality (covariates effect). Furthermore, this study's findings revealed that the household's wealth status was the most significant determinant factor affecting the regional variations in under-five child mortality. Thus, the proportional differences among children from a household in the poorest third index reduced the regional difference in under-five child mortality. In line with this study's findings, significant variations in child mortality were also observed due to the significant differences in households' wealth index in Iran (Hosseinpoor et al., 2006; Khosravi et al., 2007), Kenya (Akuma, 2013; Ikamari, 2013), Nepal (Dev et al., 2016; Goli et al., 2015), Nigeria (Adedini et al., 2015; Anyamele et al., 2015), Ethiopia (Yibrah and Nyatanga, 2017), and Mozambique (Macassa et al., 2012). The existence and persistence of socio-economic-based differences across regions could imply that some of the regions continue to have poor access to some benefits, because of problems in their economic, social, and healthcare services. On the other hand, some of the regions could be much more exposed than others to the risk of child mortality that is related to socio-economic determinant factors. Children could experience the results of inadequate nutrition and a lack of access to primary healthcare services (Gayawan et al., 2016).

The detailed decomposition analysis of this study's results revealed that antenatal healthcare visits were the major determinant factors affecting the regional variations in under-five child mortality. The findings of this study are in line with the findings of previous studies from Ethiopia (Yibrah and Nyatanga, 2017), Iran (Khosravi et al., 2007), Nigeria (Antai, 2011; Ikamari, 2013), Sri Lanka (Chaudhury et al., 2006), and Tanzania (Byaro &

Musonda, 2016). Most importantly, this finding revealed that mothers who had visited health posts or facilities at least four times for antenatal healthcare services were less likely to die than children of mothers who did not visit health posts or health facilities. A recent report by CSA, and ICF International (2016) indicated that 37 percent of women in Ethiopia had no antenatal healthcare service visits during their last pregnancy rural women were more likely to have had no antenatal healthcare service visits than urban women (41 percent and 10 percent, respectively).

Furthermore, the findings of the present study identified that mother's age at first birth played a key role in explaining the inter-regional differences in under-five child mortality. Thus, the proportional regional differences in children born to mothers whose age at first birth was less than 20 years significantly reduced the regional differentials in under-five child mortality. In line with this study's findings, it was also evident that the proportional differences in children born to mothers whose age at first birth was less than 20 years across regions significantly reduced the regional variations in child mortality in Ethiopia (Yibrah and Nyatanga, 2017), Nepal (Goli et al., 2015), and in Nigeria (Adedini et al., 2015). Most importantly, evidence consolidated the present findings by indicating that a mother who gave birth when she was younger than 20 years old could face delivery and pregnancy-related problems due to the mother's biological immaturity. Besides, a mother could not have basic knowledge on how to take care of her baby (Pandey et al., 1998) and as a result, a child born to such mother could be more likely to die than a child of a mother who was older than 20 years of age (Babson & Clarke, 1983).

Another key determinant factor affecting inter-regional variations in under-five child mortality is a child's birth order. This study's findings revealed that the variations in the proportional regional distribution of children with birth order of four or higher reduces the regional gaps in under-five child mortality in rural settings of Ethiopia. Thus, the findings of this study are also in complete agreement with some other previous empirical studies from Ethiopia (Yibrah and Nyatanga, 2017), Nepal (Goli et al., 2015), and in Nigeria (Adedini et al., 2015; Antai, 2011). How does a child's birth order determine child mortality and explain the regional gaps in child mortality? First births are more likely to be born to a young woman who is not biologically ready to accept and take care of her baby. On top of this, the young woman could have limited basic knowledge on how to care for her a baby (NIMS et al., 2012; Pandey et al., 1998). A child of higher birth order, by contrast, is most probably born to an older woman, and is more likely to be influenced by competition from older siblings in terms of resources (NIMS et al., 2012). Overall, births of a very high order (four or more) are unwanted births and if such births have occurred, these children are subject to high risks of death (Suchindran & Adlakha, 1979). Moreover, Srinivasan (2000) and Sweemer (1984) indicated that the child's birth order and child mortality had a direct relationship, as a child's birth of higher order had a higher probability of dying than a child whose birth of lower order.

A child's birth spacing (child's birth interval) was also the potential proximate determinant factor affecting inter-regional differentials in under-five child mortality in rural settings of Ethiopia. This study's findings reveal that the proportional regional distribution of shorter birth spacing between children constituted led to a reduction in regional variations in under-five child mortality across the regions. The findings of this study are in line with some other earlier studies in Ethiopia (Yibrah and Nyatanga, 2017), Iran (Hosseinpoor et al., 2006), Kenya (Akuma et al., 2013; Ikamari, 2913); Nepal (Goli et al., 2015), and Nigeria (Adedini et al., 2015). Furthermore, some previous empirical studies that consolidated the present findings of this study also indicated that a woman who experienced shorter birth spacing between children might not recover her health instantly and this could then deter the baby's growth. Thus, a child born with a birth spacing less than 24 months is more likely to die than a child born with a birth spacing of more than 24 months (Hobcraft et al., 1983; NIMS et al., 2012). Moreover, this study's findings indicated that the size of the child at birth was the most important determinant factor that explained the inter-regional differentials in under-five child mortality. The proportional differences in the distribution of child's birth size (where the child's birth size is less than average) constitutes significantly to reducing the regional variations in under-five child mortality, with a different in the magnitudes of effect, a sign of estimates, and patterns of statistical significance levels across the regions. This study's finding was in line with the findings of other previous studies from China (Wang et al., 2012) and Sri Lanka (Chaudhury et al., 2006).

In terms of environmentally related factors, the place of child delivery was also found to affect the inter-regional variations in under-five child mortality. Thus, results of this study also indicated that the unequal distribution of a child born at home (child delivery in a health institution) attributed significantly to reducing the regional gap in under-five child mortality, with considerable differences in the magnitudes of effect across the regional comparisons. This study's finding is in line with some other earlier empirical evidence from Kenya

(Ikamari, 2012), India (Patel & Sharma, 2013; Utta, 2015), Nigeria (Adedini et al., 2015), and Ethiopia (Yibrah and Nyatanga, 2017). Furthermore, institutional child delivery (child delivery at health units or facilities) could help in minimising the harmful healthcare consequences such as pregnancy complications or infections in the mother. Besides, a mother could get basic information from health facilities on the importance of having adequate nutritious food for herself and her baby (Rashad & Sharaf, 2016).

Among the socio-economic related factors, parental (maternal and father) level of education was also a key determinant factor affecting the inter-regional variations in under-five child mortality. Thus, this study's findings revealed that the parental level of education, mainly the maternal level of education was the major socio-economic determinant factor affecting the inter-regional differentials in under-five child mortality. The finding of this study is consistent with some other previous empirical findings from Ethiopia (Yibrah and Nyatanga, 2017), India (Utta, 2015), Iran (Hosseinpoor et al., 2006; Kenya (Akuma, 2013; Ikamari, 2013), Nepal (Goli et al., 2015; Dev et al., 2016), Nigeria (Adedini et al., 2015; Antai, 2011; Anyamele et al., 2015), Mozambique (Macassa et al., 2013), and Tanzania (Byaro &Musoda, 2016). Parental education is considered as the most crucial factor in improving the health of a child (Bhandari et al., 2007). Maternal education is the major determinant factor in reducing under-five child mortality by means of the provision of improved healthcare services. An educated mother can delay marriage and in doing so, she could delay early childbearing. An educated mother could also have basic knowledge about nutrition, child healthcare, and hygiene child that could significantly affect the chance of survival for the child (Caldwell, 1979). Thus, compared to uneducated mother, an educated mother at least with primary education level can reduce child mortality and in turns explains regional variations in child mortality. This could be due to the fact that an educated mother could have better behaviour in terms of hygiene, diet, healthcare, decision-making in the household and detachment from certain cultural practices that are harmful to child's health. In addition, an educated woman has an advantage over the uneducated mothers in that she could attract a husband with a job that pay well, and thus she could have relatively greater resources to meet her child's basic needs.

Most importantly, the negative contribution of the age of the child at death indicated that children of the other regions were relatively younger at time of death than children of the same cohort of the Tigrai region (the region used as a reference category) except for the

Harari and Somali regions. Moreover, the negative relative contribution of male under-five children revealed that females of the same cohort were in a more disadvantageous situation in terms of mortality in all the regions except for Tigrai-Harari region and Tigrai-Somali regions. The findings of this study are in line with the findings of Yibrah and Nyatanga (2017) and Goli et al. (2015).

6.3. Technical efficiency and productivity changes of health posts

Evaluating the efficiency of the health extension programme in the disadvantaged rural areas of Ethiopia could help in improving the healthcare system performance of the country. To the best of the author's knowledge, this study is the first to measure the technical efficiency and productivity growth or changes of the Ethiopian community-based health extension programme using health posts as decision-making units at the national level. As indicated in *Chapter Four*, to evaluate the technical efficiency and productivity changes of the health posts, a set of input and output variables were employed and analysed using an output-oriented two-stage Data Envelopment Analysis and DEA-based Malmquist productivity index techniques, respectively. In addition, the study examined the determinant factors affecting technical inefficiency disparities among the sample health posts using a second-stage regression analysis. Hence, during the study periods (2013 to 2014), the findings of the descriptive statistics indicated that there were variations in quantities of inputs being utilised and outputs being provided (produced) across the regional health posts and over the study periods. For example, the highest change in output (99 percent) was observed for under-five fully immunised children with an annual average of 21 and 42 percent in 2013 and 2014, respectively. This was followed by 93 percent increase in output of child delivery by the health extension workers with an annual average of 25 and 48 percent in 2013 and 2014, respectively. A significant reduction of 23 percent in output, however, was also observed in health education sessions provided by the health extension workers with an annual average increase of 29 and 22 percent in 2013 and 2014, respectively. Similar findings were also reported by Kirigia et al. (2007); Kirigia et al. (2011); Herna´ndez & San Sebastia´n (2014); and Zeng et al. (2014).

The results of a DEA analysis indicated that there was a substantial difference in technical and scale inefficiency levels of the sample health posts across the regions and over the examined periods. For example, in 2013, at the national level, only 3.67 and 8.25 percent of the sample health posts were defined as technically efficient, with overall average technical and pure technical efficiency estimates of 55.6 and 78.6 percent under constant and variable returns to scale assumptions, respectively, while in 2014 only 2.84 and 5.67 percent of the sample health posts were technically efficient, with overall average technical and pure technical efficiency estimates of 58 and 79.6 percent under constant and variable returns to scale assumptions, respectively. These figures indicated that, on average, an average health post could potentially produce at least 42 and 20.4 percent additional outputs under constant and variable returns to scale assumptions, respectively, while holding the current levels of input consumption fixed to operate at the efficient frontier. In support of the present findings, findings of previous studies from other countries revealed that there were significant variations in technical efficiency estimates among the health units used as decision-making units, indicating a high potential for improving the technical efficiency estimates of the health units through which efficiency of the health system or programme could substantially be improved. Studies that support the present findings of this study are Kirigia et al. (2007); Herna´ndez & San Sebastia´n (2014); and Zeng et al. (2014). Furthermore, the present study indicates that the proportion of the technical and scale efficient health posts varied significantly across regions and over the study periods. For example, in 2013, about 96.33 and 91.75 percent of the sample health posts were technically inefficient under constant and variable returns to scale assumptions, respectively. While in 2014 only 97.16 and 94.33 percent of the sample health posts were technically inefficient under constant and variable returns to scale assumptions, respectively. This study's finding is inconsistent with the findings of most other previous studies from other countries. For example, Kirigia et al. (2011) indicated that about 67 percent of the community health posts in Sierra Leone were technically inefficient. In Kenya, Kirigia et al. (2004) also indicated that 56 percent of health centres were technically inefficient, with significant variations in technical efficiency estimates among them. In Burkina Faso, about 30 percent of the health centres were technically inefficient with considerable disparities in the levels of technical efficiency (Marschall & Flessa, 2009). In Guatemala, a study by Herna´ndez and San Sebastia´n (2014) indicated that about 47 and 71 percent of the health posts were technically inefficient in 2008 and 2009, respectively. Moreover, in Ghana, 30 percent of the health centres were technically inefficient (Akazili et al., 2008a) In India about 40.75 percent of the rural health care centre programmes were found to be technically inefficient (Satyanarayana et al., 2012), and in Rwanda a study by Zeng et al. (2014) revealed that about 58 and 69 percent of the rural health centres were technically inefficient in 2006 and 2007, respectively with significant variations in magnitudes of technical efficiency levels among the health centres.

The results of the DEA analysis further indicated that the scale efficiency estimates of the health posts varied substantially across and within regional sample health posts and over the study periods. For example, in 2013 and 2014, about 20.75 and 8.7 percent of the sample health posts were scale efficient, respectively. These figures suggested that 79.25 and 91.3 percent of the sample health posts in 2013 and in 2014 were scale inefficient, respectively. In comparison, this study's findings are inconsistent with other countries' previous studies. For example, in Sierra Leone, a study by Renner et al. (2005) indicated that about 65 percent of the health units were also reported to be scale inefficient. In the same country, a study by Kirigia *et al.* (2011) revealed that about 36 percent of health posts were scale inefficient and 31.82 and 68.18 percent of them were operating at constant and decreasing returns to scale, respectively. In Guatemala, about 44 and 65 percent of health posts were scale inefficient and they were all operating at a decreasing return to scale in 2008 and 2009, respectively (Herna´ndez & San Sebastia´n, 2014). In addition, in Kenya, about 41 percent of the health posts were scale inefficient (Kirigia et al., 2004). Furthermore, the findings of this study revealed that there was a significant variation among the sample health posts in the proportion of the inputs being employed and the outputs being provided (produced). Most of the sample health posts were operating below their optimal scale size. In comparison to other previous other studies, for example, in Ghana (Akazili et al., 2008a; Akazili et al., 2008b); Guatemala (Hernández & San Sebastián, 2014); India (Satyanarayana et al., 2011); Iran (Qorbani et al., 2017); Kenya (Kirigia et al., 2004); Rwanda (Zeng et al., 2014); Seychelles (Kirigia et al., 2007); and Sierra Leone (Kirigia et al., 2011), among others, it was indicated that there was a significant variation in quantities of the inputs being utilised and in the outputs being provided across health units, which resulted in different magnitude levels of estimated technical and scale efficiency of the health units.

This study's findings of productivity analysis indicate that, on average, the health posts experienced an overall productivity improvement (progress) of 6.7 percent, with an average index of 1.067. This improvement (productivity growth) was mainly the result of technological progress or a technological efficiency change of 22.9 percent. Therefore, the technological progress was the major source of the efficiency change in the present study. Comparable results were also found in other previous studies, for example, in Guatemala, a study by Herna´ndez & San Sebastia´n (2014) found that the productivity change of the health posts was 4 percent due to technological progress. In the Seychelles, a study by Kirigia et al. (2007) reported that the overall productivity growth of the health centres was 2.4

percent due to technological progress. In Rwanda, a study by Zeng et al. (2014) also revealed that the overall productivity growth of the Rwandan rural health centres was 5.6 percent and that, the technological progress was the major source of the efficiency change.

6.3.1. Determinant factors affecting the technical efficiency variations among the health posts

As already mentioned, the evaluation of the technical efficiency indicated that there were significant variations in technical efficiency estimates among the sample health posts and across the study periods. This study also examines the determinant factors affecting the variations in the technical inefficiency estimates among the sample health posts using a second-stage regression analysis. This study's findings indicate that some of the regressed explanatory variables affected the variations in the technical inefficiency estimates among the sample health posts. For example, household's travel distance to the nearest health post affected variations in the technical inefficiency estimates among the sample health posts. Thus, the further the household's travel distance to the nearest health post, the lower the technical efficiency estimates of the health posts, which results in the households to having low access to the basic healthcare services packages of the health extension programme. This study's finding is in support of some previous studies by Akazili et al. (2008a); Bhattacharji et al. (1986); Marschall & Flessa (2009); and Stekelenburg et al. (2003), which revealed that household's travel distance to the health facilities affected the variations in the technical inefficiency estimates of the health facilities. In addition, a review by Haines et al. (2007); and Bigirwa (2009), among others, revealed that the further the household's travel distance to the nearest health facilities the more it negatively affected the variations in the technical efficiency of the community-based health worker programme or health facility. Therefore, the Ethiopian health extension workers could provide basic healthcare services to the large underserved rural people if the household's travel distance to their nearest health post reduced significantly.

Moreover, the findings of this study also show that health extension workers who are less frequently supervised by their respective supervisors affected strongly the variations in the technical inefficiency estimates of the health posts. The health posts in which health extension workers were less frequently supervised, while providing basic healthcare services to their respective communities, would be less efficient than those where health extension workers were more frequently supervised. Thus, the technical efficiency estimates of the health posts could be significantly reduced by less frequently supervised health extension workers. Hence, in line with the present study, many previous empirical studies revealed that the community-based health workers were under-supported and this, affected the variations in the technical efficiency estimates of the health units or facilities under analysis (Condo et al., 2014; Derenzi, 2012; Gautham et al., 2015; Javanparast et al., 2011; Sharma et al., 2014). Moreover, the less frequent supportive supervision made to the community-based health workers negatively affected the performance of the health workers (Stekelenburg et al., 2003). More importantly, in Ethiopia, a study by Bilal et al. (2011) also showed that the supportive supervision made to the health extension workers was very low, and varied across regions of the country. Some systematic reviews also indicated that the inadequate supportive supervision provided to the community-based health workers could significantly affect the efficiency of the community-based health worker programme (Bigirwa, 2009; Christopher et al., 2011; Haines et al., 2007; Jaskiewicz & Tulenko, 2012; Shakir, 2010, among others). On the other hand, a review made in low and middle-income countries indicated that the provision of adequate supportive supervision to the community-based healthcare workers was found to improve the performance of the community-based health worker programmes (Vasan et al., 2017).

The religious affiliation of the health extension workers was also an important determinant factor affecting the variations in the technical efficiency among the sample health posts. Hence, the present findings indicated that compared to a Christian health extension worker, a Muslim health extension worker was found to affect the variations in the technical inefficiency estimates among the sample health posts. This study's finding is in line with a study by Christopher et al. (2011) which indicated that the community health workers' religious affiliation was found to affect the technical efficiency estimates of health facilities. This study's findings diverge from some other previous studies that reported that the religion of the community-based health workers did not affect the technical efficiency estimates or performance of the community-based health worker programme (Condo et al., 2014; Javanparast et al., 2011; Sharma et al., 2014).

Another key determinant factor that affected the variations in the technical efficiency estimates among the sample health posts was the health extension workers' region of residence. This study's findings indicate that the health extension workers' region of residence significantly affected the variations in the technical inefficiency estimates of the sample health posts. Thus, finding of the present study are in line with findings of other empirical studies by Bhattacharji et al. (1986); Christopher et al. (2011); and Sharma et al. (2014) that reported that the community health workers' region of residence affected the technical efficiency levels of the health units or health facilities. This study's findings further revealed that a health extension worker who was a resident of the Tigrai region, and who was working in that region's health posts contributed to the improvement of the technical efficiency estimates of that health post compared to the health extension workers who were operating in the remaining other regional health posts.

6.4. Determinant factors affecting graduation of the health extension programme beneficiary households

Despite the major progress made concerning the deployment of trained health extension workers, and the construction of the health posts for the implementation of the health extension programme across all regions of Ethiopia, the throughput rate of graduating the programme beneficiary households as model households was very small. Most importantly, the findings of this study revealed that the throughput rate of graduating the health extension programme beneficiary households was very limited and varied significantly across regions of Ethiopia (FMoH, 2010a; Wang et al., 2016). In addition, a study by L10K (2009) indicated that only four percent of the sample households were the health extension programme beneficiary graduates as model households. Therefore, based on adjusting for the relevant demographic and socio-economic characteristics of the individual health extension programme beneficiary households, this chapter also analyse and identifies some of the key determinant factors affecting graduation of the Ethiopian community-based health extension programme's beneficiary households.

This study's findings indicated that health of the household was among the key determinant factors affecting graduation of the health extension programme beneficiary household as a model household. Thus, a female-headed health extension programme beneficiary household was more likely to graduate as a model household than their male-headed household counterpart. This study's finding is consistent with previous empirical studies by Cheng et al. (2015); Giovagnoli (2005); and Silver et al. (2008). The finding of this study is also supported by FMoH (2008), which indicated that the rate of female-headed health extension programme graduate households was higher than those of their male-headed counterparts. In addition, Yitayal et al. (2014) revealed that mothers of the health extension programme graduate households were more likely to visit health posts and were found to use modern contraceptives when compared with mothers of the non-graduate households to improve the health status of their households. This study's finding is contrary the findings of other previous studies by DeAngelo et al. (2011); Hailu & Seyoum (2015); Murray (2014); and Wedajo & Lerong (2017). Furthermore, the findings of this study revealed that the age of the mother in the health extension programme beneficiary households also affected the households' probability of graduation. Thus, this result was consistent with the previous studies by Cheng et al. (2015); and Silver et al. (2008) who found that the age of the female head of household affected the probability of programme graduation. In contradiction to the findings of this study, Gebresilassie (2013); Giovagnoli (2005); Hailu & Seyoum (2015); and Wedajo & Lerong (2017) reported that the age of the head of the households was not found to affect the households' probability of graduation. Furthermore, the results of this study indicated that family size was among the major demographic determinant factors affecting the graduation of the health extension programme beneficiary households. Hence, findings revealed that a household with relatively larger family size increased the household's probability of graduation as a model household. This study's finding is contradictory to the findings of Gebresilassie (2013); and Hailu & Seyoum (2015) who found that households with relatively larger family size was a significant determinant factor but reduced the probability of the households' graduation.

The household's arable land size was also among the major socio-economic determinant factors affecting graduation of the health extension programme beneficiary household. The results of this study indicate that a health extension programme beneficiary household with relatively large arable land size is less likely to graduate as a model household. In contradiction to the findings of this study, a study by Gebresilassie (2013) found that programme beneficiary households with relatively larger arable land size were more like to graduate than households with relatively less arable land size. In contrast to this, this study's findings were inconsistent with the findings of previous studies by Hailu & Seyoum (2015); and Wedajo & Lerong (2017) who found that households' arable land size did not affect the households' probability of graduation. Moreover, this study's results reveal that household's travel distance to the nearest health post was found to negatively affect the households' probability of graduation as a model household from the health extension programme. Alternatively, the households' probability of being health extension programme graduates reduced with households' travel distance to the nearest health post. This study's finding is inconsistent with the findings of Yitayal et al. (2014) who indicated that programme beneficiary graduate as model households who were near to the health posts found to visit more frequently. This could imply that as the households' travel distance to the nearest health post increases, the probability of being programme graduates could be reduced and as a result, the household could remain longer time being as programme beneficiary in the health extension programme. A study by USAID (2012) also indicated that about 92 percent of Ethiopia's rural households were within an average distance of 5 kilometres from their nearest health posts. It further revealed that as the households' travel distance from the nearest village health posts increased.

The parental education (mothers' and fathers' education levels) was among the key determinant factors of graduation of the health extension programme beneficiary households. The findings of this study indicated that the health extension programme beneficiary households with parents of at least a secondary school education attainment were more likely to graduate as model households. The findings of this study are in line with the findings of DeAngelo et al. (2011) that indicated that parental level of education positively affected the probability of programme beneficiary households' graduation. This study's result is inconsistent with a study by Hailu & Seyoum (2015) who found that household's literacy did not affect the households' probability of graduation. An educated health extension programme beneficiary household could understand the importance of having skills and knowledge of basic healthcare services packages of the programme. Moreover, the health extension programme beneficiary household could easily understand that the cost of medical care attendant to his/her household could be minimised with the knowledge and skills that he/she gained from the programme. Evidence indicated that literate members of the family, mainly the mother, could create favourable conditions for implementing and utilising healthcare services. This knowledge could be diffused among her family members by means of her interpersonal skills and her network (McNay et al., 2003).

The results of this study further revealed that households of agricultural extension programme beneficiaries were more likely to be health extension programme graduates as model households[35]. This study's finding was in line with previous studies by Gebresilassie (2013); Wang et al. (2016); and L10K (2009). This study's findings indicated that health

[35] The agricultural extension programme is a programme of policy instrument to bring about changes in cultural, political, social, environmental, and socio-economic aspects for rural people. Its overall objective is to assist the rural households to overcome agricultural and related problems through adopting various modern technologies and use of innovative practices that improve the livelihood of the households (Leta et al., 2017).

extension programme beneficiary households who were model households in the previous agricultural extension programme were more likely to be programme graduates as model households. Moreover, findings of this study are supported by Ethiopia's Federal Ministry of Health report (FMOH, 2008) which indicated that about 2.5 and 13.5 percent of the health extension programme beneficiary graduates were innovators and early adopters, respectively. This suggested that those innovators and early adopters, who were involved in the previous agricultural extension programme when they participated in the health extension programme, were more likely to graduate as model households than their non-innovators and non-adopters counterparts. A study by Wang et al. (2016) confirmed that it is believed that the agricultural extension programme beneficiary households were ready for change, and could also influence the behaviour of and practice of their community. Therefore, when they participated in the health extension programme, they could easily be trained to implement packages of basic healthcare services of the health extension programme.

The professional level of the health extension workers was also among the key determinant factors affecting the health extension programme beneficiary households' graduation. Thus, findings of the present study indicated that the health extension programme beneficiary households who were trained by the health extension workers with a professional level III (certificate) were more likely to graduate as model households. The health extension workers with a professional level III (certificate) have accumulated better experiences due to in-service training and upgrading their professional levels on provision of basic healthcare services. In turn, this could enable them to provide basic healthcare services in an efficient way to their respective households and communities. The findings of this study are in line with a study by FMoH (2012/13), which indicated that most of the health extension programme beneficiary households were trained by health extension workers with professional level III (certificate) and who were programme graduates of model households.

Furthermore, this study's findings indicated that households who had access to an off-farm income as a source of income for their households were less likely to graduate as model households. Therefore, this study's finding is in complete agreement with the findings of a previous study by Bazezew (2012) that indicated that an off-farm income as a determinant factor affected a household's probability of being a programme graduate. In contrast to this study's finding, Yitayal et al. (2014) found that mothers from households with a higher income level were more likely to visits health posts than mothers of households with a lower income level. This could imply that mothers from households with a high income level were more likely to graduate as a model household, than mothers of households with a lower income level.

6.5. Conclusion

This chapter presents this study's research findings and makes comparisons with other previous empirical studies. This study's tends to support findings from previous studies, while to a lesser degree contradicts findings of some other studies. The regional gaps were largely dominated by cross-regional differences in returns of the determinants of under-five child mortality (coefficients effect). The regional differences in the proportional distributions of the proximate determinant factors (such as the child's birth order, size of the child at birth, the child's birth spacing, and mother's age at first birth), the socio-economic determinant factors (such as the households' economic status, mothers' levels of education, and antenatal healthcare services), and environmental determinant factor (such as place of child delivery) were the key determinant factors affecting inter-regional differentials in under-five child mortality in rural settings of Ethiopia. Moreover, this study also evaluated the efficiency and productivity growth of the health extension programme using health posts as decision-making units. Findings revealed that most sample health posts were relatively technically inefficient and were operating below their optimal scale size, with considerable variations across regions. The overall productivity change of the sample health posts was increased by 6.7 percent due to technological progress. Furthermore, supportive supervision, household's travel distance to the nearest health post, religious affiliation, and region of residence of the health extension workers were the major determinant factors affecting the variations in technical efficiency estimates among the sample health posts.

This chapter also examined the determinant factors affecting graduation of the health extension programme beneficiary households. Results revealed that family size, parental level of education, maternal age, head of the household, households' participation in agricultural extension programme, and professional level of health extension workers were the key determinant factors affecting graduation of the programme beneficiary households. This study's findings were in complete agreement with some other previous studies' findings while contradicting with some other studies' findings. Thus, examining the determinant factors affecting health extension programme beneficiary households' graduation could significantly improve access to and use of basic healthcare services and enhance the number of health extension programme beneficiary graduates and thereby, ensure universal health coverage of the country. In turn, the regional gaps in under-five child mortality could be minimised substantially or could be redressed and thereby reduce the overall child mortality of the country.

CHAPTER SEVEN

CONCLUSIONS AND RECOMMENDATIONS

7.1. Introduction

Findings of the research analysis addressed the fundamental objectives of this study: to examine determinant factors affecting the inter-regional differentials in under-five child mortality; to evaluate the efficiency and productivity changes of the community-based health extension programme, and to examine determinant factors influencing the health extension programme beneficiary households' graduation in rural settings of Ethiopia. This concluding chapter primarily provides this study's major findings by highlighting the salient findings. It then makes some policy recommendations that could be used to enhance packages of the basic healthcare services of the Ethiopian community-based health extension programme to the largest under-served rural communities in the country. In turn, this would also improve the overall health status of the rural poor and in doing so, would minimise the regional variations in under-five child mortality, and would also reduce the overall child mortality of the country.

The chapter is organised as follows: Section 7.2 presents a brief summary of the conclusions of this study's overall key findings. This followed by a provision of the study's contribution in section7.3. Section 7.4 which provides some of the potential policy and programme recommendations, followed by a presentation of research directions for further study in section 7.5. Finally, section 7.6 presents the major limitations of the overall study.

7.2. Summary of the main findings of the overall study

Fundamentally, this study attempts to address the identified research gaps as outlined in the three specific objectives in Chapter One. Based on the secondary cross-sectional data, this study employs various statistical models (econometrics and non-parametric models) that specifically address the stated specific objectives of the study. Hence, the key findings relating to this study's stated specific objective, which was analysed and discussed in *Chapter* Five and Chapter Six, are summarised below:

The first objective of the present study was to examine major determinant factors affecting the inter-regional differentials in under-five child mortality in rural settings of Ethiopia. To identify the major determinant factors of inter-regional differentials in under-five child mortality, an extended Oaxaca-Blinder decomposition to count data model was employed. Findings of the decomposition analysis indicated that there was an over-dominance of coefficients effect across all regional comparisons. The overall contribution of the coefficients effect (61.8 percent) outweighs the covariates effect (38.2 percent) in explaining the observed regional differentials in under-five child mortality. Overall on average, around three-quarters of the regional gap in under-five child mortality was explained by the regional differences in the distribution of socio-economic and proximate determinant factors. The aggregate decomposition analysis indicated that most of the regional gaps in under-five child mortality were constituted by returns to the observable characteristics, the coefficients effect. The major part of the overall aggregate explained regional differentials in under-five child mortality, which was explained by the joint effect of the proximate determinant factors (29 percent) followed by socio-economic factors (20 percent), with a different in the magnitude of effect, a mixed sign of estimates, and patterns of statistical significance levels of the individual covariates across the regional comparisons.

The results of a detailed decomposition analysis revealed that there were significant differences in the covariates effect, coefficients effect, and aggregate effect across the regional comparisons. The regional differences in proportional distributions of the households' economic status, mothers' levels of education, the child's birth order, the child's birth spacing, antenatal healthcare visits, household size, and place of delivery were the determinant factors affecting the inter-regional differentials in under-five child mortality. The magnitudes of effect and levels of significance of these determinant factors varied significantly across and within the regional comparisons. In rural Ethiopia, therefore; the observed under-five child mortality differentials among the regions were largely due to the reflection of the wide regional differentials of these determinant factors.

Another objective of the study was to evaluate the efficiency and productivity changes (growth) of the health extension programme using health posts as decision-making units. An output-oriented Data Envelopment Analysis technique and DEA-based Malmquist productivity index were employed to potentially evaluate the technical efficiency and productivity changes of the sample health posts, respectively. Moreover, the study also examined the technical efficiency variations among the health posts and the determinant factors affected these variations using the Tobit and ordinary least square regression models as second-stage regression analysis. This study employed two input and six output variables to evaluate the technical efficiency and productivity changes of the health extension programme using health posts as decision-making units.

The number of inputs being employed (mainly the health development armies) and the number of outputs being provided or produced varied significantly within the sample health posts, across regions, and over the two study periods. Furthermore, the results indicated that there was a substantial variation in technical and scale efficiency levels of the sample health across the regions, and over the study periods. This indicated that there was significant potential room for improving the programme's efficiency by improving the scale and technical efficiency of the relatively technical inefficient health posts. For example, the overall average technical efficiency level of the sample health posts was 55.6 and 78.6 percent, respectively under constant and variable returns to scale assumptions, with an average scale efficiency level of 70.6 percent in 2013. In 2014, the average technical efficiency estimates were 58 and 79.6 percent, respectively under constant and variable returns to scale assumptions, with an average scale efficiency level of 72.4 percent. Despite the level of differences in the magnitudes of estimates, the average technical efficiency level improved by about 4.14 and 1.26 percent for sample health posts under constant and variable returns to scale assumptions, respectively. Similarly, there was an improvement in the average scale efficiency level of the sample health posts as evidenced by a 2.5 percent improvement over the two study periods.

Across periods, there were significant differences in the number of scale and relatively technically efficient health posts within and across the regions. The number of relatively technical efficient health posts reduced by about 29.23 percent from 3.67 to 2.84 percent under constant returns to scale assumption in 2013 and 2014, respectively. Moreover, the number of relatively technically efficient health posts was reduced by about 45.5 percent from 8.25 to 5.67 percent under variable returns to scale assumptions. Over the same periods, the number of scale efficient health posts reduced by more than twice (138.5 percent) from 20.75 to 8.7 percent.

Furthermore, there were substantial differences in the number of scale and relatively technically efficient health posts across the regions. For example, the largest 18.63 percent of the Tigrai regional health posts were scale efficient and were operating at their optimal scale size while none of the Harari regional health posts was scale efficient and all of them were operating below their optimal scale size. Similarly, the largest 19.88 percent of the Tigrai regional health posts were relatively technically efficient while none of the Gambella, Benshangul-Gumuz, and Harari regional sample health posts was fully technically efficient. Moreover, across periods there were significant differences in the number of health posts, operating at decreasing and constant returns to scale assumptions within and across regions. For example, across the two periods, the number of health posts that were operating at decreasing returns to scale increased from 78.93 percent in 2013 to 91.24 percent in 2014, a 13.5 percent increase. This indicates they had the potential to downsize their scale size in order to operate at the efficient frontier. Likewise, all the Harari regional health posts were operating at decreasing returns to scale, while about 80.13 percent of the Tigrai regional health posts were operating at decreasing returns to scale. The results show that the number of inputs needed to be reduced and outputs need to be added to make the relatively technically inefficient health posts efficient. This varied significantly within and across the regional health posts.

The results of the Malmquist analysis revealed that the overall productivity of the sample health posts improved by nearly 6.7 percent due to technological progress. The most important source of this improvement in productivity was attributed to the average technological progress of 22.9 percent. The improvement in the productivity was the net outcome of improvement in the technological efficiency change (as a major source of efficiency change). Moreover, none of the health posts attained pure efficiency change of greater than unity both at the regional and national levels, implying that the relative technical efficiency changes of the health posts remained unchanged. Results also revealed that was a significant difference in magnitudes of changes for the total factor productivity, technological, technical efficiency, pure technical efficiency, and scale efficiency within and across the regional health posts. Moreover, this study also examined whether the estimated technical efficiency differences among the health posts was due to the management practices of the programme or due to other external factors. That is, the evaluation of the technical efficiency of the health posts was also accompanied by an explanation of the variations in their technical efficiency estimates. Thus, findings of the regression analysis indicated that the household's travel distance to the nearest health posts, provision of supportive supervision to health extension workers, religious affiliation, and region of residence of the health extension workers provided a significantly explanation of the variations in the technical inefficiency estimates among the sample health posts.

Graduating of the trained health extension programme beneficiary households as model households is the key objective of the Ethiopian health extension programme as a means of enhancing access to basic healthcare services and thereby ensuring their utilisation by the largest number of rural people. Thus, to improve the throughput rate of the health extension programme beneficiary households as model households, this study also examined the determinant factors affecting the health extension programme beneficiary households' graduation as its third objective. The results of the regression analysis revealed that there were substantial variations in the throughput rate of graduating health extension programme beneficiary households as model households within and across the regions. Furthermore, the results of the analysis indicated that the programme beneficiary households with relatively larger family size, were more likely to graduate as model households. The parental level of education also significantly affected the probability of the health extension programme beneficiary households' graduation. Results further indicated that the programme beneficiary households with relatively older mothers were more likely to be programme graduates as model households. Moreover, households headed by a female, households who participated in agricultural extension programmes, and households who were trained by health extension workers (with a certificate) were also more likely to be programme graduates as model households. In contrast to this, results of the regression analysis revealed that the programme beneficiary households with relatively larger arable land size, with an off-farm income, and who living relatively far from the nearest health posts were less likely to be programme graduates as model households.

In summary, the overall findings summarised in this concluding chapter draws certain basic conclusions. Addressing some of the identified major factors affecting the health extension programme beneficiary households' graduation could significantly enhance the throughput rate of the programme beneficiary households, which, in turn, could enhance access to and utilisation of basic healthcare services of the programme across regions of the country. Increasing the number of programme beneficiary graduate households as model households could help in providing additional basic healthcare services to more underserved rural societies, as more rural households could join the programme to be trained in basic skills and knowledge of primary healthcare services packages of the programme. In doing this, the health status of the society (mainly child and maternal) could be improved, and in turn, the regional differentials in under-five child mortality could also substantially be minimised.

To enhance the technically inefficient health posts, the relatively technical inefficient health posts must provide additional outputs with the existing level of inputs to operate at their optimal scale size. In turn, this undertaking would substantially improve the efficiency and productivity of the health extension programme. As a result, a large number of rural households could be covered by the programme, and improve their overall health status. Moreover, the country's universal healthcare coverage could also be enhanced significantly. In addition, addressing the factors that affect the variations in the technical efficiency estimates among the health posts could also help in improving the efficiency of the relatively technically inefficient health posts and thus, enhance the programme's efficiency. Most importantly, addressing the identified major determinant factors affecting the inter-regional differentials in under-five child mortality could significantly minimise the observed variations in under-five child mortality among the regions and thus, reduce substantially the overall child mortality at the national level.

This study's overall findings could provide substantial evidence for policy options that are available to decision-making, health managers, potential stakeholders, regional health bureaus, the Ministry of Health, and regional and federal governments of Ethiopia to substantially improve the universal healthcare coverage of the country. Consequently, this study's findings could help the country to achieve its global sustainable development goal of reducing under-five child mortality rate to less than 25 deaths per thousand births by 2030 or before the deadline.

7.3. Originality and contribution of the present study

The reviewed literature revealed that there were limited studies on determinant factors affecting inter-regional differentials in child mortality, the efficiency of the community-based health extension programme, and factors affecting the health extension programme beneficiary households' graduation at the national level in the Ethiopian context. Therefore, this study constitutes an important contribution to the existing scarce, but growing, body of literature on the above-mentioned research gaps in the areas of health economics, economics, and demographics in developing countries, particularly in Ethiopia. It is, therefore, to necessary to highlight that the comprehensive evidence provided in this study has an enormous contribution to make in the following different aspects:

I. Theoretical contribution

- There is a paucity of explanations regarding the development of an integrated theoretical and conceptual frameworks that concurrently shows the factors affecting the inter-regional gaps in under-five child mortality, evaluate efficiency of the decision-making units, as well as the determinant factors affecting the variations in technical efficiency among the decision-making units. Unlike the other theoretical and conceptual frameworks, this study therefore contributes in developing an integrated conceptual framework, which describes the direct and indirect effect of factors that affected the under-five child mortality that conceptualised how each determinant factor affected the under-five child mortality, in turn, to explain the regional variations in under-five child mortality. Therefore, it is through the lens of this integrated framework that the interaction effect of the variables of interest can be clearly elucidated.

- This study's findings of explained inter-regional differences in child mortality could also provide empirical evidence that may be used to target areas of priority in high-risk regions of (for example, the high under-five child mortality rate) Ethiopia for the provision of high impact, cost-effective, inclusive, broad-based, and life-saving child survival interventions.

II. Policy contributions

- Findings of this study which indicates the technical efficiency differences among the regional health posts could contribute to the provision of basic information to policymakers, federal and regional health experts and health professionals at all levels of Ethiopian society so that they may have a better understanding of factors explaining disparities in technical inefficiency levels among the health posts.
- This study's findings of efficiency and productivity changes of health posts can help policymakers, federal and regional governments to create a better understanding of the performance of the health extension programme in delivering basic healthcare services to Ethiopia's rural communities.
- This study's findings of the differences of technical efficiency estimates among the regional health posts could also be used as input justification for budgetary allocation. Hence, the provision of healthcare services output could be improved and as a result, the country's universal healthcare coverage could be significantly enhanced. This is because the optimal use of the scarce resources on the healthcare services provision of the health extension programme is a fundamental aspect in improving the Ethiopian society's health status.

III. Other contributions

- This study is the first of its kind in the Ethiopian context; thus, it could be used as a benchmarking source of literature for further research work in Ethiopia and other developing countries and thus, as a quick reference point to provide comprehensive empirical evidence.

- One of the most prominent contributions of this study is that its emphasis is on explaining the regional gap in under-five child mortality by diving it into two component gaps, the covariates or characteristics effect, and coefficients effect.

7.4. Recommendations

Based on this study's overall findings, some key policy implications may be drawn from different aspects.

A. Child mortality

- To reduce the national child mortality, a priority should be given to the reduction of the regional disparities in child mortality with limited resources, which could finally have considerable impact on the reduction of the country's overall child mortality rate.
- Addressing the regional differences mainly in households' economic status and women’s education by introducing appropriate interventions that minimise the variations among the regions could further reduce the regional disparities in under-five child mortality and thus, enhance the overall child health status.
- Further sustained efforts are also needed to minimise the inter-regional differentials and accelerate the overall rate of reduction in under-five child mortality at the national level against a certain target set, for example, a 75 percent disparity reduction goal in under-five child mortality rate among regions by 2025.
- To achieve the sustainable development goal of reducing under-five child mortality rate to less than 25 deaths per thousand births by 2030 or before the deadline, Ethiopia needs to accelerate the pace of progress by addressing the proportional differences mainly in households' economic status and women’s education observed among the regions. However, focusing only on reducing under-five child mortality rate at the national level for Ethiopia might it impossible to achieve its global sustainable development goal.

B. Universal healthcare coverage

- Most health posts were not relatively technically efficient in utilising their available inputs and as a result, they were found to be relatively technically inefficient. Thus, the regional health bureaus, stakeholders, and regional and federal governments should motivate mainly the health extension workers to significantly improve the provision of basic healthcare services to their respective communities and as a result, the efficiency of the health extension programme could be considerably enhanced.

- In line with the national goal of the Ethiopian Ministry of Health's vision to enhance the country's universal healthcare coverage to 99 percent by 2025, it would be more practical to recommend that the regional health bureaus, regional and federal governments and policymakers improve the provision of basic healthcare services output through improving the health posts' efficiency.
- Due emphasis should be placed on creating enabling environments such as promoting provision of sustained in-service refresher training programmes and provision of sustained supportive supervision to the health extension workers in order to improve the provision of basic healthcare services to their respective communities. In turn, this could significantly enhance the country's universal healthcare coverage.

C. The health extension programme beneficiary graduates

- Sustained efforts are needed to intensify the number of health extension programme graduates as model households by addressing the identified determinant factors affecting graduation of the health extension programme beneficiary households.
- The upgrading programme for the health extension workers' professional levels (from level II to III) should be strengthened to enhance the number of health extension programme graduates as model households, and, as a result, improve access to and utilisation of the programme's basic healthcare services, which in turn, could also improve the country's universal healthcare coverage.
- The inclusion of households with relatively larger family size as health extension programme beneficiary households could significantly accelerate the country's universal healthcare services coverage, and, as a result, improve the rural population's health status.
- Development practitioners, regional health bureaus, and regional governments should focus on improving parental education (adult education) to significantly enhance the number of health extension programme graduates, and in doing so, would improve access to and utilisation of the programme's basic healthcare services to the country's rural areas.

D. National policy-level development

- Ethiopia needs to establish health outcomes inequality surveillance systems and carry out periodic research studies that report the differential impacts on the health outcomes indicators such as child mortality across its regions so that it may significantly reduce the overall rates of child mortality and minimise the regional disparities in under-five child mortality.

- Most importantly, this study's findings may be used as an input to the current Ethiopian Growth and Transformation Plan-II (GTP-II) in order to improve the country's universal healthcare services coverage and further to accelerate the rate of reduction in under-five child mortality, both at the regional and national levels.
- A comprehensive periodical evaluation of the health extension programme could serve to re-engineer the national policies and strategies of the programme.

7.5. Study limitations

Below, this study's major limitations are listed:

i. Data source related limitations

- Due to the lack of comprehensive data, only two-time periods were utilised to analyse the productivity growth of the health extension programme. A more extensive set of time series data could allow for providing of detailed productivity changes of the programme. The study was also unable to include other potential determinants of variations in technical inefficiency among the health posts during the regression analysis.
- This study presumes that all regions under analysis are identical. This assumption might not be useable since working schedules, quality of delivery in healthcare services outputs, healthcare technology, the degree of severity of cases treated, and others could differ among regions of the country.
- This study could not compute the allocative efficiency that would also have allowed for computing the economic efficiency of the overall health posts, due to unavailability or difficulty in getting information on the price of the employed inputs.

ii. Methodological related limitations

Despite an Oaxaca-Blinder decomposition that has commonly been applied across disciplines and the strength of DEA technique, the following are some basic limitations:

- In Oaxaca-Blinder decomposition, the most important problem is that of the index number. The selection of the reference category in the decomposition approach could influence estimates of explained and unexplained parts of the component gaps.
- The other limitation of an Oaxaca-Blinder decomposition technique is the difficulty of making inferences about the major causes of the unexplained part of the components gap.

- In DEA analysis, all deviations of the efficiency estimate of the decision-making units from the efficiency frontier are considered to be due to the inefficiency of these units.
- Data Envelopment Analysis compares the relative technical efficiency of the health posts to other health posts under analysis, but not against a theoretically based benchmark.
- The Data Envelopment Analysis technique is a deterministic model that does not consider the error term in its functional model.

7.6. Areas for further study

The present study points out some potential areas for further study.

- It is important to identify the factors affecting rural-urban variations in under-five child mortality. The factors identified in the present study may or may not affect the rural-urban variations in under-five child mortality due to differences in geographical, cultural, economic, and other important factors between rural and urban area, and therefore requires further study.
- There is a need periodically to evaluate the health extension programme's efficiency and productivity growth or changes at least once a year. This is, of course, to ensure the effective use of empirical evidence as a guideline that would help decision-makers to improve the interventions of the healthcare services, and to develop realistic policies and strategies regarding the health extension programme.
- Another avenue for further study would be to compare the Ethiopian health extension programme's efficiency to those of other Sub-Saharan African countries' community-based health worker programmes that have a similar feature.

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APPENDIX

Appendix A: Summary of reviewed literature and supportive documents

Table A- 1: Summary of previous studies on regional or inter-state differentials in child mortality rate

Authors, years	Country	Methodology	Key findings and concluding remarks
Jain (1985)	India	Multiple linear regression model	- The maternal level of education, child delivery by health personnel, households' poverty status, the child's vaccinations, access to electricity, and safe drinking water explained the regional disparities in IMR. - Improving households' poverty status and maternal education level could significantly reduce regional differentials in IMR.
Choudhury (2015)	India	Binary logistic regression model	- Maternal exposure to mass media, a mother who has a decision-making power, a father and a mother with primary education level, explained the regional differences in infant mortality rate. - The study concluded that improving parental education, maternal exposure to mass media, and socio-economic status could significantly reduce IMR across the regions.
Mukhopadhyay (2015)	India	Multiple regression model	- Female-literacy rate, per capita income, and variations of medical doctors in health facilities are the major determinants of IMR. - Improving maternal literacy and households' economic status could reduce the regional variations in infant mortality across the states.
Patel and Sharma (2013)	India	Multiple linear regression model	- Home child delivery, higher child's birth order, maternal BMI less than 17 and women whose age ranges from 15 to 49, households in the lowest wealth index, and antenatal

			healthcare services explained the inter-state differences in neonatal mortality rate. - Enhancing antenatal healthcare services and households' economic status could reduce neonatal mortality and minimise inter-state gaps in neonatal mortality.
Uttam (2015)	India	Square dummy variable model	- Access to toilet facilities, institutional delivery, an illiterate married woman, a pregnancy-related complication, and home child delivered assisted by professionals were the major determinants of inter-state differences in IMR. - In summary, access to and utilisation of healthcare services need to be developed mainly for the tribal communities living in the northeast of India.
Chaudhury et al. (2006)	Sri Lanka	Multiple logistic regression model	- Access to healthcare services, safe drinking water, low birth size, and healthcare utilisation explained the IMR variations across districts of the country. - Improving access to and utilization of healthcare could reduce district variations in IMR.
Goli et al. (2015)	Nepal	Oaxaca-Blinder decomposition technique	- Parental education level, households' wealth status, place of residence, higher child's birth order, and mother's employment status explained regional differences in U5MR. - The variations in child mortality should be addressed from an ecological region outlook through improving mainly households' economic status and parental level of education.
Dev et al.(2016)	Nepal	logistic regression model	- Mothers who perceived distance to health facilities as a major problem, maternal education, household's economic status, and number of infants that the mother had were the major determinants of IMR. - All these determinants were also the major determinants of regional variations in IMR
Wang et al. (2012)	China	Woolf method	- Gender of the infant, low birth size, pneumonia, injuries, birth asphyxia, and diarrhoea accounted for 80 percent of the regional variations in infant mortality.

			- Improving the overall healthcare services could significantly reduce the regional variations in IMR.
Hosseinpoor et al. (2016)	Iran	Concentration index	- Households' economic status, mother's education, place of residence, short birth spacing, and access to safe toilet facility explained the regional variations in IMR. - The study noted the importance of having a universal approach among the different ministries to accelerate the reduction of disparities in social determinants of IMR.
Khosravi et al.(2007)	Iran	Multiple linear regression model	- The GDP per capita, life expectancy, high literacy rate, and healthcare services accessibility were important sources of variations in child mortality across provinces. - Improving households' economic status and literacy level could minimise the regional variations in child mortality.
Terra de Souza et al. (1999)	Brazil	Linear regression model	- Under-immunised infant, households' participation in growth monitoring, ANC, households with low-income level, inadequate water supply, lack of sanitation facilities, and female illiteracy rate explained the inter-municipality disparities in IMR. - Improving the prenatal healthcare services, households' economic status, maternal literacy status, provision of water supply, and improving latrine facilities could significantly reduce the disparities in infant mortality among the municipalities.
Gayawan et al. (2016)	West African countries	spatial extension of discrete-time survival model	- Access to electricity, improved toilet facilities, institutional child delivery, household's economic status, and mother's educational status were important determinants in explaining regional differences in U5MR among regions of within countries. - The variations in child mortality was more substantial than in IMR for most of the West African countries and could be reduced by improving household's economic status, and

			mother's educational status.
Farah & Preston, (1982)	Sudan	Multiple linear regression model	- The prevalence of malaria, a poor healthcare system, poor education status, and low levels of household income were the determinants of the regional differential in child mortality. - Improving the overall health system, parental education status, and households' economic status could minimise the disparities in child mortality across the regions.
Akuma (2013)	Kenya	Multivariate logistic regression model	- Maternal education level, household's socio-economic status, and birth spacings were the major determinants of infant mortality. - The regional differentials in IMR could minimise by improving household's economic status and maternal education level.
Ikamari (2013)	Kenya	Cox-regression model	- ANC, institutional child delivery, birth spacing, the maternal age at first birth, household's economic status, maternal education level, and improved toilet facilities explained the disparities in neonatal and postnatal child mortality across the regions. - The regional disparities could be minimised by improving household's economic status, maternal education, and ANC.
Demombynes and Trommlerová (2016)	Kenya	Oaxaca-Blinder decomposition technique	- Use of insecticide-treated bed-nets and access to improved sanitation facilities explained the regional disparities in postnatal and infant mortality rates. - The study concluded that much of the regional disparities in IMR remained unexplained.
Baker (1999)	Malawi	Poisson regression model	- Mother's educational status, toilet facilities, and maternal residence distance to the nearest health centres explained the regional differentials in child mortality. - Improving maternal educational level and use of improved toilet facilities could substantially reduce child mortality and regional variation in child mortality.

Assi (2014)	Cote d'Ivoire	logistic regression model	- A woman with at least secondary school education affected positively the U5MR. - Although the study did not include many important factors, improving the maternal level of education could reduce U5MR across regions of the country.
Macassa et al. (2012)	Mozambique	Cox-regression method	- Access to toilet facilities, households' wealth status, parental educational level, and mother's region of residence were the major determinants of regional variations in U5MR. - Improving mainly maternal educational level and households' economic status could significantly reduce U5MR and minimise the regional disparities.
Antai (2011)	Nigeria	Cox-regression method	- The higher child's birth order, mother's level of education, marital status, and ANC were the main determinants of regional differentials in U5MR. - Improving maternal economic status, mainly for the disadvantageous regions of the country, could significantly reduce the regional disparities in U5MR.
Adedini et al. (2015)	Nigeria	Cox-regression method	- The community infrastructure, households' wealth status, households' poverty status, place of child delivery and place of residents explained the regional variations in U5MR. - Child's birth order, birth spacing, maternal education, and mother’s age at marriage explained the regional disparities in IMR. - Thus, improving mainly households' economic status and maternal health status could significantly reduce the regional disparities in IMR and U5MR.
Anyamele et al.(2015)	Nigeria	logistic regression model	- Households' economic status, maternal educational, use of health facility, gender of the child, and number of live births explained the regional variations in IMR and U5MR. - Enhancing maternal education, economic status, and healthcare facilities could substantially minimise regional variations in IMR and UMR.

Byaro and Musonda (2016)	Tanzania	Fixed effects model using linear regression model	- Maternal education, breastfeeding practice, child immunisation coverage, child delivery by health professionals, and ANC explained the regional differentials in IMR and U5MR. - Improving the maternal education, healthcare services, and institutional child delivery could significantly minimise the regional variations in IMR and U5MR.
Ghaffar and Bhuyan (2000)	Libya	Discriminant analysis	- Maternal age at marriage, household's socio-economic status, modern breastfeeding practice, and parental level education explained the regional variation in child mortality. - Improving the socio-economic status and parental level of education could significantly minimise the regional disparities in child mortality.
Tesemmas (2008)	Ethiopia	Descriptive analysis	- Households' poverty level, healthcare system, epidemic diseases, ANC, and family healthcare services were the determinants of the regional variations in IMR and U5MR. - Improving households' poverty status and healthcare system could reduce the regional variations in IMR and U5MR.
Bedane et al. (2016)	Ethiopia	Binary logistic regression model	- Mother's age at first birth, birth size, maternal education, multiple birth, and birth index negatively affected U5MR and regional disparities. - Enhancing maternal education and healthcare services could reduce U5MR and minimise regional variations in U5MR.
Negera et al. (2013)	Ethiopia	Cox-regression method	- Mother's level of education, birth size, birth spacing, access to an improved toilet facility, and maternal marital status were the major determinants of IMR and U5MR. - Improving the maternal educational level and healthcare services could substantially minimise the regional disparities in infant and under-five child mortality.

Source: Own compilation. Notes: ANC = Antenatal healthcare services; U5MR = Under-five child mortality rate; IMR = Infant mortality rate; GDP = Gross Domestic Product

Table A- 2: Summary of efficiency measurement studies focusing on community-based health workers programmes

Authors	Country	Method	input, output, and explanatory[EV] variables	Key findings of the study
Hernández & San Sebastián (2014)	Guatemala	DEA & DEA-based MPI	- Input: number of auxiliary nurses - Outputs: number of: new patients attended, children less than two years old in growth monitoring, prenatal following users, children receiving a third dose of the DPT vaccine, and family planning users.	- A significant variation in technical efficiency was observed across health posts over periods. - Most health posts were operating below their optimal level - Productivity of the health posts increased by 4 percent. - Producing additional outputs with the existing level of inputs could improve the efficiency of the health posts.
Zeng et al. (2014)	Rwanda	DEA, DEA-based MPI, & multiple Linear regression model	- Inputs: number of HIV/AIDS full-time equivalent personnel, non-HIV/AIDS full-time staff, percentage use rate of community-based health insurance, and amount of expenditure on HIV/AIDS - Outputs: the number of clients receiving VCT services, participants in the prevention of mother-to-child transmission, and AIDS patients receiving ART.	- The average technical efficiency estimate of the health centres was 78 percent with significant variations across the health centres. - Over the period, the productivity growth of the health centres was improved by 16 percent. - The study noted that the high use of community-based health insurance by the Rwandan rural households in the health centres can significantly enhance the HIV/AIDS healthcare service.

Kirigia et al. (2007)	Seychelles	DEA & DEA-based MPI	- Inputs: the number of doctor and nurse hours - Outputs: number of patients dressed, domiciliary cases treated, and FMAPPP	- Health centres had a variety of technical and scale efficiency estimates across periods. - Productivity has improved by 2.4 percent over the period
Marschall & Flessa (2009)	Burkina Faso	DEA & second-stage Tobit regression model	- Inputs: vaccination costs, personnel costs, costs of CSPS building, and CSPS equipment depreciation - Outputs: number of general consultations, immunisation, deliveries at health facilities, and special healthcare services - EV: Distance to health centres	- The average technical and scale efficiency estimates varied across the health centres. - Variations in efficiency was affected by households' travel distance to health centres - The technical efficiency estimates of the health centres can be improved by enhancing their access to healthcare services provision.
Akazili et al. (2008a)	Ghana	DEA & second-stage logistic regression model	- Inputs: the number of staffs, cots, and beds, costs for recurrent consumables and supplies - Outputs: number of outpatient visits, fully immunized children, ANC, child deliveries at health facilities, and family planning visits - EV: staff incentive, age of the health centre, health centres' revenue, access to electricity, transport, and safe drinking water	- The technical, scale, allocative, and economic efficiency estimates varied across the health centres. - The age of health centres and staffs' incentives were the determinants of technical efficiency disparities among the health centres. - The technically inefficient health centres should minimise wastage and costs of resources to be technically efficient and operate at the efficient frontier.

Satyanarayana et al. (2012)	India	DEA	- Inputs: number of: doctors, ANMs, nurse-midwife, health assistant, administrative staff, laboratory assistant, population size, age of the programme, users under-five years of age, health workers - Outputs: number of: doctors encounter, health assistant encounters, ANM's encounters, and total encounters	- The estimated technical and scale efficiency levels varied across and within the SCs, PHCs, and CHCs. - The study noted that introduction of "Business Process Reengineering" could improve the efficiency of the rural healthcare programme.
Qorbani et al. (2017)	Iran	SFA	- Inputs: health centre, physician, and 'Behvarz' worker all measured per thousand population - Outputs: the rate of diabetes treatment coverage	- The estimated technical and scale efficiency of the primary healthcare system varied substantially across the provinces, ranging from59.65 to 98.28 percent. - The 'Behvarz' workers improved the coverage rate of the diabetes mellitus treatment of the Iranian rural citizens.
Kawakatsu et al.(2012)	Kenya	Qualitative analysis & binary logistic regression	- EV: gender of the CHWs, age of the CHWs, marital status, family size, economic status, reporting rate, CHEs' education level, refresher training, and occupation	- Most of the community-based health workers were efficient (active-CHWs). - Differences in efficiency was affected by age of the CHWs and refresher training courses give to the CHWs.

Wangalwa et al. (2012)	Kenya	Qualitative analysis		- The health outcomes (neonatal and maternal healthcare practices) have significantly been improved. - The programme improved the maternal antenatal healthcare practices and child deliveries.
Kirigia et al. (2004)	Kenya	DEA	- Inputs: number of beds, administrative staff, clinical officers, nurses, physiotherapist, occupational therapy, public health officer, dental technologist, laboratory technicians, laboratory technologist, and non-wage expenditures. - Outputs: number of immunisation visits, outpatient visits, family planning, ANC, malaria visits, diarrhoeal visits, urinary tract infection visits, sexual transmitted infections visits, and intestinal worm visits.	- More than half of the health centres (56 percent) were technical efficient with an average technical efficiency level of 70 percent. - The study concluded that the technical efficiency of the Kenyan health centres was similar to the technical efficiency of the health units of other developing countries.
Kirigia et al. (2011)	Sierra Leone	DEA	- Input: the number of community health officers and administrative staff - Outputs: the number of health education sessions, the number of outpatients, and the number of vector control activities	- The estimated technical and scale efficiency estimates varied within and across the community health centres, health posts, and maternal and child health posts. - The utilisation of resources needs serious attention to improve the efficiency of the health units.

Renner et al. (2005)	Sierra Leone	DEA	- Inputs: number of technical staff, capital input, subordinate staff, and material and supplies. - Outputs: number of health education sessions, child delivery, family planning visits, under-five children fully immunised, growth monitoring visits, and ANC.	- The average technical and scale efficiency estimates of the health units were 78 and 82 percent, respectively with significant variations in technical efficiency estimates. - The study noted that there is less likelihood of achieving the health targets like the Abuja and MDGs targets by scaling up healthcare interventions at the regional level.
Akazili et al. (2008b)	Ghana	DEA	- Inputs: number of clinical staffs, non-clinical staffs, cots and beds, and costs on drugs and other consumables - Outputs: number of outpatients visits, antenatal healthcare visits, deliveries at health facilities, under-five fully immunised children, and family planning visits	- Few of the health centres were technical (35 percent) and scale efficient (21 percent) with considerable variations in technical efficiency levels across health centres. - They should reduce their sizeable inputs wastage to operate at the efficient frontier.
Stekelenburg et al. (2003)	Zambia	Qualitative analysis		- Less than half of the CHWs were active-CHWs. - The irregular and uneven provision of drugs to health centres were important contributors to the CHWs' poor performance.

San Sebastián & Lemma (2010)	Ethiopia	DEA & second-stage Tobit regression model	- Inputs: number of HEWs and vHWs - Outputs: number of health education sessions, child deliveries, ANC, children treated diarrheal cases, family planning visits, visits made to households by the HEWs, patients treated, and malaria treated - EV: Marital status, pregnancy status, number of children, support from village's chief, population covered, distance to health post, and HEW from village (tabia)	- Few health posts were technical efficient with considerable variations of estimates among the technical and technically inefficient health posts. - The technically inefficient health posts should produce additional outputs with existing the level of inputs to operate at the efficiency frontier. - None of the regressed determinants were found to be statistically nonsignificant
Javanparast et al.	Iran	Qualitative analysis		- The high workload, inadequacy of a supervisory system, lack of incentives, and poor support methods of the CHWs affected the performance of the behvarz workers.
Condo et al.	Rwanda	Qualitative analysis		- The high workload, irregular training, and the inadequate supervision of the CHWs affected their performance
Sharma et al. (2014)	India	Qualitative analysis		- The performance of the ASHAs was affected by a variety of factors such as professional, personal, and institutional factors.

Haines et al. (2007)	Different countries	Systematic review		- The health system, the community, the national, and the international factors affected the performance variations among the community-based health worker programmes.
Prasad and	Different countries	Review of literature		- The educational level, duration of training, population size that the CHWs served, and workload were the major factors affecting the performance of the CHWs.
Bigirwa (2009)	Different countries	Systematic review		- The experience, level of education, the length and intensity of training, population size coverage, career development structure, and socio-economic status of the CHWs were affecting the performance of the CHWs.
Shakir (2010)	Different countries	Systematic review		- Inadequate supervision, absence of incentives, insufficient training, and the undefined job description of the CHWs were the major determinants of the performance of the CHWs.
Christopher et al. (2011)	Different countries	Systematic review (descriptive analysis)		- Place of work, intensity of work, population size coverage, the payment and incentives mechanisms, level of education, religion, the gender of the CHWs, intensity of training, and the adequacy of supervision were affecting the efficiency of the CHW programme

Jaskiewicz and Tulenko (2012)	Different countries	Review of literature		- The reasonable workload, an optimum geographical distance to be covered, the availability of adequate medical equipment at the health facilities, adequate supportive supervision were the major contributing factors in improving CHWs' performance.

Source: Own compilation

Notes: i) DEA = Data Envelopment Analysis; SFA = Stochastic Frontier Analysis; and MPI = Malmquist Productivity Index.

ii) The second-stage regression analysis encompasses regressing estimates of the technical efficiency as the dependent variables, which was obtained from the first-stage of DEA or SFA analysis on the independent variables in separate regression model such as ols, or Tobit.

iii) FMAPPP = family planning clinic visits + maternal and child health visits + antenatal healthcare visits + post-natal healthcare visits + pap-smear visits + under-five children fully immunized + under-five children participating in school health programme. CSPS = Center de Sante'et d Promotion Social

iv) EV (if applicable): represents Explanatory Variables; CHW: represents community-based health worker; HEW: represents health extension worker; ANC: stands for antenatal healthcare services; vHWs: voluntary health workers

Appendix B: The description and definition of variables employed in the study

Table B- 1: Description and definition of variables employed in decomposition analysis

	Variables	Description
	($\mathrm{U5MR}_{ir}$)	Dependent variable, defined as the number of deaths of under-five children of the i^{th} household living in the r^{th} rural region per thousand live births
Proximate factors	Child's age	Age of child at death measured in years
	Child's age squared	Age of the child squared
	Male child	A dummy variable for gender of the child (1 if male, 0 otherwise, used as a reference category)
	Child's birth order	A dummy variable for the birth order of the child in which a child is born (1 if child birth-order of four or more; 0 otherwise, used as a reference category)
	Birth size	A dummy variable capturing the birth size (birth weight) of a child. Three categories were used: 1 if child's size at birth is smaller than average, 2 if it is an average, and 3 if it is larger than average (used as a reference category)
	Multiplicity of births	A dummy variable capturing whether the child is multiple birth or singleton (1 if the child is multiple births; 0 otherwise, used as a reference category).
	Short birth spacing	Dummy variable capturing mother's birth spacing or birth interval (1 if mother's birth spacing is less than 24 months after preceding birth, 0 otherwise, used as a reference category)
	Mother's age at first birth	Dummy variable capturing age of the mother at the first birth. Three categories were employed: 1 if mother's age at the first birth is less than 20 years, 2 if the mother's age at the first birth is between 20-34 years (used as a reference category), and 3 if mother's age at the first birth is greater than 35 years.
	Contraceptive	A dummy variable capturing whether the mother uses modern contraceptive methods or not (1 if the mother has ever utilised modern contraceptive (like condom, pill, IUD, injection, etc.), 0 otherwise, used as a reference category).
Socioeconomic factors	Antenatal visits	Dummy variable capturing whether a mother received antenatal healthcare service at least four times prior to birth from health

		professionals (such health extension workers, midwifery, nurse, etc.) (1 if she received; 0 otherwise, used as a reference category)
	Mother's education	Dummy variable capturing mother's education attainment(1 if mother has not yet completed primary school; 0 otherwise, used as a reference category)
	Mother's employment status	Dummy variable capturing the current mother's employment status (other than housework) (1 if mother present occupational status is working; 0 otherwise, used as a reference category)
	Gender of the household head	Dummy variable capturing the head of the head of household (1 if the household is female-headed; 0 otherwise, used as a reference category).
	Age of household head	The age of household head measured in years
	Father's education	Dummy variable capturing the father's level of education (1 if father has not yet completed primary school; 0 otherwise, used as a reference category)
	Household wealth index	A dummy variable indicating wealth status of the household. Three categories were used: 1 for poorest third household indicating household's poorest economic status, 2 for middle third and 3 for richest third (used as a reference category)
	Household size	The number of household members
Environment factors	Toilet facility	Dummy variable capturing household's access to improved toilet facilities (1 if the household has any improved toilet facilities; 0 otherwise, used as a reference category)
	Electricity facility	Dummy variable capturing whether the household has access to use of electricity facilities or not (1 if the household has access to electricity facility; 0 otherwise, used as a reference category)
	Safe drinking water	Dummy variable capturing whether the household uses safe or protected drinking water (such as piped/protected well) or not (1 if the household uses safe water; 0 otherwise, used as a reference category)
	Place of child delivery	Dummy variable capturing the place of delivery (1 if the delivery performed at home; 0 otherwise, used as a reference category)

Region	A dummy variable for the household's region of location; categorised into nine sets of dummy variables. If the household is located in Tigrai = 1 (used as a reference category), Afar = 2, Amhara = 3, Oromia = 4, Somali=5, Benshangul-Gumuz (BG)= 6, Southern Nations, Nationalities, and People (SNNP)= 7, Gambella=8, and Harari= 9.

Source: Own elaboration

Table B- 2: Description of input and output variables employed in the efficiency estimation analysis

Variables	Description
Input variables	
INHEWs	The total number of health extension workers (HEWs) operating in the health posts to deliver package of basic healthcare services of the health extension programme (HEP).
INHDAs	The total number of health development armies (HDAs) assisting the health extension workers in their respective health posts to deliver package of basic healthcare services of the HEP to their communities
Output variables	
OHEPBG	The total number of health extension programme beneficiary graduates per health extension worker per health post
ORHVHEW	The total number of rural households visited by health extension workers for basic healthcare services from the health extension programme
OHEHEWs	The total number of health education sessions provided by health extension workers to the rural communities on packages of healthcare services of the health extension programme
OCDHEWs	The total number of children delivered by health extension workers assistance at health posts
OCDHDAs	Number of children delivered by health development armies assistance
OU5CI	The total number of under-five fully immunised children per annum during the time periods under evaluation

Source: Own elaboration

Table B- 3: Description and definition of variables included in subsequent second-stage regression analysis

Variable	Description
TE_{VRS}	Estimates of technical efficiency obtained in the first-stage of BCC DEA analysis: Used as the dependent variable.
PSHEW	The percentage of population served per health extension worker for basic healthcare services
RTHEW	A dummy variable indicating whether the provision of in-service refresher training is given or not to health extension workers (yes=1; 0 otherwise, used as a reference category)
DVHP	Households' ravel distance to nearest health posts measured in Kilometers
YWHEW	The working experience of the health extension workers in the health extension programme measured in years
RPHEW	A dummy variable demonstrating whether performance reward is provided to the health extension workers or not (yes=1; 0 otherwise, used as a reference category)
AGHEW	Age of the health extension workers measured in years
MSHEW	A dummy variable indicating the present marital status of the health extension worker (single = 0 (used as a reference category), married = 1, divorced/separated = 2, and widowed = 3)
MIHEW	Monthly income of the health extension workers measured in the Ethiopian currency (Birr).
SSHEW	A dummy variable indicating whether supportive supervision is provided to health extension worker at least twice a month (yes=1; 0 otherwise, used as a reference category)
RRHEW	A dummy variable indicating the health extension programme beneficiary household's region of location (Tigrai =1 (used as a reference category), Amhara =2, Oromia=3, SNNP =4, Benshangul-Gumuz=5, Gambella=6, and Harari=7)
RLHEW	A dummy variable indicating health extension workers' religion affiliation (Christian =1 (used as a reference); Muslim =2; others =3)
ABME	A dummy variable indicating that whether basic medical equipment needed for the provision of packages of basic healthcare services are

	available at the health posts or not (1 if yes; 0 otherwise, used as a reference category)

Source: Own elaboration

Note: HEW= Health Extension Worker; HEP=Health Extension Programme; BCC DEA= Banker-Charnes-Cooper Data Envelopment Analysis; and SNNP= Southern Nations, Nationalities, and People

Table B- 4: Definitions and description of variables employed in logistic regression analysis

Variables	Definitions
HEP_i	is a binary outcome variable (dependent variable) represented by a value of 1 for a health extension programme beneficiary household graduates (HEP_i=1); 0 otherwise
AgeHH	Age of the head of the household (in years)
SexHH	A binary variable indicating head of head of the household (1 if male; 0 otherwise, used as a reference category)
Agemam	Age of a mother of the household (in years)
Occup	A dummy variable indicating the primary occupation of the household heads (Agriculture =1 (used as a reference category); pity trading =2; daily labourer =3; civil servant =4; other = 5)
Religion	A dummy variable indicating religion of head of the household (Christian =1 (used as a reference category); Muslim =2; others =3)
Landsize	Household arable land size (measured in hectare)
HPdistance	Households' travel distance to the nearest health post measured in kilometer
HEPtuser	Years the household has been a health extension programme beneficiary
Maritals	A dummy variable indicating the current marital status of the health extension programme beneficiary households (single=0 (used as a reference category), married=1, divorced/separated=2, and widowed = 3)
Familysize	Family size measured in numbers
Extensionuser	A binary variable indicating whether head of the household is an agricultural extension programme user or not (1 if yes; 0 otherwise, used as a reference category)
Mameduc	A dummy variable indicating mother's education attainment (no education =0 (used as a reference category), primary=1, and secondary and above=2)

HEPprofflevel	A dummy variable demonstrating professional level or status of a health extension worker (contract= 0 (used as a reference category), certificate or level III =1, and diploma or level IV=2)
HEWperhp	Number of health extension workers per single health post
Parentaleduc	A dummy variable demonstrating educational level of health extension programme beneficiary household (no education =0 (used as a reference category), primary =1, and secondary and above=2)
Offincome	A binary variable indicating that whether the health extension programme beneficiary household has an off-farm income or not (1 if yes; 0 otherwise, used as a reference category)
Region	A dummy variable indicating that the health extension programme beneficiary household's region of residence (Tigrai =1 (used as a reference category), Amhara =2, Oromia=3, SNNP =4, Benshangul-Gumuz=5, Gambella=6, and Harari=7)

Source: Own elaboration

Appendix C: The results of descriptive and inferential statistics

Table C- 1: The sample means (proportions) by characteristics of the eight different regions with the benchmark of Tigrai

	Characteristics (variables)	Tigrai	Afar	Amhara	Oromia	Somali	BG	SNNP	Gambella	Harari
Proximate factors	U5MR	.405	.621	.477	.433	.486	.542	.512	.341	.321
	Child's age	1.933	1.81	1.77	1.69	1.74	1.78	1.88	1.78	1.14
	Child = Male	.486	.5458	.497	.471	.483	.488	.477	.476	.489
	Child's birth order >4	.213	.248	.233	.243	.241	.223	.249	.281	.253
	Average birth size[36]	.121	.062	.104	.149	.173	.189	.144	.157	.168
	Birth size smaller than average	.021	.324	.523	.248	.321	.402	.214	.274	.352
	Multiple births	.012	.013	.136	.289	.273	.381	.283	.272	.247
	Short birth spacing	.126	.324	.249	.454	.215	.304	.329	.205	.438
	Mother's age at first birth <20	.236	.455	.347	.228	.436	.326	.237	.435	.328
Socio-economic factors	Mother's age at first birth >35	.021	.546	.347	.219	.435	.457	.542	.723	.435
	Contraceptive	.736	.214	.315	.6279	.642	.651	.362	.638	.539
	Four plus antenatal visits	.522	.423	.256	.428	.245	.542	.211	.438	.329
	Mother's education	.636	.535	.323	.422	.312	.321	.311	.651	.426
	Mother's work	.213	.303	.311	.427	.529	.619	.412	.372	.431

[36] At birth, when a child size is 2500g, the child is considered to have an average birth size while a child weigh less than 2500g is considered to have low birth size. Similarly, when a child weighs more than average at birth size, the child is considered to have more than average birth size (Albrecht et al., 1996).

	status									
	Female-head household	.417	.534	.235	.543	.284	.457	.672	.456	.621
	Age of household head	45.1	40.63	44.77	42.58	42	40.6	43.1	41.1	40.6
	Father's education level	.934	.040	.043	.06	.059	.045	.076	.278	.107
	Poorest third wealth	.202	.306	.531	.568	.575	.565	.625	.377	.876
	Middle third wealth	.324	.382	.601	.451	.672	.582	.438	.748	.362
	Household size	6.13	6.66	5.87	6.70	6.93	6.23	6.41	5.91	5.92
Environmental factors	Toilet facility	.473	.564	.674	.213	.042	.064	.323	.035	.251
	Electricity facility	.214	.356	.476	.549	.401	.546	.368	.501	.437
	Place of child delivery	.216	.036	.056	.067	.026	.027	.012	.083	. 108
	Safe drinking water	.122	.011	.117	.208	.033	.032	.144	.014	.102

Source: Own computation (EDHS, 2016)

Table C- 2: Estimates of over-dispersion (test statistics of conditional mean and conditional variance)

U5MR	Region				
	Tigrai	Percentile	Smallest		
1 percent		0	0		
5 percent		0	0		
10 percent		0	0	Obs.	380
25 percent		0	0	Sum of Wgt.	380
50 percent		1		Mean	1.352632
			Largest	Std. Dev.	1.190050
75 percent		2	5		
90 percent		3	5	Variance	1.416220
95 percent		4	5	Skewness	1.287812
99 percent		5	5	Kurtosis	4.593923
	Afar				
		Percentile	Smallest		
1 percent		0	0		
5 percent		0	0		
10 percent		0	0	Obs.	519
25 percent		0	0	Sum of Wgt.	519
50 percent		1		Mean	1.404141
			Largest	Std. Dev.	1.184964
75 percent		2	5		
90 percent		3	5	Variance	1. 472062
95 percent		4	5	Skewness	0.7041993
99 percent		5	5	Kurtosis	3.0920330
	Amhara				
		Percentile	Smallest		
1 percent		1	1		
1 percent		0	0		
5 percent		0	0	Obs.	589
10 percent		0	0	Sum of Wgt.	589
25 percent		1	0	Mean	1.227505
			Largest	Std. Dev.	1.136526
75 percent		1	4		
90 percent		2	4	Variance	1. 291691
95 percent		3	4	Skewness	1.598523
99 percent		4	5	Kurtosis	6.916459
	Oromia				
		Percentile	Smallest		
1 percent		0	0		
5 percent		0	0		
10 percent		0	0	Obs.	614
25 percent		0	0	Sum of Wgt.	614
50 percent		1		Mean	1.382736

		Largest	Std. Dev.	1.334116
75 percent	2	5		
90 percent	3	5	Variance	1. 779865
95 percent	4	5	Skewness	1.673403
99 percent	5	5	Kurtosis	6.089856
Somali				
	Percentile	Smallest		
1 percent	0	0		
5 percent	0	0		
10 percent	0	0	Obs	477
25 percent	1	0	Sum of Wgt.	477
50 percent				
	1		Mean	1.1342780
75 percent		Largest	Std. Dev.	1.065025
90 percent	2	5		
95 percent	3	5	Variance	1. 278826
99 percent	3	5	Skewness	0.6911866
1 percent	4	5	Kurtosis	2.8462870
Benshangul-Gumuz				
	Percentile	Smallest		
1 percent	0	0		
5 percent	0	0		
10 percent	0	0	Obs	485
25 percent	1	0	Sum of Wgt.	485
50 percent	1		Mean	1.581443
		Largest	Std. Dev.	1.267875
75 percent	2	4		
90 percent	3	4	Variance	1. 607506
95 percent	4	5	Skewness	1.101565
99 percent	5	5	Kurtosis	4.557031
SNNP				
	Percentile	Smallest		
1 percent	0	0		
5 percent	0	0		
10 percent	0	0	Obs	642
25 percent	0	0	Sum of Wgt.	642
50 percent	1		Mean	1. 057100
		Largest	Std. Dev.	1.028154
75 percent	2	5		
90 percent	2	5	Variance	1. 358255
95 percent	3	5	Skewness	1.086307
99 percent	5	5	Kurtosis	4.474335
Gambella				
	Percentile	Smallest		
1 percent	0	0		
5 percent	0	0		

10 percent	0	0	Obs.	237
25 percent	0	0	Sum of Wgt.	237
50 percent	1		Mean	0.8128442
		Largest	Std. Dev.	0.9015787
75 percent	2	3		
90 percent	2	3	Variance	1.1476790
95 percent	3	3	Skewness	0.6098314
99 percent	3	3	Kurtosis	2.7153390
Harari				
	Percentile	Smallest		
1 percent	0	0		
5 percent	0	0		
10 percent	0	0	Obs.	147
25 percent	0	0	Sum of Wgt.	147
50 percent	1		Mean	0.7605069
		Largest	Std. Dev.	0.8720705
75 percent	1	3		
90 percent	2	3	Variance	1.1156460
95 percent	2	3	Skewness	0.3963814
99 percent	3	4	Kurtosis	2.4606570

Source: Own computation (EDHS, 2016)

Table C- 3: Life-Table estimation for under-five child mortality of rural Ethiopia (EDHS, 2016)

Regions		Beg. Total	Deaths	Lost	Survival	Std. Error	[95% Conf. Int.]	
Tigrai (51 death per 1,000 live births)								
0	1	668	33	146	0.9445	0.0094	0.9229	0.9602
1	2	489	33	131	0.8709	0.0150	0.8382	0.8975
2	3	325	29	124	0.7749	0.0215	0.7293	0.8138
3	4	172	29	83	0.6027	0.0328	0.5353	0.6635
4	5	60	11	49	0.4859	0.0520	0.3936	0.5650
Afar (77 deaths per 1,000 live births)								
0	1	389	39	119	0.8816	0.0178	0.8416	0.9121
1	2	231	25	71	0.7689	0.0262	0.7127	0.8155
2	3	135	28	56	0.5677	0.0380	0.4899	0.6381
3	4	51	8	25	0.4497	0.0478	0.3545	0.5402
4	5	18	6	12	0.2249	0.0692	0.1070	0.3692
Amhara (61 deaths per 1,000 live births)								
0	1	800	49	147	0.9326	0.0093	0.9117	0.9486
1	2	604	68	124	0.8156	0.0156	0.7827	0.8439
2	3	412	39	140	0.7226	0.0197	0.6819	0.7590
3	4	233	37	106	0.5740	0.0268	0.5197	0.6245
4	5	90	17	73	0.3916	0.0409	0.3116	0.4706
Oromia (64 deaths per 1,000 live births)								
0	1	898	61	266	0.9203	0.0098	0.8987	0.9374
1	2	571	53	184	0.8184	0.0158	0.7850	0.8472
2	3	334	44	119	0.6872	0.0225	0.6409	0.7289
3	4	171	27	78	0.5467	0.0300	0.4859	0.6033
4	5	66	23	43	0.3641	0.0434	0.3834	0.4517
Somali (68 deaths per 1,000 live births)								
0	1	570	38	125	0.9251	0.0117	0.8986	0.9449
1	2	407	27	116	0.8536	0.0171	0.8164	0.8837
2	3	264	30	116	0.7292	0.0255	0.6754	0.7757
3	4	118	24	54	0.5369	0.0386	0.4584	0.6090
4	5	40	17	23	0.3167	0.0517	0.2253	0.3243
Benshangul-Gumuz (74 deaths per 1,000 live births)								
0	1	511	44	105	0.9040	0.0138	0.8732	0.9277
1	2	362	32	103	0.8109	0.0199	0.7682	0.8465
2	3	227	29	84	0.6838	0.0274	0.6266	0.7340
3	4	114	17	58	0.5470	0.0369	0.4719	0.6159
4	5	39	14	25	0.2580	0.0558	0.1568	0.3714

SNNP (67 deaths per 1,000 live births)								
0	1	923	75	226	0.9074	0.0102	0.8853	0.9254
1	2	622	45	179	0.8307	0.0144	0.8004	0.8569
2	3	398	36	137	0.7400	0.0192	0.7001	0.7754
3	4	225	33	104	0.5988	0.0270	0.5437	0.6495
4	5	88	25	63	0.3339	0.0423	0.2526	0.4170
Gambella (81 deaths per 1,000 live births)								
0	1	244	15	56	0.9306	0.0173	0.8875	0.9575
1	2	173	16	59	0.8268	0.0289	0.7614	0.8757
2	3	98	10	48	0.7151	0.0413	0.6251	0.7871
3	4	40	6	26	0.5562	0.0656	0.4189	0.6733
4	5	8	4	4	0.1854	0.1092	0.0353	0.4277
Harari (58 deaths per 1,000 live births)								
0	1	478	27	106	0.9365	0.0118	0.9087	0.9560
1	2	345	24	96	0.8608	0.0184	0.8202	0.8928
2	3	225	19	86	0.7709	0.0255	0.7162	0.8165
3	4	120	14	59	0.6517	0.0364	0.5753	0.7178
4	5	47	15	32	0.4163	0.0614	0.3202	0.4564

Source: Own computation (EDHS, 2016)

Table C- 4: The results of Negative binomial regression coefficient estimates

Variables	Pooled	Tigrai	Afar	Amhara	Oromia	Somali	BG	SNNP	Gambella	Harari
Child's age	0.0369	0.1435	-.00583	.15153	.64696	-.08752	.20910	.13152	.72891	1.15784
	(0.009)	(0.1908)	(.00883)	(.27722)	(.62375)	(.26008)	(.28783)	(.24970)	(1.0752)	(.71520)
Child's age squared	-0.0645	-0.1071	1.2682***	-.24640	.04439	-.151428	.04863	-.15089	-.13939	.64042
	(0.1759)	(0.1621)	(.17935)	(.28095)	(.20752)	(.22117)	(.24186)	(.25666)	(.60638)	(1.08262)
Child = Male	0.0048	-0.0203	-.03575	.4714356	.1280518	-.0318608	.2441824	-.6706473	.5147398	-.6736285
	(0.0448)	(0.2215)	(.28549)	(.30657)	(.45639)	(.16594)	(.40792)	(1.04293)	(1.21946)	(1.08264)
Child's birth order>4	.6404	.55561	.54976*	.62025**	.68041	-.04765	.87327***	-.03851	1.63158***	-.83832
	(1.0826)	(1.10179)	(.33202)	(.30071)	(.46238)	(.27751)	(.30866)	(.82081)	(.43454)	(1.08126)
Birth size < average	-0.0826	-0.4767***	-2.2752***	-.08260	-.25322	-.37005	-.90523	-.20368	-.09448	-.06848
	(0.2139)	(0.1843)	(.29357)	(.21389)	(.28022)	(.42821)	(.80124)	(.35442)	(.22228)	(.15962)
Birth size = average	-0.5774**	-0.3701	-.07015	-.20136	-.81002	.24792	.77287	-.06138	-.03799	.00255
	(0.2891)	(0.4282)	(.47047)	(.65459)	(.61193)	(.37409)	(.73212)	(.05363)	(.02354)	(.08242)
Multiple birth	0.4987***	0.2252	-.43965	.17998	-.395078	-.63660***	-.06712	-.15438**	.24312	-.35307**
	(0.149)	(0.3623)	(.26868)	(.21068)	(.27209)	(.23328)	(.35564)	(.07287)	(.17026)	(.15055)
Short birth spacing	1.1305***	0.8031***	-.08019	-.07229	-.13748*	-.71852**	.20331***	-.03380	-1.8509***	.18466
	(0.1966)	(0.3665)	(.34345)	(.16844)	(.07587)	(.43859)	(.06499)	(.24094)	(.57162)	(.20149)
Mother's age at birth <20	0.0052	0.2782	0.5133	0.7705**	-.1344*	.18761	-.15438**	-.06152***	.18760	-.1276*
	(0.0099)	(0.3566)	(0.3779)	(0.3889)	(.07576)	(.34026)	(.07287)	(.01595)	(.34026)	(.06752)
Mother's age at birth >35	0.7399	1.4903***	0.7616**	-0.1596	-.12665*	.03360	-.06258	-.08955	.24312	-.05775
	(0.7414)	(0.5181)	(0.4169)	(0.3201)	(.06479)	(.40491)	(.12316)	(.13597)	(.17026)	(.05774)
Contraceptive use	-0.1971	-0.1703	-0.0257**	-0.2998	-1.0379	-.03487	-.15527***	.00041	-.78960	-2.7333***
	(0.3404)	(0.2603)	(0.5408)	(0.2881)	(.0235)	(.02138)	(.05829)	(.04746)	(.74416)	(.38971)
Antenatal healthcare	-0.5008*	0.2914	-0.5008**	-1.1739	-0.5292*	.03798	-.03380	.63379***	-.13748*	-.06142
	(0.2031)	(0.1607)	(0.2030)	(1.1154)	(0.2994)	(.05716)	(.24094)	(.15742)	(.07587)	(.19550)
Mother's	-1.2041	1.4296*	1.1724	1.1738	1.0712	-.10617	.18092	-.07806	-.35638	.03548

education	(1.422)	(0.8693)	(1.2946)	(1.1124)	(1.1546)	(.07494)	(.30825)	(.31137)	(.32129)	(.36596)
Mother's working	1.1738	-1.2324	-0.0379	-.02504	-.13441*	-.14941	-.20045***	.21561***	-.87353	.06359
status	(1.1124)	(1.1215)	(0.0235)	(.26577)	(.07577)	(.55741)	(.07466)	(.07194)	(.80791)	(.11142)
Female	-2.4269	-0.0025	-.17490	-.20045	-.10711	-2.7235***	.08237	-.06152***	.24537	-.05301
household head	(0.0976)	(0.0524)	(.22855)	(.07466)	(.08255)	(.35488)	(.12361)	(.01595)	(.159036)	(.05233)
Age of household	-0.1267*	.15527***	-.13748	.02849***	-.15438**	.06057	-.06176	-.20045***	-.24479	.28455
head	(.06479)	(.05829)	(.07587)	(.06312)	(.07287)	(.07558)	(.16373)	(.07466)	(.23029)	(.22319)
Father's	.63378***	-.05286	-.06152***	.18761	-.35335**	.00254	-2.7235***	-.03799	-.05287	.02849
education	(.15743)	(.21678)	(.01595)	(.34027)	(.16389)	(.05242)	(.35488)	(.02354)	(.21678)	(.06312)
Poorest third	.03361	.24361	.06258	.08955	.21561***	.24351	.06258	.08955	.24312	.05775
	(.40492)	(.62683)	(.12316)	(.13597)	(.07194)	(.62683)	(.12316)	(.13597)	(.17026)	(.05774)
Middle third	-.08019	-.35353	.24312	.05776	.00255	.21561***	.17491	-.10711	-.08019	.24351
	(.34345)	(.35394)	(.17026)	(.05774)	(.05242)	(.07194)	(.22855)	(.08255)	(.34345)	(.62683)
Household size	2.42696***	.12665*	.12758*	.63379***	.89155	.15527***	.13748*	.02849	.18761	.03361
	(.09763)	(.06479)	(.06753)	(.15742)	(.16107)	(.05829)	(.07587)	(.06312)	(.34026)	(.40491)
Toilet facility	.03798	-.03380	-.06142	.06057	-.06176	-.24479	-.07015	-.81002	-.06138	-.43965
	(.05716)	(.24094)	(.19550)	(.07558)	(.16373)	(.23029)	(.47047)	(.61193)	(.05363)	(.26868)
Electricity	-.03380	.18092	-.02142	-.07806	-.10617	-.35638	-.63660***	.17998	-.39508	-.78960
facility	(.24094)	(.30825)	(.11551)	(.31137)	(.07494)	(.32129)	(.23328)	(.21068)	(.27209)	(.74416)
Place of delivery	.03548	.14941	.87353	.06359	.08237	.24537	2.27515***	.20331***	.33661*	-.36898*
	(.36596)	(.55741)	(.80791)	(.11142)	(.12361)	(.15904)	(.29357)	(.06499)	(.16998)	(.20402)
Safe drinking	.05301	-.06712	-.20136	.7789***	.24792	-.71852	-.13441*	-.35353	.86691	-.35335**
water	(.05233)	(.35564)	(.65458)	(.24498)	(.37409)	(.43860)	(.07577)	(.35393)	(.89707)	(.16389)
_cons	-.12206**	-.12901**	-.6405***	-.1525***	-.1312*	-.20307***	-.35307**	-.13727**	-.15851**	-.06331***
	(.05859)	(.06102)	(.13475)	(.05309)	(.06915)	(.06794)	(.06615)	(.06856)	(.06615)	(.01471)
Lnalpha										
_cons	-.89168***	-.03487	-2.7334***	-2.4253***	.24361	-.24312	-.08955	-.13441*	-.3534**	-2.7333***
	(.16109)	(.02138)	(.38971)	(.09472)	(.62683)	(.17026)	(.13597)	(.07577)	(.16389)	(.38971)
Alpha										
N	4090	380	519	589	614	477	485	642	237	147

Source: Own computation (EDHS, 2016)

Notes: i) Asterisks denote the level of significance: *** p<0.01, ** p<0.05, * p<0.1; ii) Robust standard errors are given in parenthesis

Table C- 5: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and BG regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Explained gap	.092445	.029984	3.08	0.005	.033684	.151204	37.12
Unexplained gap	.156594	.046417	3.37	0.002	-.208323	.026369	62.88
Raw differences	.2490374	.35437	0.70	0.491	-.94359	.44554	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
childage	-.0072902	.014683	-0.49	0.000	-.021488	.036069	-2.93
childage2	-.0000223	.000552	-0.04	0.968	-.001105	.001060	-.01
childsex=male	-.0062870	.000764	-8.22	0.000	-.001491	.001504	-2.52
birthorder>4	.0310163	.015824	1.96	0.025	-.023537	.038495	12.46
birthsize<aveg	.090078	.021693	4.15	0.000	-.060932	.024107	36.17
birthsize=aveg	.0234521	.0281015	0.83	0.404	-.0316422	.0785462	14.71
multiplebirth	.0003115	.000899	0.35	0.729	-.002075	.001452	.13
shortbirthspace	-.0040586	.003201	-3.31	0.001	-.016864	.004312	-13.63
motherageatbirth<20	-.020605	.005121	-4.02	0.000	-.010567	.030644	-38.27
motherageatbirth>35	.028621	.023523	1.22	0.234	-.021034	.071176	11.49
contracepuse	.001702	.001444	1.18	0.239	-.004533	.001129	.68
antenatalvisit	-.020217	.011312	-1.79	0.074	-.042389	.001955	-8.12
mothereducation	.059824	.011825	5.06	0.000	-.029159	.017195	24.02
motherworkstatus	-.030266	.005104	-0.59	0.553	-.006977	.013031	-12.53
househead=female	-.015711	.028855	-0.68	0.503	-.072266	.040844	-6.31
agehousehold	-.0366434	.051372	-0.71	0.239	-.102379	.099000	-6.27
fathereducation	-.0013335	.006489	-2.05	0.040	.000616	.026055	-.53
wealth=poor	-.0453531	.021130	-2.15	0.032	.003938	.086768	-18.21
wealth=middle	.0097213	.006811	1.43	0.166	-.013897	.012805	3.91
householdsize	-.0020304	.006562	-3.09	0.002	.007441	.033167	-11.82
toiletfacility	-.0003886	.000691	-0.56	0.574	-.000966	.001744	-.16
electricityfacility	.0076749	.003226	-1.10	0.269	-.002758	.009888	3.08
placedelivery	-.0085042	.004770	-1.78	0.088	-.009309	.009305	-3.41
safedrinkingwater	.0052148	.007416	0.70	0.482	-.019750	.009320	2.09

Due to Difference in Coefficients (Unexplained)

variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
childage	.0009549	.001361	0.70	0.483	-.001713	.003623	-.34
childage2	-.0050724	.009423	-0.54	0.590	-.023542	.013397	2.09
childsex=male	.0038141	.035987	1.06	0.289	-.032393	.10867	-1.31
birthorder>4	-.032799	.038116	-0.86	0.390	-.10751	.041908	13.71
birthsize<aveg	-.021313	.029671	-0.72	0.473	-.07947	.036843	8.58
birthsize=aveg	-.043829	.031967	-1.37	0.183	-.010875	.021092	17.23
multiplebirth	-.0025938	.006128	-0.42	0.672	-.014606	.009418	1.41
shortbirthspace	.029372	.018534	1.58	0.127	.015457	.057198	-11.95
motherageatbirth<20	.021406	.052156	0.41	0.681	-.08082	.12363	-8.95
motherageatbirth>35	.017418	.026622	0.65	0.513	-.034761	.069597	-6.94
contracepuse	-.0352995	.018279	-1.93	0.065	-.057822	.013831	14.74
antenatalvisit	.104784	.075506	1.39	0.177	.048683	.247301	-42.75
mothereducation	-.092516	.022847	-4.05	0.000	-.054031	.035528	37.49
motherworkstatus	-.060136	.26793	-0.22	0.822	-.58528	.465021	24.47
househead=female	.015713	.02893	0.54	0.587	-.04099	.072417	-6.09
agehousehold	.02563	.012145	2.11	0.035	.001826	.049434	-10.91
fathereducation	.011873	.008771	1.35	0.176	-.005318	.029064	-4.90
wealth=poor	.033343	.07447	0.45	0.654	-.11262	.1793	-13.88
wealth=middle	.025296	.013585	1.86	0.063	-.001331	.051923	-10.57
householdsize	-.026246	.025093	-1.05	0.304	-.047394	-.050971	10.19
toiletfacility	.0053383	.009173	0.58	0.561	-.012641	.023317	-2.44
electricityfacility	-.023031	.046829	-0.49	0.623	-.11479	.068786	9.35
placedelivery	-.033877	.012563	-2.70	0.007	-.058502	-.009253	13.04
safedrinkingwater	-.029574	.28004	-0.11	0.916	-.57845	.5193	11.75
_cons	-.004347	.030172	-0.14	0.885	-.063485	.054791	17.55

Source: Own computation (EDHS, 2016)

Table C- 6: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Harari regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Explained	.09173	.0087054	10.53	0.000	.262360	.07889	41.57
Unexplained	.11118	.095593	1.16	0.245	.076182	.29854	58.43
Raw differences	.019452	.036189	0.54	0.591	-.051478	.09038	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
childage	.0156821	.0022597	6.93	0.000	-.004272	.004585	8.62
childage2	-.011312	.1637701	-0.07	0.945	-.332291	.309672	-5.15
childsex=male	-.0009581	.0009881	-0.97	0.251	-.000283	.000645	-4.93
birthorder>4	.4174368	.0432765	9.65	0.000	.332500	.502373	17.01
birthsize<aveg	.1290202	.0748046	1.72	0.085	-.017794	.275834	-3.45
birthsize=aveg	-.0569538	.0444071	-1.28	0.200	-.144109	.030201	-10.55
multiplebirth	.0004779	.0069544	0.07	0.945	-.013153	.014109	12.45
shortbirthspace	-.0335364	.0468338	-0.72	0.474	-.125454	.058381	-9.29
motherageatbirth<20	.2714699	.1402381	1.94	0.053	-.003767	.546707	5.05
motherageatbirth>35	.1675758	.0569926	2.94	0.003	.055719	.279432	8.45
contracepuse	-.0918694	.0478012	-1.92	0.055	-.185685	.001946	-15.68
antenatalvisit	-.0454997	.0109701	-4.15	0.000	-.067030	-.023969	-9.86
mothereducation	.0633877	.0379026	1.67	0.095	-.011001	.137777	-6.34
motherworkstatus	.0023204	.0335322	0.07	0.945	-.063402	.068043	11.93
househead=female	-.0204608	.0570082	-0.36	0.720	-.132347	.091426	-4.29
agehousehold	.0744462	1.0694021	0.07	0.945	-2.02169	2.170523	8.72
fathereducation	.0184894	.0554794	0.33	0.739	-.090396	.127375	9.39
wealth=poor	.0091321	.0018167	5.03	0.000	.005566	.012697	-9.61
wealth=middle	-.0018808	.0270228	-0.07	0.945	-.054855	.051094	-9.67
householdsize	-.0091321	.0018167	-5.03	0.000	.005566	.012697	-4.22
toiletfacility	-.0012661	.0183089	-0.07	0.945	-.037152	.03462	-6.51
electricityfacility	.1602533	.0613244	2.61	0.009	.039895	.280611	-9.42
placedelivery	-.0078005	.0384947	-0.20	0.839	-.083351	.067750	-3.43
safedrinkingwater	.0171949	.0367244	0.47	0.640	-.054882	.089272	5.08

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
childage	.0349561	1.541341	0.02	0.982	-2.98623	3.055921	19.71
childageage2	.0073686	.045031	0.16	0.870	-.081013	.095750	45.66
childsex=male	.0744707	.041641	1.79	0.074	-.007265	.156207	-39.91
birthorder>4	.0107282	.482672	0.02	0.982	-.935312	.956772	5.15
birthsize<aveg	-.0550432	.135248	-0.41	0.684	-.320487	.210401	14.86
birthsize=aveg	.0046217	.020652	0.02	0.382	-.040015	.040939	23.75
multiplebirth	-.0067264	.293882	-0.02	0.982	-.582732	.569281	-34.57
shortbirthspace	.0438243	.073466	0.60	0.551	-.100364	.188013	24.09
motherageatbirth<20	-.0454997	.010970	-4.15	0.000	-.067030	-.023969	-17.09
motherageatbirth>35	-.050594	2.211121	-0.02	0.982	-4.38432	4.283221	-20.09
contracepuse	-.0442382	.038590	-1.15	0.252	-.119977	.031501	80.72
antenatalvisit	.1069876	.062295	1.72	0.086	-.015276	.229251	14.97
mothereducation	.0438243	.073466	0.60	0.551	-.100364	.188013	-12.13
motherworkstatus	.0084567	.371921	0.02	0.982	-.720462	.737381	43.45
househead=female	-.0204608	.057008	-0.36	0.720	-.132347	.091426	11.92
agehousehold	-.0442382	.038590	-1.15	0.252	-.119977	.031501	20.76
fathereducation	.428631	18.731213	0.02	0.982	-3.28332	7.142110	23.52
wealth=poor	-.0710682	.080007	-0.89	0.375	-.228093	.085957	-9.26
wealth=middle	-.0366008	.044403	-0.82	0.410	-.123748	.050546	-8.68
householdsize	.0184692	.841223	0.02	0.982	-1.63032	1.667312	4.94
toiletfacility	.1602533	.061324	2.61	0.009	.03989	.280611	-14.15
electricityfacilit	.0650951	2.848321	0.02	0.982	-5.51692	5.647123	34.64
placedelivery	-.0710682	.080007	-0.89	0.375	-.22809	.085957	-22.52
safedrinkingwater	.0169512	.744103	0.02	0.982	-1.44152	1.475423	7.14
_cons	-.1527368	.169229	-0.90	0.367	-.48487	.179412	-17.62

Source: Own computation (EDHS, 2016)

Table C- 7: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Amhara regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Explained	.004143	.0059159	0.70	0.514	-.016787	.0064032	31.13
Unexplained	.015317	.0270627	0.56	0.412	-.085282	.020804	68.87
Raw differences	.019461	.038402	0.51	0.612	-.055806	.094729	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Childage	.00051456	.0013995	0.37	0.713	-.002228	.003257	3.64
childage2	.0013321	.016299	0.08	0.935	-.030614	.033278	6.84
childsex=male	-.0003447	.019978	0.00	0.997	-.039068	.039215	-.50
birthorder>4	.0016788	.0002425	6.92	0.000	.001203	.002154	8.62
birthsize<aveg	-.0092034	.1886915	0.05	0.961	-.360976	.379382	-14.73
birthsize=aveg	-.00083797	.0025646	-0.33	0.744	-.005864	.004188	-4.30
multiplebirth	.00055554	.0011533	0.48	0.630	-.001704	.002816	2.85
shortbirthspace	-.0065692	.0014087	-4.00	0.000	-.007330	.001808	-33.75
motherageatbirth<20	.00068455	.0007009	0.98	0.329	-.000689	.002058	3.51
motherageatbirth>35	.0050446	.0089867	0.56	0.575	-.012569	.022659	25.92
contracepuse	.0017935	.0014893	1.20	0.228	-.001125	.004712	9.21
antenatalvisit	.0016603	.0009112	1.82	0.068	-.003446	.000125	8.53
mothereducation	-.035353	.0095258	-3.71	0.000	-.0540389	-.016667	-13.07
motherworkstatus	.0018546	.0027482	0.67	0.500	-.003531	.007241	9.52
househead=female	-.0005757	.0086127	-0.07	0.947	-.017457	.016305	-2.95
agehousehold	-.002869	.0022843	-1.26	0.209	-.007346	.001608	-14.74
fathereducation	-.0016687	.027374	-0.06	0.951	-.055322	.051985	-8.57
wealth=poor	.0008639	.0004143	2.09	0.037	.000808	.000815	24.43
wealth=middle	.0664383	.24146	0.28	0.783	-.407271	.540147	-6.27
householdsize	-.001945	.000632	-3.08	0.002	-.003184	.000705	-9.99
toiletfacility	-.0006119	.001511	-0.40	0.686	-.003574	.002350	-3.14
electricityfacility	-.0006235	.006301	-1.09	0.277	-.000192	.000054	-3.20
placedelivery	.0005262	.0001353	3.89	0.000	.000260	.000791	-12.14
safedrinkingwater	.0007464	.0009601	0.78	0.437	-.001135	.002628	3.83

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
childage	.0042599	.013329	0.32	0.749	-.021865	.030385	21.88
childageage2	-.0020685	.0086613	-0.24	0.811	-.019045	.014908	-10.62
childsex=male	-.0043793	.0037679	-1.16	0.245	-.011764	.003005	-22.50
birthorder>4	-.0014985	.0049239	-0.30	0.761	-.011149	.008152	-7.70
birthsize<aveg	.003984	.0044247	0.90	0.368	-.004688	.012656	20.47
birthsize=aveg	.013525	.028787	0.47	0.638	-.042898	.069948	9.49
multiplebirth	-.0012596	.0004322	-2.91	0.004	-.002106	-.000412	-6.47
shortbirthspace	.0059058	.0027967	2.11	0.035	.004242	.011387	30.34
motherageatbirth<20	-.0038168	.0062132	-0.61	0.539	-.015995	.008361	-9.61
motherageatbirth>35	-.0021921	.0039455	-0.56	0.578	-.009925	.005541	-11.26
contracepeuse	.013998	.022602	0.62	0.536	-.030302	.058299	71.92
antenatalvisit	.0042107	.0048195	0.87	0.382	-.005235	.013657	21.63
mothereducation	-.0090648	.030756	-0.29	0.768	-.069346	.051216	-46.57
motherworkstatus	.0031792	.026105	0.12	0.903	-.047987	.054345	16.33
househead=female	.0006286	.000768	0.82	0.414	-.000878	.002135	3.22
agehousehold	-.0010103	.001593	-0.63	0.526	-.004134	.002113	-5.19
fathereducation	.0019917	.0013516	1.47	0.141	-.000657	.004640	10.23
wealth=poor	-.0011341	.0022378	-0.51	0.612	-.005520	.003252	-5.82
wealth=middle	-.002012	.002828	-0.71	0.477	-.007554	.003531	10.33
householdsize	.001529	.0014981	1.02	0.307	-.001407	.004465	7.85
toiletfacility	-.0067121	.012494	-0.54	0.932	-.025547	.023431	-34.49
electricityfacilit	-.0033965	.0095467	-0.36	0.722	-.022108	.015315	-17.45
placedelivery	-.0022182	.0015968	-1.39	0.165	-.005347	.000911	-11.39
safedrinkingwater	.0018432	.0048056	0.38	0.701	-.007575	.011262	9.47
_cons	.0010242	.0038722	0.26	0.791	-.006565	.008613	5.26

Source: Own computation (EDHS, 2016)

Table C- 8: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Oromia regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Explained	.018992	.002549	7.45	0.000	.068957	.030972	46.04
Unexplained	.022263	.037187	0.60	0.549	.095149	.050622	53.96
Raw differences	.041256	.026191	1.58	0.115	.092591	.010079	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
childage	.0058892	.22812	0.03	0.979	-.441232	.453012	-14.27
childage2	.1120476	.17867	0.63	0.531	-.238490	.462585	7.47
childsex=male	-.0001620	.00631	-0.03	0.980	-.012536	.012212	.39
birthorder>4	.0854777	.19208	0.44	0.656	-.291361	.462317	3.44
birthsize<aveg	1.13487	.12117	9.37	0.000	.897298	1.372442	-11.49
birthsize=aveg	.0000403	.00006	0.64	0.524	-.000083	.000164	5.65
multiplebirth	.028949	.04769	0.61	0.544	-.064625	.122523	-9.56
shortbirthspace	.4460716	.03596	12.40	0.000	.375517	.516626	-23.02
motherageatbirth<20	.0018728	.00120	1.55	0.121	-.000494	.004240	-22.85
motherageatbirth>35	-.017871	.04520	-0.40	0.693	-.106462	.070722	43.31
contracepuse	.000683	.00566	0.12	0.904	-.010431	.011796	9.32
antenatalvisit	-.217399	.01982	-10.97	0.000	-.256262	-.178537	26.39
mothereducation	-.2287659	.10741	-2.13	0.033	-.439494	-.018037	-13.77
motherworkstatus	.0030796	.11928	0.03	0.979	-.230721	.236872	-7.46
househead=female	-.0009429	.00195	-0.48	0.629	-.004768	.002882	12.88
agehousehold	-.0030677	.02082	-0.15	0.883	-.043917	.037782	-4.53
fathereducation	-.0824884	.14048	-0.59	0.557	-.358101	.193124	13.27
wealth=poor	-.0404672	.28068	-0.14	0.885	-.591117	.510182	-15.43
wealth=middle	-.1438571	.21900	-0.66	0.511	-.573515	.285801	9.85
householdsize	.2799286	.14358	1.95	0.051	-.001762	.561619	7.80
toiletfacility	-.1103619	.34076	-0.32	0.746	-.778885	.558162	19.69
electricityfacility	-.0004488	.01737	-0.03	0.979	-.034512	.033614	10.79
placedelivery	2.042724	.40144	5.09	0.000	1.255161	2.830287	-36.81
safedrinkingwater	-.003232	.12537	-0.03	0.979	-.248962	.242491	13.58

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Childage	-.2658586	.230645	-1.15	0.249	-.7183451	.18662	16.74
Childageage2	.0882221	.158830	0.56	0.579	-.2233747	.39981	-11.13
childsex=male	-.1336831	.159431	0.84	0.402	-.1790969	.44646	5.61
birthorder>4	.0437315	.003181	13.74	0.000	.0374861	.04997	5.69
birthsize<aveg	.0296862	4.034112	0.01	0.994	-7.8771002	7.93650	-7.96
birthsize=aveg	.1336831	.159433	0.84	0.402	-.1790969	.44646	-7.40
multiplebirth	-.0005191	.07061	-0.01	0.994	-.1389201	.13788	11.25
shortbirthspace	4.0543281	1.443698	2.81	0.005	1.2220491	6.88660`	-14.68
motherageatbirth<20	-.0094254	.003878	-2.43	0.015	-.0170344	-.00181	-7.68
motherageatbirth>35	-.0002103	.000306	-0.69	0.492	-.0008109	.00039	23.91
contracepuse	.2670187	.200596	1.33	0.183	-.1265171	.66055	3.76
antenatalvisit	-.4467419	.191535	2.33	0.020	.0709834	.82250	5.17
mothereducation	-.0170974	.005361	-3.19	0.001	-.0276198	-.00657	16.92
motherworkstatus	-.0468012	.296982	-0.16	0.875	-.6294278	.53582	12.85
househead=female	-.011884	1.614911	-0.01	0.994	-3.1771002	3.15330	8.80
agehousehold	.0854777	.192082	0.44	0.656	-.2913617	.46231	-2.93
fathereducation	-.0093295	.004772	-1.95	0.051	-.0187051	.00004	8.11
wealth=poor	.5665642	.544631	2.88	0.004	.4980937	2.63503	-15.23
wealth=middle	.2572016	.13267	1.94	0.053	-.0030875	.51749	17.49
householdsize	.0664383	.24146	0.28	0.783	-.4072711	.54014	30.63
toiletfacility	.2875289	.12360	2.33	0.020	.0450342	.53002	-9.61
electricityfacility	.0003298	.000811	0.41	0.684	-.0012595	.00191	-9.18
placedelivery	4.054328	1.44369	2.81	0.005	1.2220491	6.88660	8.19
safedrinkingwater	.008931	1.21372	0.01	0.994	-2.370021	2.38790	-21.68
_cons	-4.260867	.77284	-5.51	0.000	-5.777050	-2.74468	7.92

Source: Own computation (EDHS, 2016)

Table C- 9: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Somali regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Explained	-.237332	.08949	-2.65	0.014	-.51274	-.16192	43.85
Unexplained	-.146353	.12977	-1.13	0.269	-.30069	.20799	56.15
Raw differences	-.38368	.08839	-4.34	0.000	-.55693	-.21044	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Childage	-.051548	.061541	-0.84	0.402	-.172171	.069072	13.45
Childageage2	-.061633	.056843	-1.08	0.278	-.173051	.049781	16.04
childsex=male	-.0030434	.005113	-0.60	0.552	-.013066	.006979	2.79
birthorder>4	-.0086128	.017739	-0.49	0.627	-.043381	.026155	2.24
birthsize<aveg	.4502047	.043404	10.37	0.000	.365032	.535376	-19.63
birthsize=aveg	.0021796	.004246	0.51	0.608	-.006144	.010504	-2.56
multiplebirth	.0841611	.039432	2.13	0.033	.006783	.161538	19.76
shortbirthspace	-.070013	.042205	-1.66	0.097	-.152731	.012708	-18.48
motherageatbirth<20	-.014634	.014616	-1.00	0.317	-.043281	.014012	3.82
motherageatbirth>35	.0034041	.004965	0.69	0.493	-.006327	.013136	-.82
contracepuse	.0037643	.026981	0.14	0.889	-.049118	.056647	-8.98
antenatalvisit	-.0452008	.010098	-4.48	0.000	-.065016	-.025385	-10.85
mothereducation	-.0001841	.009570	-0.02	0.985	-.018943	.018574	14.04
motherworkstatus	-.0061272	.015842	-0.39	0.699	-.037178	.024924	13.69
househead=female	.0013799	.005788	0.24	0.812	-.009966	.012726	-5.34
agehousehold	-.020496	.012113	-1.69	0.091	-.044238	.003245	15.32
fathereducation	-.0003516	.002240	-0.16	0.875	-.004742	.004039	1.09
wealth=poor	.0027289	.019907	0.14	0.891	-.036289	.041747	-.74
wealth=middle	.0042378	.017302	0.24	0.806	-.029673	.038145	-12.45
householdsize	-.0709902	.017949	-3.96	0.000	-.106172	-.035812	18.02
toiletfacility	-.0016382	.013826	-0.12	0.906	-.028738	.025462	.42
electricityfacility	.0016947	.004162	0.41	0.684	-.006462	.009852	-1.47
placedelivery	.2188198	.130602	1.68	0.094	-.037456	.475096	-29.58
safedrinkingwater	-.0052725	.019174	-0.27	0.783	-.042854	.032309	13.42

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Childage	.24562	.79891	0.31	0.759	-1.3202	1.81152	-64.01
Childageage2	-.11445	.44636	-0.26	0.798	-.98931	.76041	29.82
childsex=male	-.038171	.19805	-0.19	0.847	-.42635	.35001	9.94
birthorder>4	.24098	.6929	0.35	0.728	-1.1171	1.59911	-62.88
birthsize<aveg	-.008258	.18014	-0.05	0.963	-.36134	.34482	2.15
birthsize=aveg	-.043135	.19021	-0.23	0.821	-.41596	.32969	11.24
multiplebirth	.013104	.03901	0.34	0.737	-.063373	.089581	-3.41
shortbirthspace	-.043584	.17218	-0.25	0.800	-.38106	.29389	11.35
motherageatbirth<20	-.193	.54546	-0.35	0.723	-1.2621	.87610	50.31
motherageatbirth>35	-.0052116	.09918	-0.05	0.958	-.19962	.18919	1.35
contracepuse	.013489	.03885	0.35	0.728	-.062658	.08963	-3.51
antenatalvisit	-.11937	.43823	-0.27	0.785	-.97831	.73957	31.11
mothereducation	.12483	.56329	0.22	0.825	-.97921	1.22891	-32.53
motherworkstatu	-.00057121	.06427	-0.01	0.993	-.12656	.12541	9.18
househead=female	-.082169	.22196	-0.37	0.711	-.51722	.35288	21.41
agehousehold	-.6868	1.8426	-0.37	0.709	-4.2983	2.92417	1.79
fathereducation	.052888	.77401	0.07	0.946	-1.4642	1.56991	-13.78
wealth=poor	.03755	.44805	0.08	0.933	-.84062	.91572	-9.78
wealth=middle	.035183	.11019	0.32	0.750	-.1808	.25116	-9.16
householdsize	-.52073	1.5002	-0.35	0.728	-3.4607	2.41921	15.72
toiletfacility	.023336	.1121	0.21	0.835	-.19641	.24308	-6.08
electricityfacility	-.020496	.07378	-0.28	0.781	-.16512	.12412	5.32
placedelivery	.23558	1.1152	0.21	0.833	-1.9502	2.42141	-61.24
safedrinkingwater	-.032805	.17113	-0.19	0.848	-.36822	.30261	8.55
_cons	.83983	2.7806	0.30	0.763	-4.6101	6.28981	-28.89

Source: Own computation (EDHS, 2016)

Table C- 10: The results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Afar regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Explained	-.034722	.018384	-1.89	0.059	-.070752	.0013124	41.04
Unexplained	-.049873	.043353	-1.15	0.250	-.13485	.0351011	58.96
Raw differences	-.084593	.036558	-2.31	0.021	-.15625	-.01294	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Childage	-.0661028	.043452	-1.52	0.128	-.1513541	.0191484	-3.06
Childageage2	.0925383	.101324	-0.91	0.361	-.2913284	.1062518	2.32
childsex=male	-.0768215	.119591	-0.64	0.521	-.3114396	.1577966	4.10
birthorder>4	.0052867	.162291	0.03	0.974	-.31281	.3233821	-6.22
birthsize<aveg	.0278411	.011628	2.39	0.017	.0050277	.0506545	-17.64
birthsize=aveg	-.0463691	.193743	-0.24	0.811	-.4264792	.1532421	6.34
multiplebirth	-1.727995	.484432	-3.57	0.000	-2.678366	-.7776251	-.13
shortbirthspace	-3.605734	6.36992	-0.57	0.571	-16.10239	8.8909252	17.68
motherageatbirth<20	-.0811389	.046118	-1.76	0.079	-.1716197	.009342	-21.71
motherageatbirth>35	.0572695	.039478	1.45	0.147	-.0201832	.134722	-3.95
contracepuse	.1325209	.136088	0.97	0.330	-.1344745	.399516	9.79
antenatalvisit	.4768388	.040200	11.86	0.000	.397968	.555709	-18.81
mothereducation	-.0658342	.034269	-1.92	0.055	-.1331554	.0014871	-19.58
motherworkstatus	-.0294617	.044757	-0.66	0.510	-.1172717	.058348	3.59
househead=female	-.097727	.059355	-1.65	0.100	-.2141785	.018724	-2.28
agehousehold	-.0002961	.000561	-0.53	0.598	-.0013979	.000805	-15.12
fathereducation	-.0656442	.051886	-1.27	0.206	-.1674409	.036152	7.37
wealth=poor	-.0045397	.002983	-1.52	0.128	-.010393	.001313	9.58
wealth=middle	-.0001435	.000328	-0.44	0.662	-.0007881	.000501	-13.97
householdsize	.0211638	.061562	0.34	0.731	-.099616	.141943	-5.02
toiletfacility	.0201537	.043749	0.46	0.645	-.0656789	.105986	-2.62
electricityfacility	-.0099146	.160084	-0.06	0.951	-.3239874	.304158	-.33
placedelivery	-.0339407	.035735	-0.95	0.342	-.1040513	.036169	-6.06
safedrinkingwater	-.0037741	.011021	-0.34	0.732	-.0253953	.017847	4.24

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Childage	-.0498821	.0858406	-0.58	0.561	-.218284	.118524	3.06
Childageage2	-.0710241	.0803648	-0.88	0.377	-.228685	.086637	9.75
childsex=male	.0758938	.1051746	0.72	0.471	-.130440	.282227	-53.42
birthorder>4	.0075041	.003122	2.40	0.016	.001379	.013628	10.04
birthsize<aveg	.0023836	.002851	0.84	0.403	-.003207	.007974	-41.36
birthsize=aveg	.1557476	.0592586	2.63	0.009	.039492	.272002	6.14
multiplebirth	.0000176	.0000344	0.51	0.608	-.000049	.000085	3.29
shortbirthspace	.0529493	.0720138	0.74	0.462	-.088329	.194227	6.78
motherageatbirth<20	-.289074	.1750597	-1.65	0.099	-.632510	.054362	22.69
motherageatbirth>35	.0399326	.0458401	0.87	0.384	-.049997	.129862	32.22
contracepuse	.1412876	.0890766	1.59	0.113	-.033464	.316040	-.34
antenatalvisit	.1530617	.0912112	1.68	0.094	-.025878	.332001	-9.07
mothereducation	-.0008363	.0157648	-0.05	0.958	-.031764	.030091	-37.84
motherworkstatu	-.0659413	.0907752	-0.73	0.468	-.244026	.112143	-3.07
househead=female	-.0053413	.0026008	-2.05	0.040	-.010443	-.000239	-36.67
agehousehold	-.0916106	.1337346	-0.69	0.493	-.353974	.170753	12.08
fathereducation	.1076288	.0922957	1.17	0.244	-.073439	.288696	9.62
wealth=poor	.061149	2.440201	0.03	0.980	-4.72172	4.844021	-7.02
wealth=middle	.0042344	.0017158	2.47	0.014	.00086	.007600	-5.32
householdsize	.1476543	.0720071	2.05	0.041	.00638	.288926	3.62
toiletfacility	-.0269397	.0090735	-2.97	0.003	-.044741	-.009138	-23.93
electricityfacility	-.000611	.0001567	-3.90	0.000	-.000918	-.000303	1.31
placedelivery	-.0000716	.0414935	-0.00	0.999	-.081478	.081335	6.91
safedrinkingwater	.083578	.0389541	2.15	0.032	.007153	.160002	33.12
_cons	.1097677	.0537879	2.04	0.041	.004241	.215295	12.19

Source: Own computation (EDHS, 2016)

Table C- 11: Results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and SNNP regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Explained	.040941	.02509	1.63	0.103	.090117	.0082364	30.54
Unexplained	.017895	.03887	0.46	0.645	.094086	.058296	69.46
Raw differences	.058835	.02755	2.14	0.033	.11283	.0048366	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Childage	.0098951	.0370229	0.27	0.789	-.062724	.082514	-6.81
Childageage2	.0131487	.0314556	0.42	0.676	-.048550	.074848	2.42
childsex=male	.0428947	.0386704	1.11	0.267	-.032956	.118746	5.27
birthorder>4	-.0118359	.0436922	-0.27	0.787	-.097537	.073865	32.42
birthsize<aveg	-.0064434	.0426848	-0.15	0.880	-.090168	.077282	-8.42
birthsize=aveg	.0590581	.0477954	1.24	0.217	-.034691	.152807	-11.95
multiplebirth	.00014421	.004695	0.03	0.975	-.009058	.009346	-.21
shortbirthspace	-6.959131	23.01915	-0.30	0.762	-52.1186	38.2003	19.82
motherageatbirth<20	.0056873	.0804515	0.07	0.944	-.152116	.163491	-9.07
motherageatbirth>35	-.00030056	.009743	-0.03	0.975	-.019398	.018797	29.51
contracepuse	.0677512	.041977	1.61	0.107	-.014587	.150089	-4.64
antenatalvisit	.1221879	.032669	3.74	0.000	.058107	.186268	-21.62
mothereducation	.0922884	.076397	1.21	0.227	-.057563	.242139	13.61
motherworkstatu	.0781684	.094571	0.83	0.409	-.107364	.263701	-6.64
househead=female	.002193	.001494	1.47	0.142	-.000738	.005124	9.28
agehousehold	.0049706	.033051	0.15	0.880	-.059858	.069799	-32.64
fathereducation	-.0875414	.129991	-0.67	0.501	-.342517	.167434	-5.58
wealth=poor	-.0653921	.013441	-4.87	0.000	-.09174	-.039041	-13.77
wealth=middle	-.0002641	.000406	-0.65	0.516	-.001061	.000533	8.99
householdsize	.0759812	.065703	1.16	0.248	-.052919	.204879	3.54
toiletfacility	-.0509917	.128312	-0.40	0.691	-.302724	.200740	-2.96
electricityfacility	-.0989665	.081326	-1.22	0.224	-.258486	.060553	9.04
placedelivery	-.0637939	.014320	-4.45	0.000	-.091869	-.035719	-17.13
safedrinkingwater	-.0037745	.122541	-0.03	0.975	-.243961	.236411	6.41

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]	Pct.
Childage	.779949	.091465	8.53	0.000	.600510	.959389	-16.13
Childageage2	.089649	.089653	1.00	0.318	-.086234	.265533	6.05
childsex=male	.261784	.060918	4.30	0.000	.142271	.381296	5.33
birthorder>4	-.119291	.088319	-1.35	0.177	-.292558	.053975	-8.72
birthsize<aveg	-.006412	.120421	-0.05	0.958	-.242451	.229621	10.99
birthsize=aveg	.084687	.118136	0.72	0.474	-.147076	.316450	28.94
multiplebirth	-.247711	.092419	-2.68	0.007	-.429022	-.066400	1.38
shortbirthspace	.007427	.139311	0.05	0.957	-.265621	.280472	-12.24
motherageatbirth<20	-4.38422	.686503	-6.39	0.000	-5.73099	-3.037402	20.52
motherageatbirth>35	-.028136	.178152	-0.16	0.875	-.377640	.321367	-4.55
contracepuse	-.000820	.000457	-1.79	0.073	-.001718	.000077	-3.35
antenatalvisit	.799755	.301745	2.65	0.008	.207784	1.391727	-13.85
mothereducation	-.003919	.003890	-1.01	0.314	-.011551	.003712	-11.21
motherworkstatu	-.009409	.176761	-0.05	0.958	-.355861	.337041	15.93
househead=female	-.000329	.007007	-0.05	0.962	-.014065	.013405	6.51
agehousehold	.291804	.121363	2.40	0.016	.053752	.529856	-5.06
fathereducation	.106803	.048721	2.19	0.029	.011236	.202369	-11.63
wealth=poor	-.103980	.038792	-2.68	0.007	-.180071	-.027890	25.55
wealth=middle	.070690	.031867	2.22	0.027	.008182	.133198	-14.26
householdsize	.071604	.033734	2.12	0.034	.005435	.137773	6.76
toiletfacility	.007816	.001433	5.45	0.000	.005005	.010627	21.14
electricityfacility	.143842	.063716	2.26	0.024	.018864	.268820	-5.55
placedelivery	-.048790	.009483	-5.14	0.000	-.067392	-.030187	9.66
safedrinkingwater	-.164461	.153974	-1.07	0.286	-.466478	.137555	8.24
_cons	.453099	.036783	12.32	0.000	.380949	.525251	13.82

Source: Own computation (EDHS, 2016)

Table C- 12: Results of detailed Oaxaca-Blinder decomposition analysis: Tigrai and Gambella regions

Component gaps	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Explained	.203076	.04115	4.92	0.000	.39645	2.00969	35.75
Unexplained	.067638	.11451	0.59	0.555	.156801	.29208	64.25
Raw differences	.049317	.077912	0.63	0.527	.20202	.10339	

Due to Difference in Characteristics (Explained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Childage	-.0038201	.0043587	-0.88	0.381	-.0123631	.004723	7.746
Childageage2	-.0018472	.0017768	-1.04	0.299	-.0053296	.001635	3.74
childsex=male	-.0012301	.0022717	-0.54	0.588	-.0056826	.003222	2.44
birthorder>4	.1564314	.0610659	2.56	0.011	.0366151	.276247	-23.68
birthsize<aveg	-.0011973	.0024501	-0.49	0.625	-.0059995	.003604	12.42
birthsize=aveg	.0015391	.0022939	0.67	0.502	-.0029569	.006035	-3.12
multiplebirth	-.0039037	.0024496	-1.59	0.111	-.0087049	.000897	7.91
shortbirthspace	-.015156	.0088918	-1.70	0.088	-.0325841	.002271	-30.73
motherageatbirth<20	-.0065113	.0070454	-0.92	0.355	-.0203201	.007297	13.23
motherageatbirth>35	.0040528	.0086176	0.47	0.638	-.0128381	.020943	-5.31
contracepuse	.0006504	.0043674	0.15	0.882	-.0079097	.009210	-1.31
antenatalvisit	-.029137	.0320012	-0.91	0.363	-.0918561	.033582	59.02
mothereducation	.0003730	.0036422	0.10	0.918	-.0067657	.007511	-6.75
motherworkstatu	.004175	.015461	0.27	0.787	-.0261291	.034479	-8.46
househead=female	.0076495	.027389	0.28	0.780	-.0460322	.061331	-15.51
agehousehold	.011072	.066952	0.17	0.869	-.1201501	.142301	22.45
fathereducation	-.071629	.021875	-3.27	0.001	-.1145001	-.028755	-26.72
wealth=poor	.0050867	.020327	0.25	0.802	-.0347541	.044928	-10.31
wealth=middle	.0032427	.019266	0.17	0.866	-.0345118	.041003	-6.57
householdsize	-.073835	.023308	-3.17	0.002	-.1195201	-.028152	49.72
toiletfacility	.0001309	.002075	0.06	0.950	-.0039365	.004198	-.26
electricityfacility	-.005235	.010221	-0.51	0.609	-.0252671	.014797	10.61
placedelivery	.003852	.001531	2.52	0.012	.0008479	.006852	-27.12
safedrinkingwater	-.007259	.021728	-0.33	0.738	-.0498461	.035329	14.71

Due to Difference in Coefficients (Unexplained)

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]		Pct.
Childage	.048373	.201151	0.24	0.810	-.345891	.442631	-8.08
Childageage2	-.061614	.155421	-0.40	0.692	-.366241	.243011	24.93
childsex=male	-.040621	.062076	-0.65	0.513	-.162292	.081048	82.37
birthorder>4	-.026465	.060398	-0.44	0.661	-.144851	.091916	53.63
birthsize<aveg	-.013568	.048463	-0.28	0.780	-.108562	.081422	27.52
birthsize=aveg	-.0013575	.043599	-0.03	0.975	-.086812	.084097	2.75
multiplebirth	.0017456	.007919	0.22	0.826	-.013776	.017267	-3.53
shortbirthspace	.4121455	.038551	10.69	0.000	.336508	.487787	9.67
motherageatbirth<20	-.019514	.078371	-0.25	0.803	-.173122	.134090	39.69
motherageatbirth>35	.020836	.040731	0.51	0.609	-.059013	.100681	-42.49
contracepuse	.036019	.038887	0.93	0.354	-.040199	.112241	-73.36
antenatalvisit	-.028232	.031491	-0.90	0.370	-.089953	.033492	30.24
mothereducation	.19474	.382501	0.51	0.611	-.554971	.944452	-3.88
motherworkstatu	.0071605	.040769	0.18	0.861	-.072746	.087067	-14.19
househead=female	-.029223	.045753	-0.64	0.523	-.118911	.060452	59.56
agehousehold	-.14524	.227241	-0.64	0.523	-.590631	.300151	24.5
fathereducation	.04743	.127212	0.37	0.709	-.201119	.296761	-9.74
wealth=poor	-.063722	.121061	-0.53	0.599	-.301211	.173552	19.21
wealth=middle	-.0071678	.021733	-0.33	0.742	-.049765	.035431	14.34
householdsize	-.10869	.117261	-0.93	0.354	-.338521	.121151	22.38
toiletfacility	-.093359	.079098	-1.18	0.238	-.248391	.061673	-10.52
electricityfacility	.028453	.114361	0.25	0.804	-.195691	.252601	-30.77
placedelivery	-.12181	.080355	-1.52	0.130	-.279311	.035683	13.48
safedrinkingwater	-.02056	.044161	-0.47	0.642	-.107112	.065996	41.69
_cons	-.0373091	.145278	-0.26	0.797	-.322352	.247739	-6.64

Source: Own computations (EDHS, 2016)

Table C- 13: Summary of average regional health posts' outputs and inputs targets

Region	Output targets						Input targets	
	O_1	O_2	O_3	O_4	O_5	O_6	I_1	I_2
Tigrai	382.6	622.5	30.7	58.2	33.4	43.9	0.15	4.94
Amhara	392.5	387.8	36.2	80.5	34.9	51.0	0.12	3.94
Oromia	318.0	394.7	29.3	77.4	45.3	52.3	0.05	8.75
SNNP	335.8	419.2	27.0	71.7	40.9	56.3	0.03	10.06
BG	318.8	411.9	30.5	52.3	36.4	61.5	0.05	9.72
Gambella	302.3	407.9	31.0	49.4	36.1	61.9	0.13	21.64
Harari	382.1	518.0	37.7	55.4	42.2	42.2	0.11	14.60
National	336.9	435.8	29.1	69.2	41.9	53.0	0.08	8.22

Source: Own computation (RHB, 2013/14)

Note: i) O_1, O_2, O_3, O_4, O_5, and O_6 indicates the average number of: HEP beneficiary graduates, households visited by HWEs, health education sessions provided by HEWs, child delivery by HEWs, child delivery by HDA, and under-five children fully immunized, respectively (average outputs targets)

ii) I_1 number of HEWs and I_2 respresents number of HDAs needed to be reduced (average health input targets).

Table C- 14: Average quantity of output gains needed to make health posts efficient

Outputs	Potential improvement in percent					
	2013		Output gains	2014		Output gains
Number of:	Actual values	Target values		Actual values	Target values	
▪ HEP beneficiary graduates	141.67	206.32	51.81	242.27	338.03	43.81
▪ Households visited by HEWs	191.07	295.92	98.27	282.79	437.67	54.77
▪ Health education sessions provided by HEWs	27.96	39.37	59.10	21.90	29.35	34.04
▪ Child delivery by HEWs	24.40	39.47	95.89	46.68	69.13	48.09
▪ Child delivery by HDAs	16.88	31.02	83.77	31.85	42.11	32.22
▪ Under-five children fully immunized	20.51	27.01	36.41	41.34	53.40	29.17
National Average	70.42	106.52	70.88	111.14	161.62	40.35

Source: Own computation (RHB, 2013/14)

Table C- 15: Test of multicollinearity: An ordinary least square regression analysis

Variable	VIF	1/VIF
pshew	1.08	0.929870
_Irthew_2	1.02	0.980828
dvhp	1.17	0.858079
ywhew	1.12	0.893491
_Irphew_2	1.72	0.582526
aghew	1.03	0.966864
_Imshew_2	1.01	0.987130
_Irphew_2	1.72	0.582526
_Imshew_3	2.11	0.473934
Mihew	1.02	0.980061
_Isshew_2	1.71	0.583669
_Irrhew_2	2.55	0.392152
_Irrhew_3	3.08	0.324335
_Irrhew_4	2.34	0.427901
_Irrhew_5	1.31	0.764497
_Irrhew_6	1.84	0.542108
_Irrhew_7	1.17	0.853744
_Irlhew_2	1.00	0.995889
_Irlhew_3	1.01	0.993182
Mean VIF	1.47	

Source: Own computation (RHB, 2013/14)

Table C- 16: Determinants of inter-health posts disparities in technical inefficiency: Estimates of Tobit regression analysis

Number of obs	= 1,552	Prob > F	= 0.0000
F(16, 1536)	= 11.54	Pseudo R2	= 0.0799

teincrs	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
pshew	-.0005125	.0004619	-1.14	0.256	-.0014312	.0003809
_Irthew_2	-.0012015	.0241023	-0.05	0.960	-.0484784	.0460754
dvhp	.0426932	.0168427	2.50	0.013	.009056	.0751303
ywhew	-.0018808	.0041558	-0.45	0.651	.0062689	.0100306
_Irphew_2	-.0541271	.0370628	-1.46	0.144	-.1268261	.018572
aghew2	.0000123	.0000639	0.17	0.868	-.0001147	.0001359
mihew	-.0000106	.0000152	-0.69	0.492	-.0000409	.0000197
_Isshew_2	.0716466	.0346601	2.08	0.038	.0039605	.1399327
_Irrhew_2	.2481992	.0462035	5.37	0.000	.1575707	.3388278
_Irrhew_3	.1833519	.0424147	4.32	0.000	.1001549	.2665488
_Irrhew_4	.4766447	.0494174	9.64	0.000	.379312	.5731773
_Irrhew_5	.3938849	.0641415	6.13	0.000	.2649727	.5167972
_Irrhew_6	.4166089	.0509413	8.17	0.000	.3153092	.5153086
_Irrhew_7	.5710835	.1244821	4.58	0.000	.3347953	.8113717
_Irlhew_2	.1343642	.0295805	4.54	0.000	.0763864	.1923418
_Irlhew_3	-.0157653	.0243459	-0.65	0.596	-.0634832	.0319526
_cons	.4924136	.1129789	4.36	0.000	.2708044	.7140229
/sigma	.4587443	.009372			.440361	.4771276

44 left-censored observations at teincrs <= 0
1,508 uncensored observations and 0 right-censored observations

Source: Own computation (RHB, 2013/14)

Table C- 17: Determinants of inter-health posts disparities in technical inefficiency: Estimates of an ordinary least square regression analysis

Number of obs	=	1,552	Prob > F	=	0.0000
F(17, 1534)	=	15.59	R-squared	=	0.0790
			Root MSE	=	.19573

teinvrs	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
pshew	-.0000516	.0002064	-0.25	0.803	-.0004565	.0003533
_Irthew_2	-.0028431	.0104739	-0.27	0.786	-.0233877	.0177015
dvhp	.033927	.016693	2.03	0.042	.0011835	.0666706
ywhew	-.000564	.0018223	-0.31	0.757	-.0030105	-.0041385
_Irphew_2	-.0227557	.0164086	-1.39	0.166	-.0549414	.0094301
aghew2	.0007792	.0003429	2.27	0.023	.0001067	.0014518
mihew	-.000015	.0000148	-1.01	0.312	-.0000439	.000014
_Isshew_2	.0652023	.0328942	1.98	0.048	.0006799	.1297246
_Irrhew_2	.242993	.0442444	5.49	0.000	.1562071	.3297789
_Irrhew_3	.1781272	.0401684	4.43	0.000	.0993363	.2569181
_Irrhew_4	.4721131	.0479926	9.84	0.000	.3779749	.5662512
_Irrhew_5	.377772	.0636021	5.94	0.000	.2530158	.5025283
_Irrhew_6	.4006149	.0492081	8.14	0.000	.3040925	.4971372
_Irrhew_7	.5426077	.1232746	4.40	0.000	.3008031	.7844122
_Irlhew_2	.135419	.0293049	4.62	0.000	.0779372	.1929008
_Irlhew_3	.0023475	.0198061	0.12	0.906	-.0365023	.0411973
_cons	.8650184	.3015559	2.87	0.004	.273513	1.456524

Source: Own computation (RHB, 2013/14)

Table C- 18: Determinants of health extension programme beneficiary households: Odds ratio logistic regression analysis

Number of obs	= 3,197	Prob > chi2	= 0.0000
Wald chi2(31)	= 31.41	Pseudo R2	= 0.0228

hepgraduate	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AgeHH	.9980808	.0045841	-0.42	0.676	.9891365	1.007106
_ISexHH_1	1.028889	.0118771	2.47	0.014	1.005872	1.052433
Agemam	1.0116499	.0064988	1.81	0.070	.976076	.1000966
_IOccup_2	1.356964	.5062085	0.82	0.413	.6531786	2.819063
_IOccup_3	1.018969	.1089551	0.18	0.861	.8263129	1.256542
_IOccup_4	1.134043	.0972005	1.47	0.142	.9586762	1.34149
_IOccup_5	.8230283	.2705495	-0.59	0.554	.4321196	1.567565
_Ireligion_2	.9849764	.0760604	-0.20	0.845	.8466337	1.145925
_Ireligion_3	2.776923	2.165141	1.31	0.190	.6024071	12.80082
landsize	.9942241	.002185	-2.64	0.008	.9899538	.9985128
HPdist	.7413967	.1022308	-2.17	0.030	.5658209	.9714542
HEPtuser	6.155199	4.762683	2.35	0.019	1.350863	28.04612
familysize	3.108836	1.308319	2.70	0.007	1.362634	7.092778
_Imaritalst_1	1.086246	.1018657	0.88	0.378	.9038671	1.305425
_Imaritalst_2	.6862358	.2116832	-1.22	0.222	.3748894	1.256156
_Imaritalst_3	.6796514	.241086	-1.09	0.276	.3391158	1.362149
_IExtension_1	9.834475	11.804989	1.89	0.063	.3176507	.2302468
HEWperhp	.9641219	.0907785	-0.39	0.698	.8016516	1.15952
_Iregion_2	.8485699	.1573011	-0.89	0.376	.5900634	1.220328
_Iregion_3	.908761	.1666892	-0.52	0.602	.6343344	1.30191
_Iregion_4	.973457	.1891699	-0.14	0.890	.6651269	1.424718
_Iregion_5	.9615697	.1955524	-0.19	0.847	.6454664	1.432478
_Iregion_6	.8617961	.2039267	-0.63	0.530	.5419819	1.370327
_Iregion_7	.7425666	.2141137	-1.03	0.302	.4219855	1.306692
_IHEWprofle_1	1.00093	.0004865	1.91	0.056	.9999766	1.001883
_IHEWprofle_2	1.145616	.1039288	1.50	0.134	.9590012	1.368545
_Imameduc_1	1.24004	.1532281	1.74	0.082	.9733193	1.579851
_Imameduc_2	1.425495	.3113117	1.62	0.105	.9291226	2.187048
_Iparentale_1	.9599273	.0787262	-0.50	0.618	.8173895	1.127321
_Iparentale_2	1.4631915	.2709392	2.06	0.040	.6018151	.145812
_Ioffincome_1	.4256243	.1183052	-3.07	0.002	.2468477	.7338778
_cons	3.108836	1.308319	2.70	0.007	1.362634	7.092778

Source: Own computation (RHB, 2013/14)

Table C- 19: Determinants of health extension programme beneficiary households: Coefficient estimates of logistic regression

```
Number of obs     =      3,197              Prob > chi2       =     0.0000
Wald chi2(31)     =      31.41              Pseudo R2         =     0.0228
```

hepgraduate	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AgeHH	-.0019211	.0045929	-0.42	0.676	-.0109229	.0070808
_ISexHH_1	.0284798	.0115436	2.47	0.014	.0058547	.0511048
Agemam	.0116246	.0064237	1.81	0.070	.0242149	.0009657
_IOccup_2	.3052499	.3730449	0.82	0.413	-.4259046	1.036404
_IOccup_3	.018791	.1069269	0.18	0.861	-.1907818	.2283638
_IOccup_4	.1257895	.0857115	1.47	0.142	-.0422019	.2937809
_IOccup_5	-.1947647	.3287245	-0.59	0.554	-.8390529	.4495234
_Ireligion_2	-.0151376	.0772206	-0.20	0.845	-.1664872	.1362119
_Ireligion_3	1.021344	.7796905	1.31	0.190	-.5068218	2.549509
landsize	-.0057926	.0021961	-2.64	0.008	-.0100971	-.0014883
HPdistance	-.2992194	.1378894	-2.17	0.030	-.5694778	-.0289611
HEPtuser	1.817297	.7737659	2.35	0.019	.3007437	3.333858
familysize	1.134248	.4208388	2.70	0.007	.3094194	1.959077
_Imaritals_1	.0827281	.0937777	0.88	0.378	-.1010729	.266529
_Imaritals_2	-.3765339	.3084701	-1.22	0.222	-.9811242	.2280563
_Imaritals_3	-.3861752	.35472	-1.09	0.276	-1.081414	.3090633
_IExtension_1	2.2858941	1.200368	1.89	0.063	1.4416947	4.5611861
HEWperhp	-.0365375	.0941567	-0.39	0.698	-.2210811	.1480062
_Iregion_2	-.1642029	.185372	-0.89	0.376	-.5275253	.1991195
_Iregion_3	-.0956732	.1834247	-0.52	0.602	-.4551789	.2638326
_Iregion_4	-.0269017	.1943279	-0.14	0.890	-.4077774	.353974
_Iregion_5	-.0391882	.2033679	-0.19	0.847	-.4377821	.3594056
_Iregion_6	-.1487365	.2366299	-0.63	0.530	-.6125226	.3150495
_Iregion_7	-.2976428	.2883428	-1.03	0.302	-.8627843	.2674987
_IHEWproffl_1	.0009291	.000486	1.91	0.056	.0000234	.0018817
_IHEWproffl_2	.1359425	.0907187	1.50	0.134	-.0418629	.3137479
_Imameduc_1	.2151438	.123567	1.74	0.082	.0270431	.4573307
_Imameduc_2	.3545191	.2183885	1.62	0.105	-.0735146	.7825527
_Iparentale_1	-.0408977	.0820126	-0.50	0.618	-.2016395	.1198441
_Iparentale_2	.3806204	.1851697	2.06	0.040	.7435463	.0176946
_Ioffincome_1	-.8541983	.2779569	-3.07	0.002	-1.398984	-.3094127
_cons	1.134248	.4208388	2.70	0.007	.3094194	1.959077

Source: Own computation (RHB, 2013/14)

Table C-20: Summary statistics of Goodness-of-fit test analysis

(Table collapsed on quantiles of estimated probabilities)

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.5572	172	169.6	148	150.4	320
2	0.5795	180	182.3	140	137.7	320
3	0.5953	196	188.0	124	132.0	320
4	0.6073	192	191.9	127	127.1	319
5	0.6183	190	196.2	130	123.8	320
6	0.6304	171	199.8	149	120.2	320
7	0.6418	221	203.0	98	116.0	319
8	0.6551	216	207.6	104	112.4	320
9	0.6733	210	212.1	110	107.9	320
10	0.8484	226	223.6	93	95.4	319

```
     number of observations =      3197
           number of groups =        10
    Hosmer-Lemeshow chi2(8) =        18.00
                Prob > chi2 =         0.2132
```

Source: Own computation (RHB, 2013/14)

Appendix D: Supplementary information

Table D- 1: Letter of research ethics committee approval for this thesis proposal

UNIVERSITY OF KWAZULU-NATAL™
INYUVESI YAKWAZULU-NATALI

18 June 2018

Mr Yibrah Hagos Gebresilassie (214584997)
School of Accounting, Economics & Finance
Pietermaritzburg Campus

Dear Mr Gebresilassie,

Protocol reference number: HSS/0981/015D
New project title: Inter-regional Child differentials, programme efficiency, and throughput: An evaluation of the Ethiopian Health Extension Progrogramme

Approval Notification – Amendment Application

This letter serves to notify you that your application and request for an amendment received on 13 June 2018 has now been approved as follows:

- Change in Title

Any alterations to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form; Title of the Project, Location of the Study must be reviewed and approved through an amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for period of 3 years from the date of original issue. Thereafter Recertification must be applied for on an annual basis.

Best wishes for the successful completion of your research protocol.

Yours faithfully

....

Professor Shenuka Singh (Chair)

/ms

cc Supervisor: Dr Phocenah Nyatanga
cc Academic leader Research: Dr Josue Mbonigabe
cc School administrator: Ms Jerusha Singh

Humanities & Social Sciences Research Ethics Committee
Dr Shenuka Singh (Chair)
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Telephone: +27 (0) 31 260 3587/8350/4557 **Facsimile:** +27 (0) 31 260 4609 **Email:** ximbap@ukzn.ac.za / snymanm@ukzn.ac.za / mohunp@ukzn.ac.za
Website: www.ukzn.ac.za

Table D- 2: Letter of confirmation from CSA to access the EDHS data

የኢትዮጵያ ፌዴራላዊ ዲሞክራሲያዊ ሪፐብሊክ
በገንዘብና ኢኮኖሚ ልማት ሚኒስቴር
ማዕከላዊ ስታቲስቲክስ ኤጀንሲ

THE FEDERAL DEMOCRATIC REPUBLIC OF ETHIOPIA
MINISTRY OF FINANCE AND ECONOMIC DEVELOPMENT
Central Statistical Agency

ቁጥር 1-9-3/1573
Ref. No.
ቀን 04 FEB 2015
Date

To University of KWAZULU-NATAL

School of Accounting, Economics and Finance

Dear, Dr. Phocenah Nyatanga

Subject: Access to EDHS Data

In response to your letter of requesting "EDHS Data" for Mr. Yibrah Hagos Gebresilassie. I confirm you that the Central Statistical Agency (my office) can provide him the EDHS data for the year 2000, 2005 and 2011.

Kind regards,

Amare Legesse
Statistical Surveys & Censuses Deputy
Director General

Federal Democratic Republic of Ethiopia Ministry of Finance and Economic Development Central Statistical Agency

Table D- 3: Letter of confirmation from federal ministry of Ethiopia to access the regional health bureaus data (health extension programme) for my study purpose

የኢትዮጵያ ፌዴራላዊ ዲሞክራሲያዊ
ሪፐብሊክ
የጤና ጥበቃ ሚኒስቴር

Federal Democratic Republic of
Ethiopia
Ministry of Health

ቀን 3/02/2015
Date

ቁጥር [illegible]/26/5Y/79
Ref. No.

To: UNIVERSTY OF KWAZULU-NATAL COLLEGE OF LAW & MANAGEMENT STUDIES
SCHOOL OF ACCOUNTING, ECONMICS & FINANCE
SOUTH AFRICA

Subject: Letter of Confirmation

Thank you for your letter of 20 January 2015 which asks a conformation letter to utilize data from the Federal Ministry of Health (FMOH), especially data on the Ethiopian Health Extension Program for academic purpose to Mr Yibrah Hagos Gebresilassie Via his supervisor (Dr Phocenah Nyatanga). We are also interested and encouraging such doctorial research study in particular Health Extension Program (HEP) of Ethiopia.

The Health Extension and Primary Care Service Directorate of Federal Ministry of Heath Ethiopia is one of the health provider of the ministry to oversee HEP at national level. Actually public health research issues are a mandate for Ethiopian Public Health Institution. However this directorate has a responsibility to design and operate the program at national level so in such matter the directorate provides program related learning and job aids Data, and therefore the PhD Student can able to access those Data's for his study purpose.

Sincerely,

Meseret Yetubie Werkie
Health Extension & Primary
Health Services Director

Federal Democratic Republic of Ethiopia Ministry of Health

251-(0)11-5517011
251-(0)11-5515425
251-(0)11-5159869
251-(0)11-5518031
Fax 251-(0)11-5519366
251-(0)11-5159657
251-(0)11-5524549
E-mail:moh@ethionet.et
Web site: www.moh.gov.et
1234
Addis Ababa,
Ethiopia

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This is to certify that I, Susan Erasmus, BA (Hons) HDE, have edited the thesis of Yibrah Hagos Gebresilassie, submitted to the University of KwaZulu-Natal for Examination of the Degree of Doctor of Philosophy (Ph.D.) in Economics

I am an experienced academic editor, with three decades of experience of working for a variety of Publishers (Nasou Via-Afrika, Lux Verbi, LAPA), media publications (Media24, Health24, Fin24) and universities, including the University of Stellenbosch.

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