MATERNAL AND CHILD HEALTH OUTCOMES IN RELATION TO ACCESSIBILITY, SPATIAL DISTRIBUTION, INEQUALITY AND FREE MATERNAL CARE IN KENYA

By

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Thesis Presented for the Degree of Doctor of Philosophy

in the School of Economics

University of Cape Town

December 2022

DECLARATION

I, Susan Wambui Kamundia, hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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DEDICATION

To my late father, Mr John Kamundia Waweru and my lovely mother, Mrs Agnes Wothaya Ndiritu for instilling the love of education in me and being my greatest supporters and cheerleaders in this journey.

ACKNOWLEDGEMENTS

First and foremost, to my supervisor, Professor Murray Leibbrandt, thank you for your mentorship, invaluable support and immense patience throughout the development of my thesis. I appreciate the timely feedback, dedication and guidance that have led to the successful completion of this thesis. Thank you for believing in me and helping me build confidence in my research.

To my family, thank you for being my pillar of support throughout this PhD journey. Thanks to my mum Agnes for being my rock, always encouraging and uplifting me through it all. To my brothers, Waweru and Gerald and sisters Lydia, Charity and Grace, thank you for always motivating me, to my nephews Kwame, Faraji, Lemaiyan and Jelani, thank you for always putting a smile on my face even when the going got tough. I’m eternally grateful to have a family that provided me with financial, emotional and mental support that kept me balanced throughout the ups and downs of doing a PhD and I remain forever grateful and indebted to you.

Thank you to my friends and colleagues Diana, Bongai, Betty, Sam, Malefeu, Godfrey, Arindam, Nyasha and Grace for the amazing comments and feedback on my thesis and for giving me a sounding board for my ideas and sometimes just a forum to vent and clear my mind. Thank you to the School of Economics staff especially Paula Bassingthwaighte, Haajirah Esau and Thembisa Nyamakazi for the support for making my stay at the school as comfortable as possible by giving timely assistance when needed.

I would like to appreciate the African Economic Research Consortium (AERC) for providing the funds that enabled me to start my PhD studies. Thanks to my supervisor for providing additional funding through the South African Labour and Development Research Unit (SALDRU) and African Centre of Excellence for Inequality Research (ACEIR) without which the final leg of the PhD would not have been completed. Special thanks to the group A AERC 2019 June and December biannual conferences participants for their constructive comments, especially Professor Femi Ayadi who took a lot of care to advise me during the conceptual stages of my thesis and helped me fine-tune my ideas.

Special thanks to the African Centre of Excellence for Inequality Research (ACEIR) and Professor Richard Harris from the University of Bristol for organising training on mapping and modelling geographical data. This training was very enlightening and provided much more clarity in my third chapter.

I owe immense appreciation to the United Nations University – World Institute for Development Studies (UNU-WIDER) for having given me an opportunity to participate in their prestigious PhD fellowship program in September-November 2021 during which I completed chapter four of my thesis and for inviting me to the WIDER Development Conference on Reducing Inequality in 2022 which provided a forum for me to present my paper and get constructive feedback. More specifically, I owe my gratitude to Dr Simone Schotte for the guidance, remarkable input and mentorship during and after the duration of my fellowship. Thank you to Dr Carlos Gradin for the valuable comments on my chapter.

I am grateful to the University of Cape Town Digital Library Services especially geographical information systems (GIS) officer Thomas Slingsby, for his invaluable support in acquiring some of the data used in this thesis. My appreciation also goes to the University of Cape Town high performance computing (HPC) team especially Andrew Lewis for giving me access to their resources and guidance on the best way to utilise them which made the computer-intensive analysis on geographically weighted regressions in chapter three and recentered influence function decompositions in chapter four possible.

Last but not least, I thank God for giving me the graces and strength to complete this PhD journey. I do not take it for granted that I was able to come this far.

ABSTRACT

Maternal and child health outcomes are an important indicator of a country's well-being. Kenya has less maternal and child mortality levels compared to Sub-Saharan Africa averages, but it still performs worse compared to the rest of the world. Some of the reasons behind this are the prohibitive costs of accessing maternal health care, lack of access to quality health care and longer distances to health facilities. One of the ways that have been touted as a way of improving these outcomes is the utilisation of maternal health care from skilled providers. In this thesis, I seek to explore the maternal and child health outcomes in Kenya in relation to accessibility, spatial distribution, equality and free maternal care in Kenya.

The second chapter tackles the description of data, construction of variables relevant to the rest of the thesis, maps the health facilities offering maternal health care in Kenya and presents the framework within which I conduct my analysis. The data used throughout my thesis are drawn from the Kenya demographic and health surveys (DHS) collected in 2003, 2008/09 and 2014. DHS surveys have a rich set of information on individuals and households. However, it lacks information on health facility characteristics which are pertinent in determining maternal and child health outcomes. I, therefore, endeavored to introduce supply-side factors which are not traditionally included in DHS data into the analysis of issues surrounding maternal and child health. The constructed asset index shows an increase in asset wealth between 2003 and 2014. A mapping of the health facilities offering maternal health care in Kenya shows a higher density of health facilities in the western, central and southeastern parts of the country. However, the pattern of health facility service provision also follows the population density with more densely populated areas having a higher density of health facilities.

The third chapter serves a three-fold purpose. First, I trace the trend of utilization of three maternal health care services. The utilization shows a significant increase between the 2003 and 2014 surveys. Secondly, a logit regression model is used to examine the factors that determine the utilization of maternal health care when supply-side factors are controlled for. As expected, utilization of maternal health care is found to increase with increases in maternal education levels, household wealth, mother's age at the time a child is born, facility level and alternative supply of health. The utilization is lower for women in rural areas as compared to those in urban areas, for women with more than four children compared to those with less than four children, for married women/living with a partner as compared to those who are single/living alone and for women living further away from a health facility. Spatial

dependence is shown to exist in the utilisation of maternal health care and geographically weighted regression (GWR) models are used to analyze the factors explaining the utilization of maternal health care when spatial dependence is taken into account. GWR models are also used to explore the possibility of non-stationarity existing in the factors that explain the utilization of maternal health care. The largest positive effects on the utilization of maternal health care are in clusters with low maternal education levels, younger mothers and a lower alternative supply of health facilities. The largest reductions in utilization of maternal health care are in areas with mothers who have more children and in rural areas with a lower density of health facilities. Mothers are also more likely to utilize higher-level health facilities in areas with a higher density of higher-level health facilities.

High inequalities have been shown to exist in the utilisation of maternal health care services due to differences in socioeconomic, demographic and access to health facilities. In the fourth chapter, I, therefore, aim to analyse the inequality arising from socioeconomic factors, more specifically from differences in asset wealth. I describe the evolution of inequality in the utilisation of maternal health care using Wagstaff concentration indices and assess the differences in inequality arising from the introduction of the free maternal care (FMC) program in Kenya. I also decompose the factors that explain the inequality in the utilisation of maternal health care between the poor and non-poor using recentered influence functions (RIFs). The results show the presence of substantial inequalities which favour the non-poor. The main contributor to this inequality is the maternal level of education. The introduction of the FMC program saw an increase in the utilisation of maternal health care by both the poor and non-poor groups. However, the difference in inequality levels was not significant.

One of the mechanisms used by governments to encourage women to seek maternal health care services from skilled providers is the reduction or removal of user fees. In chapter five, I review the free maternal care (FMC) program introduced in Kenya in June 2013 which made antenatal, delivery and postnatal care free in public health facilities. I seek to analyse the impact of free maternal care on the levels of neonatal mortality in Kenya by comparing the births that occurred in the 16 months before and after the start of the FMC program using the matching difference-in-differences (MDID) method of estimation. The births in public health facilities make up the treated group while the births in private health facilities and at home and other places make up the control group. The results show a significant increase in the utilisation of maternal health care services after the start of the FMC program. However, the MDID results show an increase in neonatal mortality when MDID estimation is done by comparing births in public health facilities and those at home and other places. This indicates that while the cost of maternal health care services is an important determinant of utilisation, other key factors exist that also determine utilisation.

In sum, I introduce supply-side factors to the analysis of maternal and child health outcomes using demographic and health surveys. I find that spatial dependencies exist in the utilisation of maternal health care and utilise an appropriate spatial model to analyse the factors explaining the utilisation of maternal health care. I also find that inequality in the utilisation of maternal health care exists and the decomposition of the factors explaining this inequality shows that maternal education levels and place of residence are the key determinants. Finally, an investigation of the free maternal health care program shows a curious result with neonatal mortality increasing which is contrary to expectations.

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LIST OF ABBREVIATIONS

ANC	Antenatal Care
ASAL	Arid and Semi-Arid Lands
CI	Concentration Index
DHS	Demographic and Health Survey
FMC	Free Maternal Care
GWR	Geographically Weighted Regression
KM	Kilometres
KSH	Kenya Shilling
KMHFL	Kenya Master Health Facilities List
PNC	Postnatal Care
PCA	Principal Component Analysis
RIF	Recentered Influence Function
SSA	Sub-Saharan Africa
UC PCA	Uncentered Principal Component Analysis

CHAPTER ONE: INTRODUCTION

1.1.Background

Maternal and child health is an important indicator of a country's well-being. This is clearly shown by the vast number of policies initiated to improve maternal and child health outcomes. Maternal and child health falls under the third sustainable development goal (SDG) which seeks to ensure healthy lives and promote well-being for all at all ages. Under the SDGs, the maternal mortality rate and neonatal mortality are envisaged to reduce globally to less than 70 per 100,000 live births and less than 12 deaths per 1,000 live births respectively by the year 2030. For this reduction to be achievable, antenatal care, postnatal care and hospital-based deliveries will play a huge role (The United Nations, 2015).

Maternal and child health outcomes in Sub-Saharan Africa (SSA) are poor compared to the rest of the world. Figures 1.1 and 1.2 show the trend in maternal and neonatal mortality rates over time since the year 2000.[1] As of 2012, SSA had a maternal mortality ratio of 596 per 100,000 live births which was more than twice the world average which stood at 234 per 100,000 live births. With respect to neonatal mortality, SSA had 31 per 1,000 live births compared to 20.8 per 1,000 live births which was the world average. Kenya had better outcomes than SSA in the same period but still had worse outcomes than the world average. The maternal mortality ratio stood at 373 per 100,000 live births while neonatal mortality was 22 per 1,000 live births. Only 44 per cent of total births were taking place in a health facility. This problem has been attributed to a lack of access to quality health care, prohibitive costs and distance to health facilities (O'Donnell *et al.*, 2008; Bourbonnais, 2013; Lang'at and Mwanri, 2015; Njuguna, Kamau and Muruka, 2017; United Nations Children's Fund *et al.,* 2019; World Health Organisation *et al.,* 2023).

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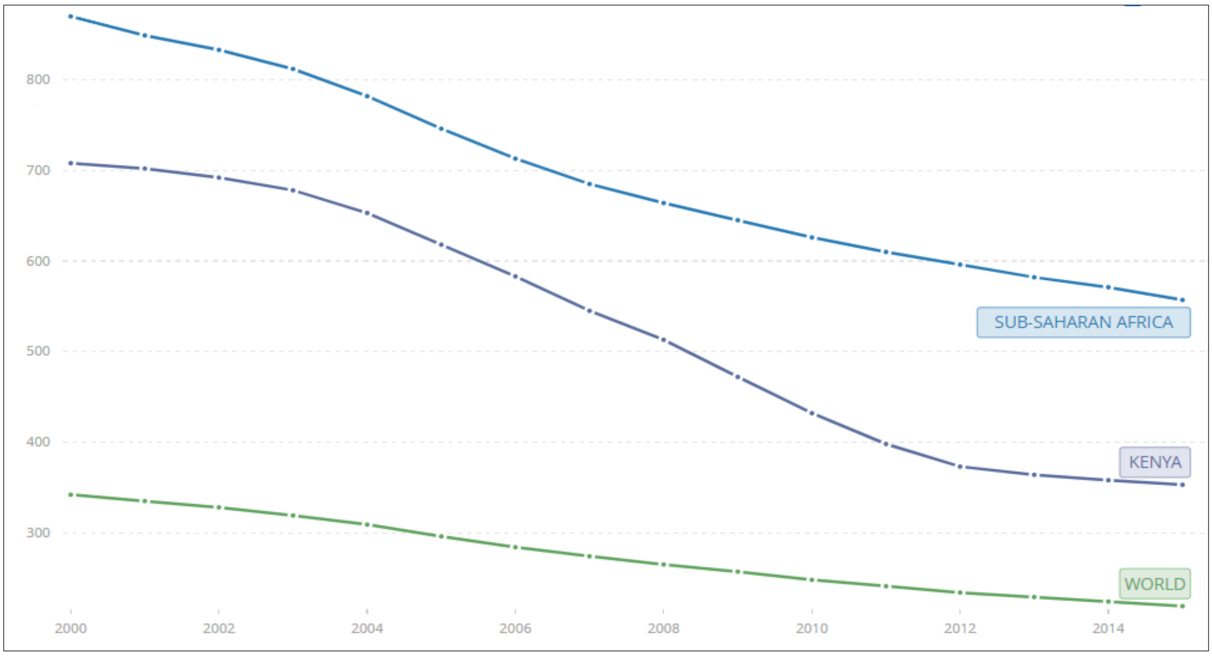
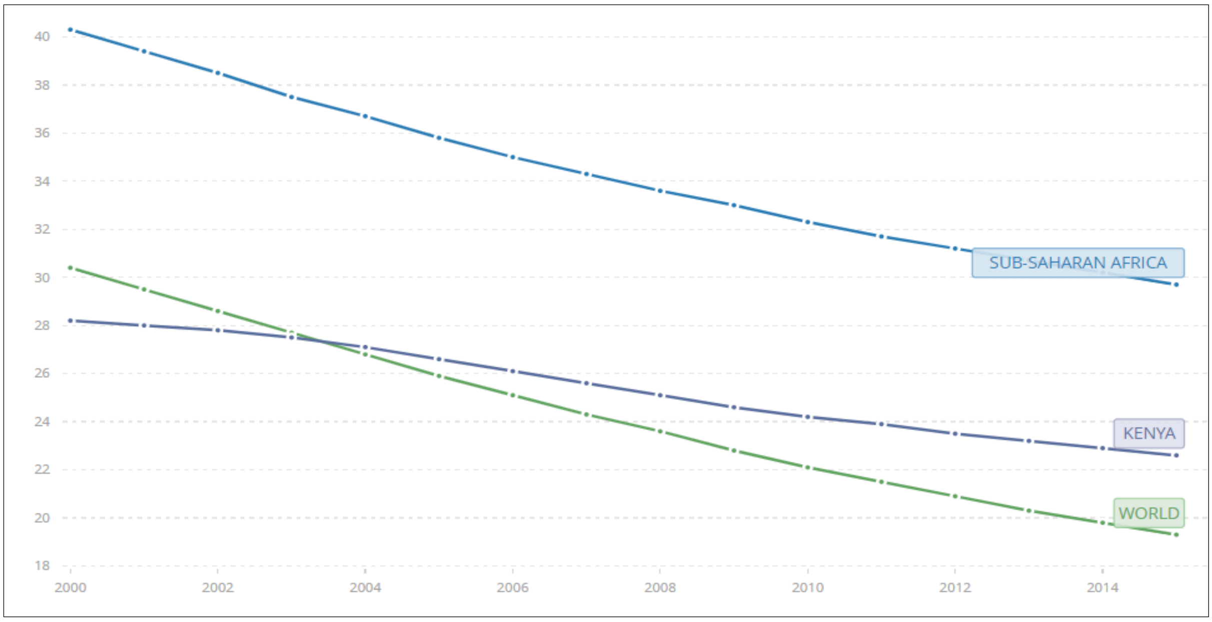
[1] *The data used in the thesis was primarily drawn from the Kenya Demographic and Health Surveys collected in 2003, 2008/09 and 2014. The data from the World Bank used in the graphs was thus extracted to match the data used in my analysis.*

Figure 1.1: Maternal mortality rate (deaths per 100,000 live births) in Kenya, Sub-Saharan Africa and the World between 2000 and 2015



Source: (World Health Organisation et al., *2019)*

Figure 1.2: Neonatal mortality rate (deaths per 1,000 live births) in Kenya, Sub-Saharan Africa and the World between 2000 and 2015



Source: (United Nations Children's Fund et al., *2019)*

Attendance of antenatal care (ANC) clinics, delivery in health care facilities and postnatal care (PNC) clinics have been shown to increase the chance of survival for pregnant women and their children before, during and after delivery. According to the World Health Organization (WHO) guidelines, an expectant woman should attend at least four antenatal care visits from a skilled provider before delivery. A skilled provider refers to a doctor or nurse. It is recommended that the first two visits should be made in the first two trimesters and that the last two visits should be made during the third trimester. Attendance of ANC clinics ensures that any issues that a mother or child may have before birth are addressed. Mothers are advised on the proper way to take care of themselves in terms of nutrition and changes they have to make to their lifestyle in light of their new status. They are also advised to get to the nearest health facility should any warning signs arise that may indicate that all is not well with the child or themselves. Attendance of ANC clinics has also been shown to increase the probability of a woman carrying a child to full term and reduce the risk of perinatal and neonatal mortality (Brown *et al.*, 2008; Arthur, 2012; Lambon-Quayefio and Owoo, 2014; Singh *et al.*, 2014; World Health Organisation, 2015; Arunda, Emmelin and Asamoah, 2017).

Deliveries in the hospital reduce the chances of maternal and neonatal mortality. Mothers are given a safe environment to deliver assisted by qualified health professionals. Any complications arising during delivery are better handled thus increasing the chances of survival for both the mother and the child. As of 2013, more than half the women in Kenya were delivered without the help of skilled birth attendants thus contributing to high maternal and neonatal mortality rates (Lang'at and Mwanri, 2015; Gitobu, Gichangi and Mwanda, 2018).

Postnatal care (PNC) visits are important in terms of immunizations of the baby to protect them from various diseases such as tuberculosis, diphtheria, polio and tetanus. This is especially important for young children since their immune systems are weak. The child's growth progress is also monitored as to whether they are gaining weight and height as they should. The mother's healing progress after birth is also monitored. Attendance of postnatal clinics has also been shown to reduce maternal mortality According to the World Health Organisation, the first postnatal care assessment should be done within the first 48 hours after delivery with additional postnatal care visits after 3 days, 7-14 days and six weeks after birth (Magadi, Diamond and Madise, 2001; World Health Organisation, 2013, 2015).

The utilisation of maternal health care services has been shown to rely heavily on socioeconomic and demographic factors. These factors predispose and enable women to be able to seek services from health facilities. Another vital component that determines utilisation is the characteristics of the health system. A health care system is defined by its organisation and the volume of resources that are allocated relative to the population served. Resources include human capital, physical capital and labour while organisation entails how the system uses its resources. The size, type and geographical distribution of health facilities are also important determinants of whether to use a health facility or not. The socioeconomic and demographic factors when coupled with the characteristics of the health system such as resources, organization and financing, determine the choice of health facility used (Andersen and Newman, 2005; McKinnon *et al.*, 2015).

The utilisation of maternal health care in health facilities is fraught with challenges. These include the prohibitive cost of access, both in terms of distance travelled to reach a health facility and costs paid at the health facility to receive the service. One of the interventions by governments to lighten the burden of prohibitive costs on mothers is the reduction or removal of user fees. Free maternal care (FMC) was introduced in public health facilities in 2013 to encourage women to take advantage of maternal health care services which in turn would help in alleviating deaths of both mother and child before, during and after delivery. The health facilities are required to provide maternal health care services for free and then the Ministry of Health later reimburses them. After the inception of the FMC program, some health facilities reported a 100% increase in facility based deliveries. For the free maternal care program to work, the government allocated Kshs. 3.8 billion (approximately USD 38 million) which was approximately 36% of the national government's budget for health to fund the free maternal care program in the 2013/2014 budget. The government would then reimburse Kshs. 17000 (approximately USD 170), Kshs. 5000 (approximately USD 50) and Kshs. 2500 (approximately USD 25) to tertiary (level six) hospitals, county (level four and five) hospitals and health centres (level two and three), respectively for every delivery conducted in the facility. The different reimbursement levels are based on the different capacities that hospitals on distinct levels have in managing delivery complications. Both normal and caesarean deliveries were reimbursed the same amount. An additional Kshs. 3.6 billion (approximately USD 36 million) was also allocated to hiring 7500 additional workers to cope with the expected increase in hospital attendance. The reimbursement amount to the health facilities has not changed since the inception of the free maternal care program (Bourbonnais, 2013; The World Bank Group, 2014; Ministry of Health, 2015; Wamalwa, 2015; Njuguna, Kamau and Muruka, 2017; Tama *et al.*, 2017; Gitobu, Gichangi and Mwanda, 2018).

Given the importance of the services described above, I therefore endeavour to explore issues around maternal health care in relation to the utilisation of maternal health care services and maternal and child health outcomes. This is done in a couple of contexts. First, I introduce supply-side variables to demographic and health survey data. This allows for an investigation of the importance of accessibility and quality of health facilities in determining utilisation and inequality in the utilisation of maternal health care services. Secondly, an exploration of spatial dependency in the utilisation of maternal health care allows for the use of appropriate spatial models for analysis. Lastly, an examination of the free maternal care program in Kenya allows for an assessment of the effects and impacts of subsidising the costs associated with the utilisation of maternal health care.

1.2.The Organisation of the Thesis

The rest of the thesis is organised into five chapters. Chapter two presents the data sources and the variables that will be retrieved from each source. Mapping of health facilities offering maternal health care in Kenya is also undertaken. I conclude the chapter by presenting the framework within which the analysis is conducted, defining the variables as used in the context of this thesis and noting the data limitations. In chapter three, I analyse the factors that explain the utilisation of maternal health care when supply-side factors are introduced to the analysis. I test for the presence of spatial dependency in the utilisation of maternal health care services and spatial non-stationarity in the factors that explain this utilisation. In chapter four, I investigate whether inequality exists in the utilisation of maternal health care between the poor and non-poor in Kenya and decompose the factors that explain this inequality. In chapter five, I evaluate the impact of the FMC program in Kenya on neonatal mortality. In the last chapter, I present the summary of findings, policy recommendations that can be drawn from the analysis in this thesis and possible areas for further research.

CHAPTER TWO: DESCRIPTION OF DATA, VARIABLE CONSTRUCTION AND DATA LIMITATIONS

All the core chapters in this thesis use the same data sources. Therefore, in this chapter, I address data issues to avoid repeating them in subsequent chapters. Firstly, I present the source of the data used in this thesis and construct variables which are not provided in the sources but are core to the analysis; i.e., an asset index measuring the household asset wealth and supply-side variables measuring hospital characteristics. Secondly, I map the distribution of health facilities offering maternal health care in Kenya. Thirdly, I define the variables as used in the context of this thesis and provide descriptive statistics for the data. Fourthly, I present the framework within which the analysis in this thesis is conducted. Finally, the limitations of the data are discussed.

2.1. Data Sources

2.1.1. Demographic and Health Surveys (DHS)

DHS surveys provide data on the socioeconomic and demographic characteristics of the individuals and the maternal health outcomes of interest in this thesis. Data from the 2003, 2008/09 and 2014 surveys are utilised. The choice of these three surveys is mainly driven by the availability of a homogenous set of data that is used in the construction of the asset index. The data was collected through a two-stage sampling design framework. A sampling frame is constructed from the most recent census which gives a complete list of primary sampling units/enumeration areas/clusters and their populations. The 2003 and 2008/09 sampling frames are based on the 1999 population and housing census while the 2014 sampling frame was based on the 2009 population and housing census. The primary sampling units are first stratified by geographical areas; i.e., provinces, and secondly by urban and rural differences. Systematic sampling is then done within the clusters to determine the households that will be included in the sample. The data are then weighted such that the sample is considered to be nationally representative. Table A1 in appendix A presents an overview of the clusters and number of women interviewed in each of the DHS surveys and the number of children born to women interviewed in each survey. DHS also provides geographical coordinates for the centroid of the clusters interviewed which will be useful in the construction of supply-side variables as described later in this chapter. The Kenya 2014 DHS data was conducted in 1612 clusters. 1594 of these clusters had the necessary sample for use in this thesis; i.e., births within 5 years of the 2014 DHS survey. The data used has births that occurred within five years of the 2003, 2008/2009 and 2014 surveys. Within this period, 32930 children were born; i.e., 5940, 6059 and 20931 children in the 2003, 2008/2009 and 2014 surveys, respectively. These children were born to 22963 individual women; i.e., 3968, 4071 and 14924 women in the 2003, 2008/2009 and 2014 surveys, respectively. Figure A1 in appendix A shows the distribution of the clusters interviewed in the Kenya 2014 DHS survey (Central Bureau of Statistics, Ministry of Health and ORC Macro, 2004; Kenya National Bureau of Statistics and ICF Macro, 2010; Kenya National Bureau of Statistics and ICF International, 2015).

2.1.2. Kenya Master Health Facilities List (KMHFL)

While DHS are rich in demographic and socioeconomic characteristics of the women and households that make up the samples in these surveys, they are lacking in health facility information. This implies that most studies which use DHS data lack information on the accessibility and characteristics of health facilities which are pertinent in explaining utilisation and in turn maternal and child health outcomes. This thesis, therefore, aims to introduce supply-side variables by appending health facility data from the Kenya master health facilities list (KMHFL) to DHS data. The KMHFL provides a list of health facilities currently providing antenatal care, postnatal care and maternity services. The KMHFL provides data on all facilities in Kenya classified in terms of the services they provide, type of facility, ownership, number of beds and cots available, location, operational status and operational hours. Data on the facility level is utilised to represent the quality of the health facility. As of June 2021, there were a total of 13,233 health facilities in Kenya. Out of these, 5,895 were offering antenatal care services, 3,353 were offering maternity services and 3,614 were offering postnatal care services (Kenya Ministry of Health, 2021). Since the DHS data being used is not current, this necessitated determining the health facilities which were open at the time when the survey was conducted to allow for the generation of supply-side variables. To the best of my knowledge, the only dataset containing such information was collected in 2015 (OpenAFRICA and Muthami, 2015). As such, I can only generate supply-side variables for the 2014 survey by trimming down the health facilities to incorporate only those that were operational at that time. This ensures comparability between the data used from the DHS survey and data on health facilities. There were 10,505 operational health facilities in 2015. Out of these, 3,208, 2,103 and 2,155 offered antenatal care, maternity services and postnatal care, respectively. Data from

KMHFL is appended to DHS data and used to construct the variables that will be used in the subsequent chapters of this thesis.[2]

2.1.3. Kenya District Information System (DHIS2), Google Earth and ArcGIS

Data extracted from the KMHFL identifies the location of health facilities up to the ward level which is the lowest administrative level in Kenya. Precise locations are required to enable the calculation of the distance to health facilities variable. Therefore, GPS coordinates of health facilities are sourced from the DHIS2, Google Earth and ArcGIS. These data sources provide data on the latitudes and longitudes of the facilities offering maternal health care services in Kenya. A proportion of the geographical coordinates for the health facilities (62.3%) are then sourced from the Kenya District Health Information Systems (DHIS2), 3.08% from Google Earth, 11.71% from ArcGIS and 22.91% from a dataset on public health facilities in Sub-Saharan Africa. Data with GPS coordinates for Kenya's country boundaries are sourced from Data World (Data World, 2017; Kenya Ministry of Health, 2018; Google, 2019; Maina *et al.*, 2019; Environmental Systems Research Institute, 2020).[3]

2.2 Construction of Variables

2.2.1. Creation of the Asset Index using Uncentered Principal Components Analysis

The socioeconomic status of a mother is a key factor in explaining maternal and child health outcomes. Income and consumption expenditures are good indicators of socioeconomic status. However, the collection of such data has severe limitations due to the intense data collection needed to accomplish this task, seasonal fluctuations, recall problems and reluctance of people to give their actual income figures. Given this, the DHS surveys do not collect incomes or expenditures. Asset-based measures of socioeconomic status are often used instead to represent socioeconomic status (Vyas and Kumaranayake, 2006; Davila *et al.*, 2014).

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2 The data from the KMHFL is appended to DHS data since the data is for two different entities. The KMHFL has information on health facilities and DHS data contains data on individuals and households. Since the two datasets do not share any observations, the data is appended rather than merged. The system in ideal situations is intended to function in a pyramid-like system where the patients

3 Data are presented in the form of Microsoft Excel sheets. Quantum Geographic Information System (QGIS) software (QGIS.org, 2022) is used to generate shapefiles for subsequent use by Stata.

The user-written Stata (StataCorp, 2021) command shp2dta (Crow, 2006) is used to convert shapefiles containing the GPS coordinates on the position of health facilities and the boundaries of Kenya into a format readable by the Stata program.

These measures are calculated using household asset ownership and access to basic facilities. The asset index provided by DHS is calculated using the principal components analysis. However, the components included are not the same over the years. To deal with this challenge, an asset index is created to indicate the socioeconomic status of the households to which the individual women belong. The asset index pools a set of assets owned by the households and the characteristics showing a household's access to basic services which are common across the years. The inclusion of common assets ensures comparability across surveys. An index based on these indicators is also more dependable since people are less likely to give false information about such as compared to when they are asked about their income. The assets are also observable to the interviewer unlike incomes (Fry, Firestone and Chakraborty, 2014; Wittenberg and Leibbrandt, 2017).

The index is thus calculated using indicators for both private assets and access to basic services as shown in Table A2 in appendix A. Categorical variables are converted into binary variables using the definitions by Croft, Marshall and Allen (2018) and Florey and Taylor (2016) since the UC PCA cannot be calculated using categorical variables. The index is calculated using pooled data from three surveys collected in 2003, 2008/09 and 2014 since they contain common assets that are important in explaining the wealth index which are similar across the three surveys. These variables are the source of drinking water, type of toilet facility, the main material for roof and floor, cooking fuel, electricity, radio, television, refrigerator, bicycle, motorcycle, car/truck, telephone/mobile phone, solar panels, land/agricultural land and the number of rooms for sleeping. Table A3 in appendix A shows the proportion of households that own private assets and have access to the basic services that are under consideration to be included in the calculation of the asset index in the surveys. The ownership of motorcycles, phones and solar and access to improved water, improved roof and electricity show an increase from the 2003 to the 2014 survey.

The wealth index is created using the Uncentered principal component analysis (UC PCA) as stipulated in Wittenberg and Leibbrandt (2017).[4] The UC PCA has advantages over conventional methods of calculating asset indices such as factor analysis (FA), principal component analysis (PCA) and multiple correspondence analysis (MCA) since it does not yield negative weights. This ensures that assets that are traditionally considered rural do not give an

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4 Ado file for running UC PCA in Stata is available in Shifa and Ranchhod (2019).

illusion of the owners being worse off than those without the said assets due to being given negative weights. The UC PCA is similar to the PCA in many ways. Therefore, a discussion of the PCA is included and the point of divergence is then discussed. The PCA is formed from a linear combination of weighted assets as shown in equation 2.1, with the first principal component accounting for the highest covariance in the asset index distribution (Shifa and Ranchhod, 2019).

$$\mathrm{a}_1 = \mathrm{v}_{11}\mathrm{A}_1 + \mathrm{v}_{12}\mathrm{A}_2 + \cdots \dots \dots \dots . + \mathrm{v}_{1\mathrm{k}}\mathrm{A}_\mathrm{k}$$

$$\mathrm{a}_2 = \mathrm{v}_{21}\mathrm{A}_1 + \mathrm{v}_{22}\mathrm{A}_2 + \cdots \dots \dots \dots . + \mathrm{v}_{2\mathrm{k}}\mathrm{A}_\mathrm{k}$$

$$\vdots$$

$$\mathrm{a}_\mathrm{k} = \mathrm{v}_{\mathrm{k}1}\mathrm{A}_1 + \mathrm{v}_{\mathrm{k}2}\mathrm{A}_2 + \cdots \dots \dots \dots . + \mathrm{v}_{\mathrm{kk}}\mathrm{A}_\mathrm{k}$$

(2.1)

where:

- a_k represents the k number of assets
- A_k represents the unobserved components that are uncorrelated to each other.

Writing equation 2.1 in vector form:

$$\mathrm{a} = \mathrm{VA}$$

(2.2)

This implies that:

$$\mathrm{A} = \mathrm{V'a}$$

(2.3)

The first component from equation 2.3 can be written as:

$$\mathrm{A}_1 = \mathrm{v}_{11}\mathrm{a}_1 + \mathrm{v}_{12}\mathrm{a}_2 + \cdots \dots \dots \dots . + \mathrm{v}_{1\mathrm{k}}\mathrm{a}_\mathrm{k}$$

(2.4)

Equation 2.4 represents the first principal component analysis (PCA) index. If the indicator variables do not have a mean of zero and a variance of one, they are standardized by first demeaning and dividing the result by the standard error as in equation 2.5.

$$A_1 = v_{11}\frac{a_1 - \overline{a_1}}{s_1} + v_{12}\frac{a_2 - \overline{a_2}}{s_2} + \cdots \ldots \ldots \ldots . + v_{1k}\frac{a_k - \overline{a_k}}{s_k}$$

(2.5)

The uncentered PCA differs from the PCA method since it does not demean the variables. Rather, standardisation is done around zero (Wittenberg and Leibbrandt, 2017). This ensures that the weights are always positive. Standardization is done by dividing the score from the principal component calculation by the mean of the variable. The standardization thus becomes:

$$A_1 = \frac{v_{11}}{\mu_1}a_1 + \frac{v_{12}}{\mu_2}a_2 + \cdots \ldots \ldots \ldots . + \frac{v_{1k}}{\mu_k}a_k$$

(2.6)

Table A4 in appendix A shows the weights from the uncentered principal components analysis compared to the weights from the other methods of calculating the asset index.[5] The results show that the FA and PCA methods of calculating the asset index give negative weights to ownership of bicycles and land. This would imply that owners of these assets are worse off compared to those without these assets. This chapter will therefore use the UC PCA method to calculate the asset index.

Sensitivity analysis is then done to determine the variables that are most important in explaining the variability of the index. This is done by stepwise elimination of the variable with the lowest score and testing the sensitivity of the index to the exclusion of the variable. The smaller the score, the lower the variation among households. This implies that either, the asset is owned by very few or most of the households. To test for the sensitivity of the UC PCA index to the elimination of a variable, Cronbach's alpha is calculated to measure the internal reliability of the UC PCA index. An index is reliable if $\boldsymbol{\alpha}$ is at least equal to or greater than 0.7. An increase in Cronbach's alpha when a variable is excluded means that the internal consistency of the UC PCA index has increased. An increase in internal consistency implies that the remaining assets being used in the calculation of the UC PCA index are more homogenous than before the variable was dropped and therefore the variable should be

5 Multiple correspondence analysis weight is not included in the comparison since MCA is more suitable when variables included are categorical (Greenacre and Blasius, 2006).

excluded from subsequent sensitivity tests of the UC PCA index (Davila *et al.*, 2014). The Cronbach's alpha is calculated as:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k}\sigma_{\gamma_i}^2}{\sigma_x^2}\right)$$

(2.7)

Where:

- k is the number of variables
- σ_x^2 is the variance of the asset index
- $\sigma_{\gamma_i}^2$ is the variance of the individual asset making up the asset index

Feldt's test is also used to decide whether or not to drop a variable (Feldt, Woodruff and Salih, 1987). It calculates the statistic:

$$t = \frac{(\hat{\zeta}_1 - \hat{\zeta}_2)(N-2)^{\frac{1}{2}}}{[4(1-\hat{\zeta}_1)(1-\hat{\zeta}_2)(1-\rho^2)]^{\frac{1}{2}}}$$

(2.8)

Where:

- $\hat{\zeta}_i$ is the $\boldsymbol{\alpha}$ score for model i
- $\boldsymbol{\rho}$ is the correlation coefficient between the two $\boldsymbol{\alpha}$ scores of the models being compared

The Feldt W-statistic tests the hypothesis that the difference in the internal reliability of the $\boldsymbol{\alpha}$ scores from the two models is not statistically significant:

$$H_0 : \hat{\zeta}_1 = \hat{\zeta}_2$$

(2.9)

The results of the Cronbach alpha and the Feldt statistic are given in Table A5 in appendix A. Out of the available 16 available variables, 10 are selected for the calculation of the UC PCA asset index namely ownership of a radio, television, refrigerator and phone. Also included are access to improved water, improved sanitation, improved floors, improved roof, clean cooking fuel and electricity. Table A6 in appendix A presents the weights of the individual components given in the calculation of the UC PCA index for the 2003, 2008/09 and 2014 DHS surveys.

The highest weight is given to owning a refrigerator which is typically owned by more wealthy individuals.

The Spearman rank correlation test is then done to determine whether the ranking of households by the DHS wealth index which is calculated by the PCA method in each survey and the calculated wealth index by the UC PCA method is the same. Table 2.1 shows the results of the Spearman Rank correlation test. The first row presents the Spearman rank correlation test for the full set of indicators as presented in table A2 in appendix A. The second row presents the same coefficient for a reduced sample of assets which are common across the 2003, 2008/09 and 2014 surveys that have been chosen using the Alpha and Feldt tests described above. The following hypothesis is tested:

$$\begin{gathered}\mathrm{H_0}\text{: there is no association between two variables} \\ \text{(rankings are independent)}\end{gathered} \tag{2.10}$$

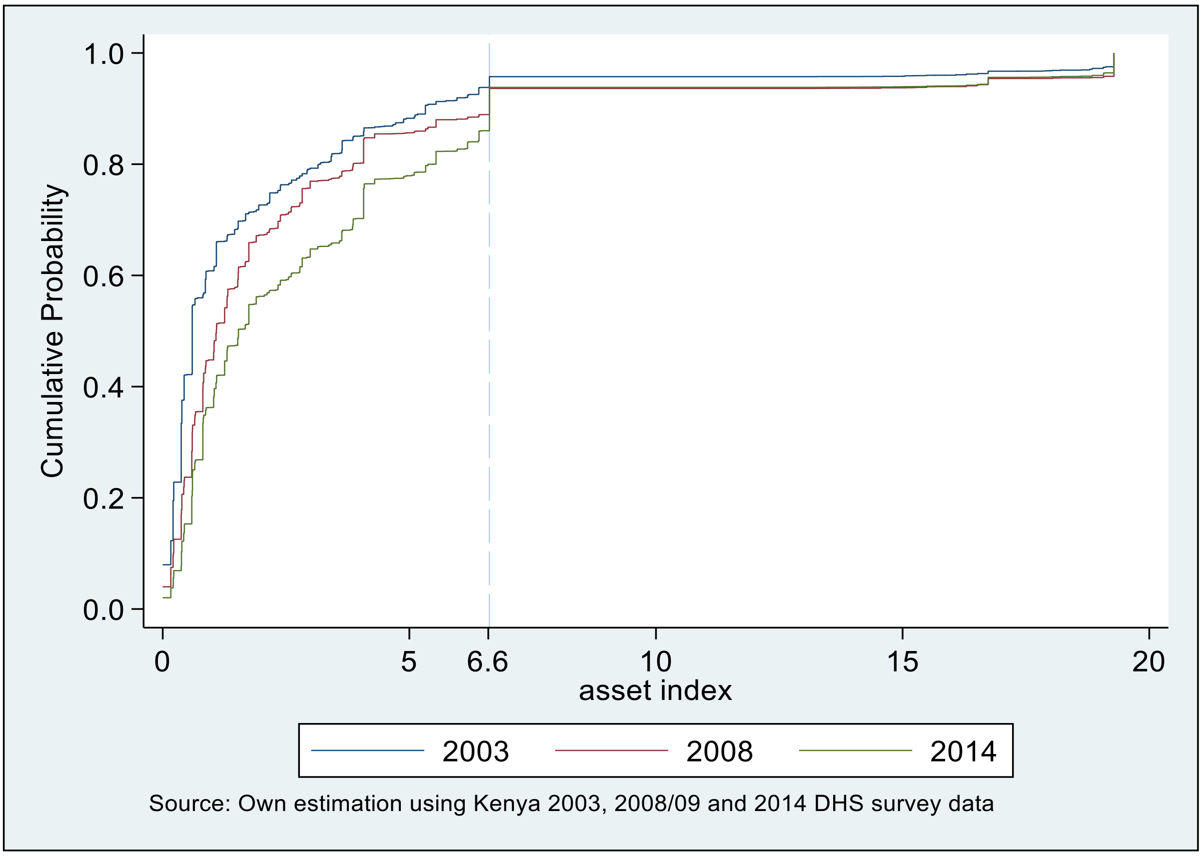
Table 2.1: Spearman's Rank Correlation Coefficient (rho)

	2003	***2008/09***	***2014***
full sample	0.7804	0.8133	0.8094
reduced sample	0.8654	0.8660	0.8541

The results show a high correlation between the rankings of the household under the two methods. This shows that the ranking of individuals by the two methods of calculating the wealth score is very similar. The correlation between the wealth indices provided by DHS is higher when the reduced sample of common assets across surveys is used to calculate the asset index compared to the full sample of assets. The UC PCA method of calculating wealth indices, therefore, performs well by having about the same information as the DHS index calculated using the PCA method while also ensuring that all the wealth scores are always positive. However, the UC PCA still maintain the weaknesses of the PCA. The binary nature of the indicators used in its calculation does not give a higher weight to households owning more than one instance of the same asset. For example, a household owning one fridge will be ranked the same as a household owning more than one fridge.

Figure 2.1 shows the cumulative distribution function (cdf) of the asset index across surveys. The asset index is steep towards the lower end of the asset index distribution. This is as a result of a high proportion of the households being asset-poor and thus clustered towards the lower end of the asset index distribution. The distribution for the 2003 survey is the highest followed by the cdf for 2008 and lastly for the 2014 survey. This is especially so below the 6.6 asset index mark where the cdfs experience a jump beyond which the 2003 cdf remains higher while the 2008 and 2014 cdfs are seemingly on the same level. This shows an improvement in the asset wealth across surveys given that the proportion of households below any specific point is lower, especially on the lower end of the distribution.

Figure 2.1: Cumulative density curves of households across the asset index distribution by survey[6]



2.2.2. Supply-Side (Health Facility Characteristics) Variables

I start by introducing hospital characteristic variables to DHS data which has traditionally not included these variables. These variables are distance to the nearest health facility, size of the

6 Plotted in Stata using the command cdfplot (Mander, 2008).

nearest health facility and alternative supply of health facilities within five kilometres of the dwelling place of an individual. The size of the health facility is given in the KMHFL provided by the Kenya Ministry of Health (2021). The distance to the nearest health facility is not provided and thus must be calculated. The alternative supply of health facilities variable also requires distances to health facilities within a 5-kilometre radius of an individual's residence to be calculated. This section, therefore, explains the procedure of deriving these variables.

As of 2015, 3208, 2103 and 2155 facilities were offering antenatal care, maternity services and postnatal care, respectively. Calculation of the distance to health facilities from the clusters is done by appending the GPS data from the Kenya 2014 DHS survey data on the centroids of clusters to GPS data on health facilities offering maternal health care services. This allows for the calculation of the distance between attributes; i.e., cluster centroids and nearest health facility. Distance to health facilities is calculated as the Euclidean; i.e., straight line, distance between the DHS clusters shown in figure A1 in appendix A and the nearest health facility offering the respective maternal health care service.[7] Alternative supply is calculated as the total health facilities within a five-kilometre radius.[8] A total of thirteen clusters were dropped from the analysis. Of these, 9 clusters were dropped from the analysis since no geographical coordinates were provided and thus supply-side characteristics for these clusters cannot be established. Four clusters were dropped since they could not be mapped to the Kenyan map thus their validity could not be ascertained.[9] Table A7 in appendix A presents the proximity of the clusters interviewed in the KDHS 2014 to facilities offering maternal health care services. 67.05%, 59.47% and 61.30% of the clusters interviewed are within a 5 km radius of a health facility offering antenatal care, maternity services and postnatal care, respectively. A health facility is considered accessible to an individual if it is within 5 km of their dwelling place (Ministry of Health, 2014).

7 Distance to health facilities is calculated using the user-written Stata command nearstat (Jeanty, 2012).

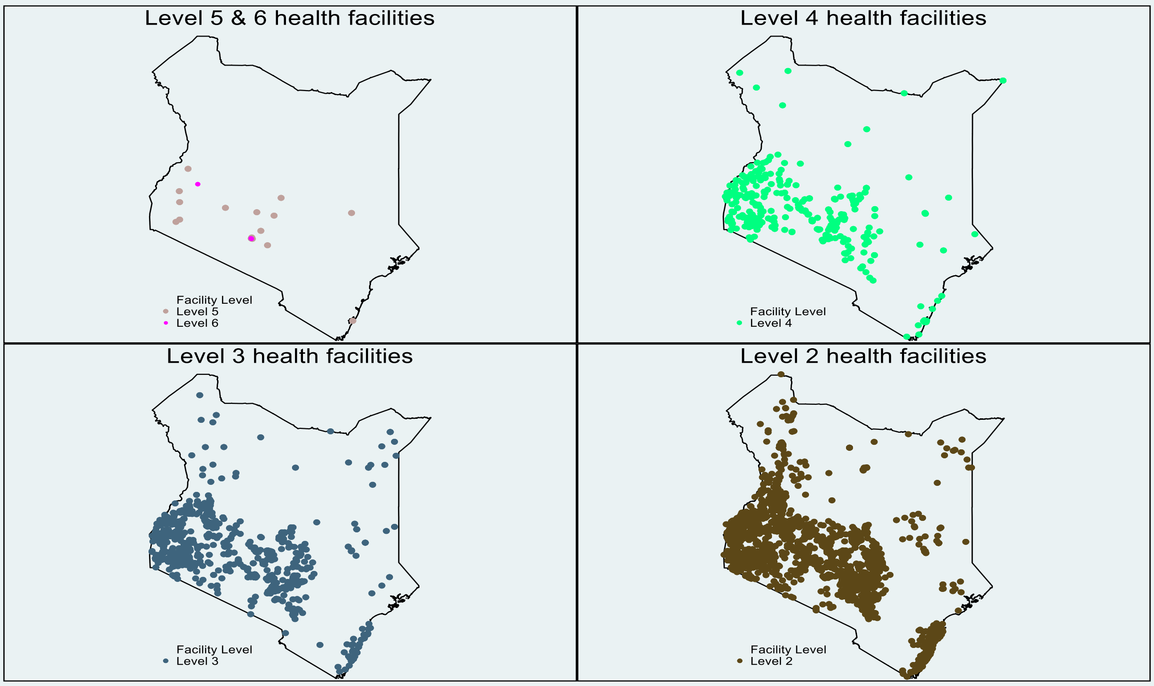
8 The identification of the health facilities within 5 km of a cluster is done using the user-written geonear command (Picard, 2012).

9 GPS coordinate validity tested using a Stata user written program gpsbound (Brophy, Daniels and Musundwa, 2015).

2.3. Spatial Distribution of Health Facilities Offering Maternal Health Care Services in Kenya

The Kenyan health system is ranked from levels 1 to 6. Level 1 are the community health facilities, level 2 are health dispensaries, level 3 are health centres, level 4 are county hospitals, level 5 are county referral hospitals and level 6 are the most specialised; i.e., national referral hospitals. The system in ideal situations is intended to function in a pyramid-like system where the patients start by seeking health care from the lowest level and are referred up the system by a health care professional. However, this is seldom the case as in most situations, the patients decide where to seek health services. This section maps the location of facilities ranked from levels 2 to 6 since community facilities do not offer maternal health care services (Mwabu, 1989; Mariita, 2019). Figure 2.2 shows the distribution of facilities offering maternal health care services pre-2015 across Kenya.[10]

Figure 2.2: Spatial distribution of health facilities offering maternal health care in Kenya as of 2015



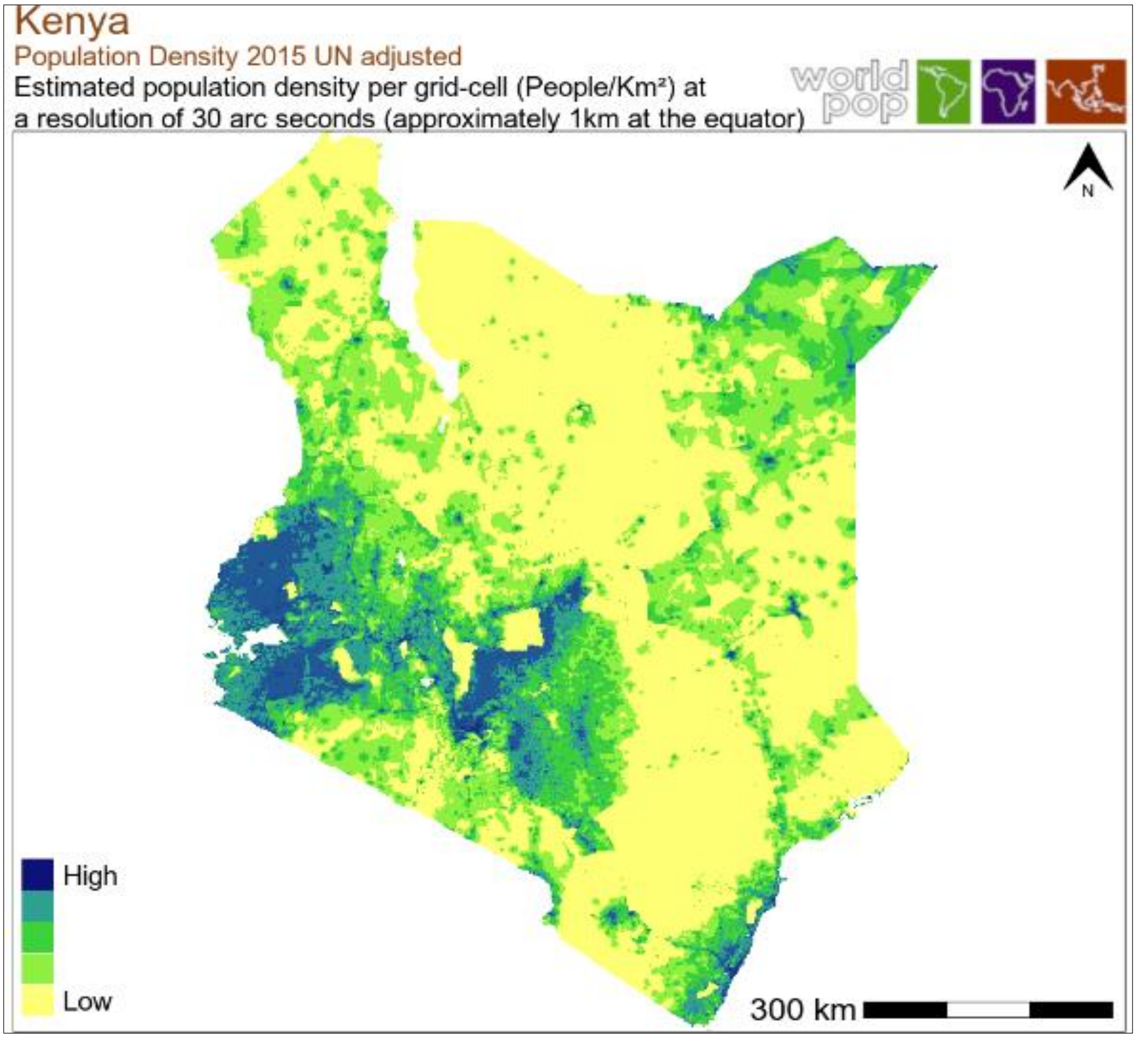
Source: Own illustration using data from KMHFL, DHIS2, Google Earth and ArcGIS

10 *The data are mapped on Stata using a user-written command spmap (Pisati, 2007).*

It is evident that the number of health facilities offering maternal health care services reduces as the level of specialisation increases. The number of tertiary hospitals; i.e., Level 6 health facilities offering maternal health care, was only three as of 2015. Of these, two are located in the Nairobi area while one is located in the North Rift area in Eldoret. This leaves an exceptionally large area of Kenya without any specialist services and as such, women needing these services would have to travel exceedingly long distances to have access. There are 16 Level 5 (county referral), 335 Level 4 (county), 746 Level 3 (health centres) and 2182 Level 2 (dispensaries) health facilities offering maternal health care services in Kenya as of 2015. The health facilities are more concentrated in the western, central and south-eastern areas of the country. The rest of the country has a low density of health facilities offering maternal health care to large areas, especially in the northern region showing no presence of level 5 and 6 facilities while the level 2, 3, and 4 health facilities are sparsely distributed. The lower the density, the higher the likelihood of having to travel long distances before accessing a health facility offering maternal health care. The lowest density of health facilities are areas that are considered arid and semi-arid lands (ASAL) in the north and north-eastern parts of Kenya which are traditionally considered marginalised due to the extreme poverty levels, lack of access to education and health facilities, poor infrastructure and lack of food security (Commission on Revenue Allocation, 2012; Mwase *et al.*, 2018).

A possible explanation for the distribution of health facilities is that the health facility pattern follows the demand; i.e., there are more health facilities in areas with a higher population density. Figure 2.3 shows the population density for every 1 km square as of 2015. The mapping is done using a random forest-based asymmetric redistribution which combines remotely sensed data e.g. land cover, observed lights at night and geospatial data such as road networks and census data to generate population densities (Stevens *et al.*, 2015). The densities are adjusted to match the United Nations population estimates. The population density has a similar distribution to the health facility distribution observed in figure 2.2.

Figure 2.3: Kenya's population density for every 1 km2 as of 2015[11]



Source: WorldPop and Center for International Earth Science Information Network (2018)

Figure A2 in appendix A shows the average utilisation of maternal health care services across the clusters interviewed in the Kenya DHS 2014 survey. The patterns of utilisation are similar to the density of health facilities shown in figure 2.2. The utilisation of all the services is higher in the central and western parts of the country which has the highest density of health facilities offering maternal health care services. The areas on the south-eastern boundary of the country also show high utilisation levels even with a lower health facility density compared to the central and western parts of the country. On average, most women did not get the first PNC check from a skilled provider within two days after delivery with most clusters having less than

11 Map is not overlaid with the health facility vectors since the population density map is masked in the areas with high health facility density

20% of the children in the cluster with mothers accessing this service. The highest utilisation of maternal health care is clearly in areas with a higher density of health facilities. Hanlo*n et al.* (2012) hypothesise that it is cheaper for the government to provide services and health infrastructure in more densely populated areas thus resulting in higher coverage of maternal health care in more densely populated areas.

2.4. Theoretical and Conceptual Framework

This section presents the theoretical and conceptual framework within which the analysis in this thesis will be conducted. This thesis adopts the flow model of demand for health care since it incorporates the health care system characteristics as determinants for hospital utilisation alongside user characteristics. Demand for health care is the maximisation of the sum of individual demands subject to the interaction between access to health facilities, population/individual characteristics and supply-side factors such as perceived availability and institutional characteristics of hospital systems (Oliveira, 2002). Assuming an individual i and hospital j, demand constitutes the maximisation of utility, subject to individual characteristics, accessibility costs and hospital characteristics; i.e.,

$$\mathrm{U_i} = \mathrm{f_i}\left(\mathrm{X_i}, \mathrm{G_{i,j}}, \mathrm{A_{i,}} \mathrm{I_{i,j}}, \widetilde{\mathrm{D}}_{\mathrm{i,j}}\right) \tag{2.11}$$

where:

- X_i represents individual characteristics
- $G_{i,j}$ represents accessibility costs
- A_i represents perceptions of hospital care availability
- $I_{i,j}$ represents institutional characteristics
- $\widetilde{D}_{i,j}$ represents the alternative supply of health facilities

The individual socioeconomic and demographic characteristics utilised are well motivated in previous studies on maternal health care utilisation. These characteristics are the mother's education level, wealth, region of residence, place of residence, mother's age when the child is born, parity and marital status (Kovsted, Pörtner and Tarp, 2002; Ejiagha, Ojiako and Eze, 2012; Asamoah, Agardh and Cromley, 2014; Ganle *et al.*, 2014; McLaren, Ardington and Leibbrandt, 2014; Anafcheh *et al.*, 2018; Okosun, 2018).

Accessibility costs are directly related to the distance to the health facility. The higher the distance, the higher the accessibility cost.

$$G_{i,j} = f_i(d_{i,j}) \tag{2.12}$$

Perceptions of hospital care availability depend on accessibility costs, hospital supply and institutional characteristics.

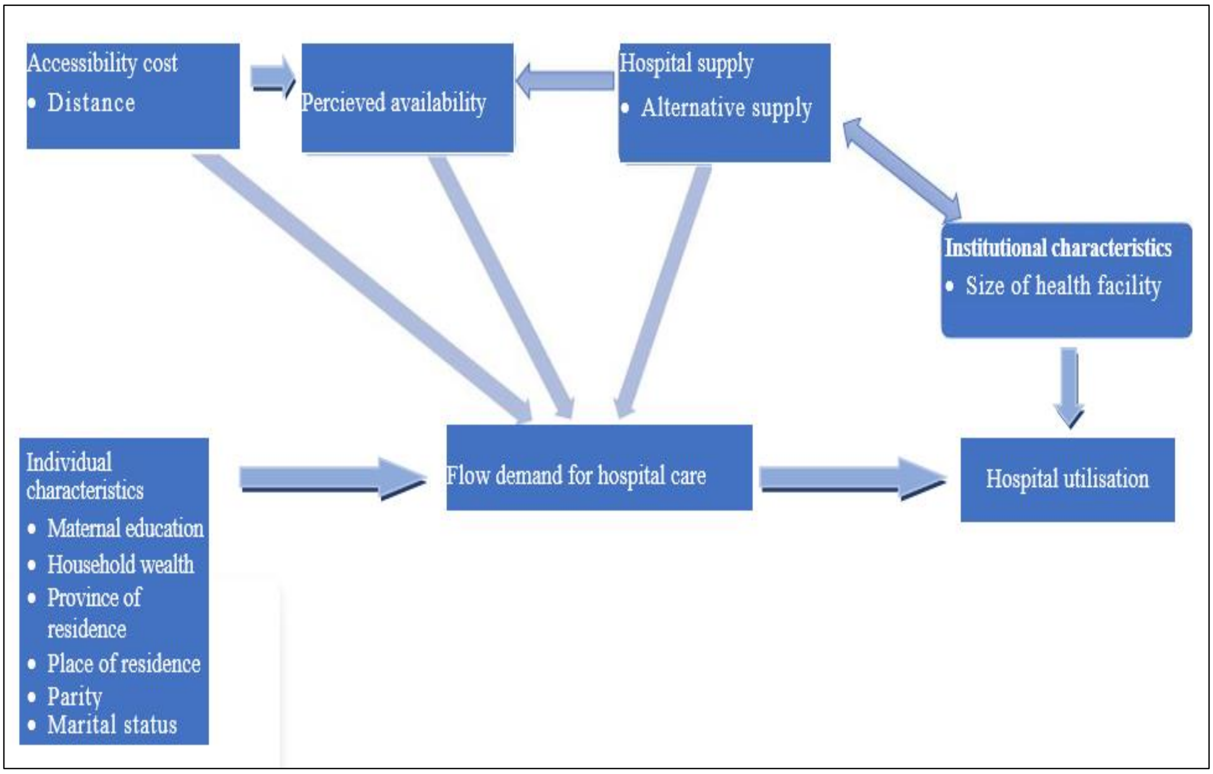
$$A_i = f_i(G_{i,j}, I_j, \widetilde{D}_{i,j}) \tag{2.13}$$

where:

- I_j is the size of the hospital site j
- $\widetilde{D}_{i,j}$ is an index for alternative supply

A summary of the conceptual framework is thus presented in figure 2.4.

Figure 2.4: Framework for analysing utilisation of maternal health care



Source: Adapted from Oliveira (2002)

Table A8 in appendix A presents the definition of variables as used in the context of this thesis. The explanatory variables used throughout this thesis are at various levels:

- Individual mother's level; i.e., mother's education, province of residence, mother's age when the child was born, parity and marital status.
- Household-level; i.e., asset wealth.
- Cluster level; i.e., place of residence, distance to the nearest health facility, size of nearest health facility and alternative supply of health facilities within 5 km of an individual's dwelling.

The characteristics of individuals predispose them to seek maternal health care. However, the woman must also deem the health facility to be available, both in terms of numbers and quality of the health facilities in the vicinity of the individual. The bridge between the demand for health care and the supply of health facilities is the distance between the two entities; i.e., individual women and the health facilities, which determines the accessibility cost, both monetary and time costs that are associated with going to a health facility. The interaction of these three components determines the utilisation of maternal health care.

2.5. Data Limitations

A couple of limitations exist in the use of DHS survey data. One of the contributions of this thesis is the introduction of health facility characteristics to DHS survey data which traditionally have socioeconomic and demographic characteristics of households and individuals. One of the variables introduced is the distance to health facilities. I use GPS coordinates to calculate the distance between the households and health facilities offering maternal health care services. However, the coordinates reported by DHS surveys are for the clusters interviewed rather than for the individual households. As such, the distances to health facilities are equal for all the households in a cluster. At the same time, the distance is calculated as a Euclidean; i.e., a straight-line, distance. This means that the distance calculated does not consider obstacles, infrastructure or geographical attributes that might make the actual distance travelled to the health facility longer. Additionally, since the data on the mode of transport to health facilities is not available, the calculation of travel time to health facilities, which would have been a better indicator of the accessibility cost, cannot be calculated.

The geographical coordinates for the clusters interviewed in the DHS surveys are displaced to make them unidentifiable. The range of displacement is up to 2 kms for clusters in urban areas, 5 km for clusters in rural areas and 10 km for every 100th rural cluster. This results in a measurement error in the distances calculated between health facilities and the DHS clusters (Burgert *et al.*, 2013; Perez-Heydrich, Warren and Emch, 2013). However, this limitation is addressed in section 3.2.2.2.

The KMHFL only shows information about current operational health facilities. Therefore, any information about health facilities which were operational as of 2015 but have subsequently closed is not available. Finally, data collection for the Kenya DHS 2014 started 11 months after the free maternal care program was initiated. Given that a lag might have existed before the program became fully operational, the analysis in the fifth chapter might not fully capture the impact of the free maternal care program.

CHAPTER THREE: ACCESSIBILITY, SPATIAL DISTRIBUTION AND UTILISATION OF MATERNAL HEALTH CARE IN KENYA

3.1. Introduction

In this chapter, I explore the issues surrounding the utilisation of maternal health care in Kenya. I begin by tracking the trend in the utilisation of antenatal care, delivery, and post-natal care by skilled providers in Kenya. Secondly, I examine factors that determine the utilization of maternal health care services. Previous analysis using demographic and health survey (DHS) data has been done only using socioeconomic and demographic factors. Proximity to a health facility determines health-seeking behaviour. Accessibility to health facilities bridges the demand and supply of services. In the DHS 2014 survey in Kenya, 23 per cent of women cited distance to health facilities as impeding the utilization of health facilities (Kenya National Bureau of Statistics and ICF International, 2015).

According to a Kenya Ministry of Health policy report, a health facility is considered accessible to a person if it is within 5 kilometres of their dwelling place (Ministry of Health, 2014; Kenya National Bureau of Statistics and ICF International, 2015). This chapter seeks to incorporate supply-side variables into the analysis of factors determining the utilisation of maternal health care. Lastly, I determine whether spatial non-stationarity exists in the factors that explain maternal health outcomes. Spatial non-stationarity implies that a variable coefficient varies depending on the location of the individual/household. The socioeconomic, demographic and health facility characteristics are bound to be different across space, especially for a large study area such as a country (Ejiagha, Ojiako and Eze, 2012; Harris, 2019). As such, the effect of these characteristics on the utilization of maternal health care varies depending on the location of the individual. Geographic positioning system (GPS) coordinates are used to indicate the spatial location of an individual which is more precise compared to traditional analysis that uses provinces to indicate spatial location. To the best of my knowledge, this kind of analysis has not been done for Kenya.

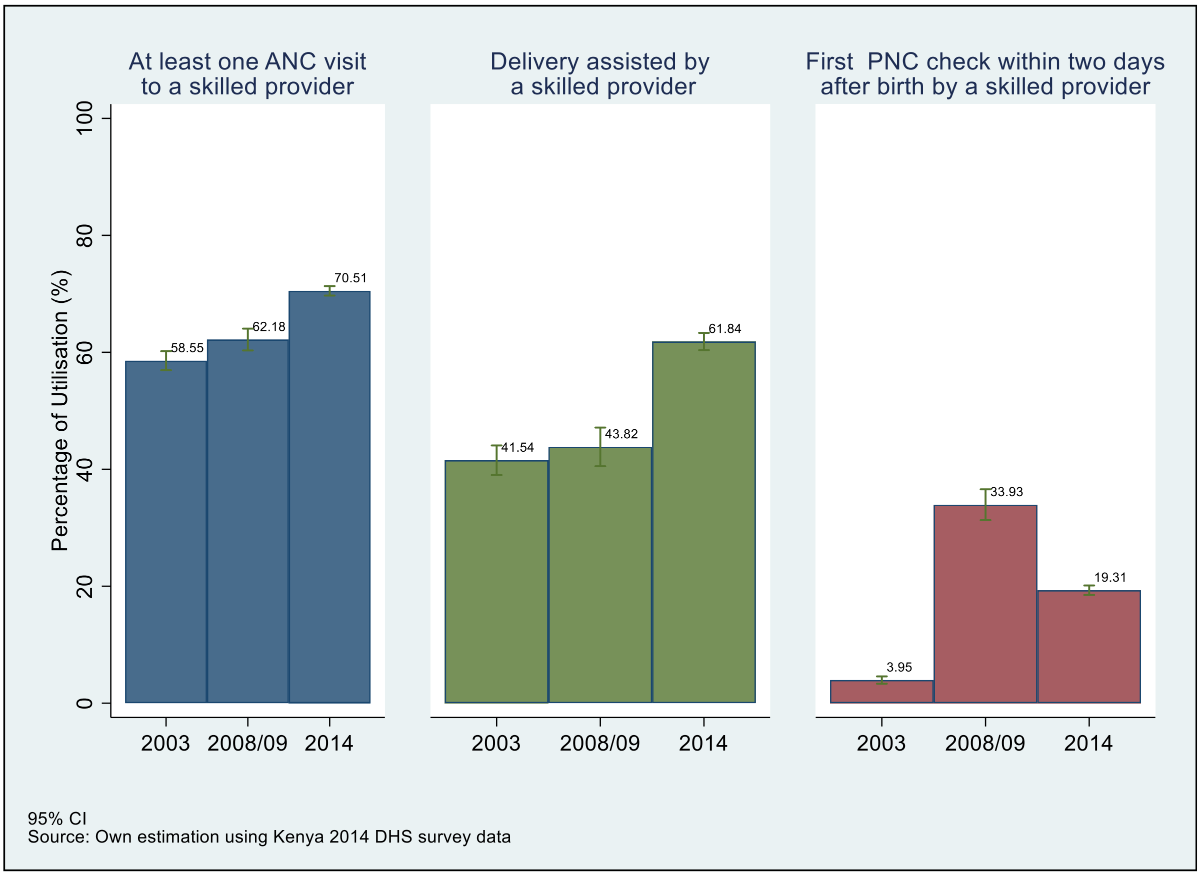
3.2. Methodology and Results

3.2.1. Trend in the Utilization of Antenatal Care, Facility-Based Deliveries and Post-Natal Care Services

This chapter considers children born within five years of the 2003, 2008/09 and 2014 DHS survey dates. The outcome variables are at least one ANC visit to a skilled provider, delivery assisted by a skilled provider and a first PNC check from a skilled provider within two days after delivery. I seek to investigate the trend of these outcome variables across the 2003, 2008 and 2014 Kenya DHS surveys.

Figure 3.1 shows an overview of the utilisation of maternal health care services in Kenya.

Figure 3.1: Utilisation of maternal health care services by survey



The utilisation of ANC and PNC services displays an increase between 2003 and 2008 and a decrease between the 2008 and 2014 surveys. Deliveries assisted by a skilled provider show a decrease between the 2003 and 2008/09 surveys and an ultimate increase in the 2014 survey. These differences in the utilisation of maternal health care services between surveys are all statistically significant except for the increase in deliveries assisted by a skilled provider between 2003 and 2008/09 which is not statistically significant. However, the differences between 2003 and 2014 show a statistically significant increase in the utilisation of maternal health care which spells progress in improving maternal and child health outcomes.

3.2.2. Factors Influencing Utilisation of Maternal Health Care Services in Kenya

3.2.2.1. *Descriptive Statistics*

The sample used in the regressions in this chapter consists of 20,783 children born to 14,820 women and delivered within five years of the 2014 Kenya DHS survey. These women were from 14,294 individual households drawn from 1,581 clusters. There are three outcome variables; at least one ANC visit to a skilled provider, delivery assisted by a skilled provider and first PNC check from a skilled provider within two days after delivery.

Tables B1 and B2 in appendix B present the summary statistics for the data. Only 16.86% of the population received all the maternal health care services under consideration, 33.86% utilised two of the services, 33.36% utilised one of the services and 15.92% did not use any of the maternal health care services under consideration. More than half the women have primary education (54.41%) while women with higher than secondary education have the least proportion at 9.69%. Women with no education and secondary education are 9.74% and 26.15% of the sample, respectively. Rift Valley province makes up the largest proportion of the population at 27.67% while the smallest population is from Nairobi Province at 11.54%. Central, Coast, Eastern, Nyanza, Western and North Eastern provinces make up 10.51%, 10.14%, 12.71%, 13.77%, 11.08% and 2.58% of the population, respectively. Women in the 20-29 age bracket make up the highest proportion of the population at 57.40%. Teenage mothers make up 10.75% of the population and women between the ages of 30-39 years and 40-49 years make up 27.87% and 3.98% of the population, respectively. Women with low parity; i.e., four or fewer live births, are 65.24%.and 81.51% of the women are either married or living with a partner. Households in the 2nd quintile in terms of assets make up the largest proportion at 22.05% while 1st, 3rd, 4th and 5th asset quintile households are 17.29%, 21.81%, 20.16% and 18.69% of the population, respectively.

Rural areas have 56.19% of the population. On hospital characteristics, the average distance to the nearest health facility offering ANC, maternity services and PNC services is 4.27, 5.55 and 6.08 km, respectively. Of interest is that some women are up to 91.73 km away from health facilities offering ANC and maternity services and up to 154.54km away from health facilities offering PNC services. The largest proportion of the women has a level 2 facility as the nearest health facility. This is expected since level 2 facilities are more as compared to health facilities at other levels as shown in figure 2.2. The average alternative supply of health facilities within a 5 km vicinity is approximately 8, 3 and 5 for ANC, maternity services and PNC, respectively.

Interestingly, some of the women have zero alternative supply of health facilities which implies that they have either 0 or 1 health facility offering the respective maternal health care service within a radius of five kilometres.

3.2.2.2. Logit Regression for Maternal Health Care Utilisation in Kenya

I use a logit model for analysis since all the outcome variables used in the chapter are binary. The model is represented as shown in equation 3.1:

Outcome variable=f (mother's education levels, household wealth, region of residence, place of residence, mother's age, parity, marital status, the actual distance to the nearest health facility, size of nearest health facility, alternative supply of health facilities) *(3.1)*

Where outcome variables are at least one ANC visit to a skilled provider, delivery by a skilled provider and first PNC check from a skilled provider within two days after delivery (Ejiagha, Ojiako and Eze, 2012; Asamoah, Agardh and Cromley, 2014; Ganl*e et al*, 2014; McLaren, Ardington and Leibbrandt, 2014; Anafcheh *et al*, 2018; Okosun, 2018).

The distance between a household and the nearest health facility is measured by calculating the distance between their geographical coordinates. However, the geographical coordinates provided by DHS are displaced to make the precise locations unidentifiable. As such, the distance calculated is measured with an error as shown in equation 3.2.

$$\text{actual distance} = \text{calculated distance} + \mathrm{U} \tag{3.2}$$

where $U \in [-2,2]$ for urban clusters, $U \in [-5,5]$ for rural clusters and $\mathrm{U} \in [-10,10]$ for every 100th rural cluster (Burgert *et al.*, 2013; Perez-Heydrich, Warren and Emch, 2013).

To counter this, we use the technique presented in Perez-Heydrich, Warren and Emch (2013) to predict the true distance to health facilities given the observed distances and measurement error. The predicted value of the distance variable is calculated as:

$$\hat{x}_i^{(t)} = \hat{\mu}_x + \frac{\hat{\sigma}_x^2}{\hat{\sigma}_u^2 + \hat{\sigma}_x^2}\left(x_i^{(0)} - \hat{\mu}_x\right) \tag{3.3}$$

where:

- $\hat{x}_i^{(t)}$ is the predicted true value of the distance variable
- $\hat{\mu}_x$ is the mean of the observed value of the distance variable
- $\hat{\sigma}_x^2$ is the variance of the observed value of the distance variable
- $\hat{\sigma}_u^2$ is the variance of the measurement error
- $x_i^{(0)}$ is the observed value of the distance from a cluster to the nearest health facility

Since the specific errors for each cluster are not provided, I generate the measurement error using a random uniform number generator which takes into account the bounds of the measurement error as stipulated in equation 3.2. Table 3.1 presents the regression results for the utilisation of maternal health care services. For each outcome variable, two sets of results are presented. The first column for each outcome presents standard logit regression results using socioeconomic and demographic variables that are traditionally included in DHS surveys while the second column includes the results of the calibrated regression which incorporates hospital characteristics calculated using data from DHS, KMHFL and geographical coordinates.[12]

12 First set of analysis uses the standard logit regression model since it is conducted using only variables from the DHS surveys and therefore it does not have the distance variable that has a measurement error.

Table 3.1: Marginal effects of covariates on utilisation of maternal health care services

VARIABLES	***ANC by Skilled Provider***		***Delivery assisted by Skilled Provider***		***First PNC check within two days by a Skilled Provider***	
	Socioeconomic and demographic characteristics	*Socioeconomic, demographic and supply-side characteristics*	*Socioeconomic and demographic characteristics*	*Socioeconomic, demographic and supply-side characteristics*	*Socioeconomic and demographic characteristics*	*Socioeconomic, demographic and supply-side characteristics*
	Mother's Education (Omitted category: No Education)					
Primary	0.0929***	0.0813***	0.1500***	0.1339***	0.0662***	0.0642***
	(0.0110)	(0.0112)	(0.0190)	(0.0189)	(0.0113)	(0.0117)
Secondary	0.1693***	0.1581***	0.2797***	0.2624***	0.1130***	0.1097***
	(0.0141)	(0.0143)	(0.0208)	(0.0207)	(0.0149)	(0.0153)
Higher	0.1808***	0.1682***	0.4004***	0.3825***	0.1192***	0.1166***
	(0.0193)	(0.0195)	(0.0267)	(0.0267)	(0.0197)	(0.0199)
	Asset Wealth (Omitted category: Quintile 1)					
Quintile 2	0.0408***	0.0377***	0.0644***	0.0572***	0.0391***	0.0384***
	(0.0101)	(0.0100)	(0.0150)	(0.0148)	(0.0091)	(0.0092)
Quintile 3	0.0720***	0.0680***	0.1694***	0.1616***	0.0696***	0.0688***
	(0.0107)	(0.0108)	(0.0160)	(0.0157)	(0.0094)	(0.0094)

Quintile 4	0.1213***	0.1154***	0.2785***	0.2652***	0.1186***	0.1179***
	(0.0132)	(0.0132)	(0.0198)	(0.0198)	(0.0125)	(0.0127)
Quintile 5	0.1612***	0.1535***	0.3724***	0.3524***	0.1230***	0.1189***
	(0.0203)	(0.0210)	(0.0279)	(0.0302)	(0.0184)	(0.0181)
	Place of Residence (Omitted category: Urban)					
Rural	-0.0117	-0.0023	-0.0652***	-0.0407***	-0.0167*	-0.0114
	(0.0090)	(0.0093)	(0.0129)	(0.0128)	(0.0089)	(0.0095)
	Province (Omitted category: Nairobi)					
Central	0.0999***	0.1151***	0.2154***	0.2502***	0.0262	0.0489*
	(0.0266)	(0.0291)	(0.0415)	(0.0425)	(0.0234)	(0.0284)
Coast	0.0671**	0.0823***	0.0499	0.1002**	0.0132	0.0275
	(0.0272)	(0.0292)	(0.0424)	(0.0430)	(0.0222)	(0.0249)
Eastern	0.1084***	0.1232***	0.0651	0.1023**	0.0663***	0.0876***
	(0.0266)	(0.0289)	(0.0409)	(0.0420)	(0.0232)	(0.0283)
Nyanza	0.0290	0.0377	0.0745*	0.0980**	0.0366*	0.0551**
	(0.0268)	(0.0289)	(0.0414)	(0.0413)	(0.0217)	(0.0257)
Rift Valley	0.0127	0.0272	-0.0312	0.0070	-0.0042	0.0164
	(0.0262)	(0.0287)	(0.0397)	(0.0411)	(0.0207)	(0.0263)
Western	0.0387	0.0475	-0.0293	0.0013	-0.0375*	-0.0201
	(0.0273)	(0.0293)	(0.0420)	(0.0426)	(0.0219)	(0.0260)
North Eastern	-0.1291***	-0.0988***	0.0171	0.0778*	-0.0887***	-0.0693***
	(0.0309)	(0.0320)	(0.0474)	(0.0465)	(0.0233)	(0.0265)

	Mother's age at child's birth (Omitted category: 15-19 years)					
20-29 years	0.1030***	0.1021***	0.0053	0.0044	0.0253**	0.0245**
	(0.0128)	(0.0128)	(0.0122)	(0.0120)	(0.0119)	(0.0119)
30-39 years	0.1697***	0.1680***	0.0288*	0.0256	0.0570***	0.0558***
	(0.0156)	(0.0156)	(0.0163)	(0.0163)	(0.0144)	(0.0145)
40-49 years	0.2486***	0.2474***	0.0321	0.0310	0.0552**	0.0523**
	(0.0202)	(0.0202)	(0.0254)	(0.0254)	(0.0235)	(0.0234)
	Parity (Omitted category: low parity)					
High parity	-0.0113	-0.0104	-0.1136***	-0.1121***	-0.0188*	-0.0176*
	(0.0101)	(0.0100)	(0.0114)	(0.0114)	(0.0101)	(0.0102)
	Marital Status (Omitted category: (Not married/not living together)					
Married/Living Together	-0.1001***	-0.0993***	-0.0018	-0.0003	-0.0467***	-0.0464***
	(0.0098)	(0.0098)	(0.0114)	(0.0113)	(0.0106)	(0.0106)
	Size of the nearest health facility (Omitted category: Level 2)					
Level 3		0.0030		0.0397***		-0.0111
		(0.0088)		(0.0125)		(0.0096)
Level 4		0.0212*		0.0441***		-0.0048
		(0.0116)		(0.0162)		(0.0107)
Level 5		0.0537		0.0788*		0.0093
		(0.0328)		(0.0473)		(0.0255)

Level 6				0.1449**		0.0642*
				(0.0650)		(0.0354)
Alternative supply		0.0007		0.0043**		0.0016*
		(0.0006)		(0.0020)		(0.0009)
Distance		-0.0017***		-0.0022***		-0.0001
		(0.0004)		(0.0005)		(0.0003)
Observations	20,783	20,783	20,783	20,783	20,740	20,740

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The coefficients for most of the variables, except for the province coefficients reduce once the supply-side variables are introduced. The standard errors show a mixed result after the introduction of supply-side variables. The probability of a woman using maternal health care increases with an increase in education levels, asset wealth and age at which they bear a child. However, for the case of maternal age at a child's birth, the result for deliveries assisted by a skilled provider is only significant for women between ages 30-39 at the time a child is born compared to teenage mothers. Women living in rural areas are less likely to be delivered by a skilled provider compared to their urban counterparts. Women in Central, Coast, Eastern and Nyanza provinces have a higher probability of utilising maternal health care compared to Nairobi province. The North eastern province presents mixed results with the probability of women utilising ANC and PNC services being lower and that of utilising delivery by a skilled provider being higher compared to women in Nairobi province. The utilisation of maternal health care is higher for women with lower parity; i.e., less than four live births compared to those with high parity. Married women are also less likely to use ANC and PNC services compared to their single counterparts/those living alone. With regard to hospital characteristics, utilisation increases with women having a higher probability of utilising delivery by a skilled provider when the nearest health facility is a level 3, 4, 5 or 6 compared to level 2 facilities. Increasing the alternative supply of health facilities in a 5 km vicinity of an individual increases the probability of utilising deliveries assisted by a skilled provider and receiving the first PNC check from a skilled provider within two days after delivery. Higher distances to the nearest health facility only reduce the probability of receiving ANC and deliveries by a skilled provider.

3.2.3. Spatial Dependency in the Utilisation of Maternal Health Care Utilisation in Kenya

Spatial dependencies exist when measured attributes of entities in one area are dependent on the attributes of surrounding areas. This arises due to two phenomena. The first is spatial heterogeneity which implies that the measured attributes in one area are most likely different from those in other areas across a study space. Secondly, neighbouring areas tend to have very similar measured attributes. This is referred to as spatial clustering. If areas with a high measured attribute are close to other areas with high measured attributes, this is positive spatial autocorrelation. The same applies to areas with low measured attributes surrounded by low measured attributes. If an area with a high measured attribute is close to an area with a low measured attribute and vice versa, this is referred to as negative autocorrelation. Ignoring spatial dependencies, where they exist, leads to a wrong estimation of standard errors and incorrect inferences (Anselin, 1995; Harris, 2019; Ward and Gleditsch, 2019). This section, therefore, endeavours to explore whether spatial dependencies exist in the utilisation of maternal health care in Kenya and if so, use a spatial model to analyse the factors that explain utilisation when spatial dependency is controlled for.

3.2.3.1. Spatial autocorrelation in the utilisation of Maternal Health Care Utilisation in Kenya

Figure A2 in appendix A shows the utilisation of maternal health care across the country. However, the map does not show how similar areas are to their neighbours in terms of utilisation. To assess this, the Moran I statistic is used as a measure of whether spatial autocorrelation exists between the utilisation in a cluster and its neighbours. It also explores whether there is any patterning in the measured attributes (Anselin, 1995; Brunsdon and Comber, 2018).

The first step is to define neighbours to cluster i. Neighbours are defined using a bandwidth which can either be adaptive or fixed. An adaptive bandwidth considers a certain number of clusters close to cluster i as the neighbours while fixed bandwidth considers the observations within a certain distance of cluster i as neighbours. I utilise the adaptive bandwidth since the clusters interviewed are not uniformly distributed as shown in figure A1 in appendix A. As such, the adaptive bandwidth is more appropriate since it takes account of the differences in the distribution. Therefore, a cluster will always have a neighbour even in sparsely distributed areas where the distance between the clusters is large.

The optimal number of neighbours is determined using a bisquare kernel bandwidth which employs a distance decay function where the observations on coordinate *i* are given the highest weight of one and have the largest influence on the local regression for coordinate *i*. The weights of the observations away from coordinate *i* reduce as the distance increases with the observations which are furthest away receiving the lowest weights. The use of a lower bandwidth means that the weights will reduce rapidly with increasing distance while the use of higher bandwidth will result in the weights being almost constant for all the observations used in the local regression (Brunsdon, Fotheringham and Charlton, 1996; Lu *et al*, 2014; Gollini *et al*, 2015; Hajarisman and Karyana, 2016). The more preferable option is to allow the statistical package that is being used to estimate the model, to determine the optimal bandwidth rather than producing one. The optimal bandwidth is calculated as 20.[13]

I then use Moran's I statistic to test the null hypothesis that the observations are spatially independent. It is calculated as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.4}$$

where:

- y_i are the individual observations, in this context clusters
- y_j are cluster i's neighbours
- $w_{i,j}$ is the i, j[th] element of the distance weight matrix. It is a binary indicator equal to 1 if i and j are neighbours and zero otherwise
- S_0 is equal to $\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$

Table 3.2 presents the results of the Moran I test.

Table 3.2: Moran I statistics

	Moran I statistic	***95% CI***		***Expectation***	***p-value***
ANC by a skilled provider	0.3826	0.3680	0.3972	-0.0006	0.0000
Delivery assisted by a skilled provider	0.3933	0.3787	0.4079	-0.0006	0.0000
PNC by a skilled provider	0.2332	0.2186	0.2478	-0.0006	0.0000

The presence of spatial autocorrelation in the utilisation of maternal health care is statistically significant as shown by the expected Moran I statistics being outside the 95% confidence interval of the estimated statistic for all the outcomes. The sign of the statistic is positive thus indicating the presence of positive spatial autocorrelation. This implies that areas with high

13 Calculated using the GWmodel package in R (Gollini et al., 2015).

utilisation of deliveries by a skilled provider have neighbours with high utilisation and vice versa. While this is true at the country level, this scenario might not be true for all the clusters examined.

Figures B1.1-B1.3 in appendix B present the Moran scatterplots which show the different associations that exist between the utilisation within cluster x_i and the weighted mean utilisation of their neighbours Wx_i (Anselin, 2005; Ward and Gleditsch, 2019). The fitted regression line confirms the presence of positive spatial autocorrelation for all the outcomes. However, not all clusters have neighbours with similar values. The plots are divided into four quadrants. The quadrants are determined by the mean utilisation of cluster i on the x-axis and the mean utilisation of cluster i's neighbours on the y-axis. The observations in the top right and bottom left quadrants of the plot display positive spatial autocorrelation; i.e., clusters with high utilisation are surrounded by clusters with high utilisation and vice versa. However, the clusters in the top-left quadrant and the bottom-right quadrants display negative autocorrelation; i.e., clusters with low utilisation are surrounded by clusters with high utilisation and vice versa. The clusters with the highest influence on the global Moran I statistic and the outliers are indicated by crossed diamond points.

These differences in spatial autocorrelation are further investigated using local Moran statistics which are calculated for the 1581 individual clusters. The aim here is to identify pockets of non-stationarity across the study space and assess the influence of individual observations on the spatial autocorrelation observed above (Anselin, 1995). The local Moran I statistic is calculated as:

$$I_i = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{3.5}$$

where the definitions remain as in equation 3.4.

Figures B2.1-B2.3 in appendix B show the local Moran value groups which are statistically significant. The plot shows the utilisation of deliveries by a skilled provider in cluster i in relation to the weighted mean utilisation of the neighbouring clusters. The p-values are adjusted to take into account multiple testing since the local statistics are calculated over and over again for each cluster and are likely to result in false positives; i.e., an indication of spatial autocorrelation where it does not exist (Brunsdon and Comber, 2018). Clusters with high utilisation which have neighbours with high utilisation are mainly concentrated in the central and south-eastern parts of the country. The clusters with low utilisation which have neighbours with low utilisation are mainly in the northern part of the country.

3.2.3.2. Spatial heterogeneity in the utilisation of maternal health care in Kenya

The second aspect of spatial dependency seeks to explore spatial heterogeneity in the utilisation of maternal health care. This would imply that the local statistics at cluster i are statistically different from the global statistics (Brunsdon and Comber, 2018). I use the mean utilisation of maternal health care to assess whether spatial heterogeneity exists. The geographically weighted local means are calculated for each of the 1581 clusters. The calculation employs a distance decay function as before in section 3.2.3.1 where observations in cluster i have a weight of 1 and the weight reduces as one moves away from cluster i. Outside the optimal bandwidth, observations are given a weight of zero. Figures B3.1-B3.3 show the geographically weighted means calculated at the local level. While the local means in most of the clusters are not significantly different from the global mean, some of the clusters in the north of Kenya have significantly lower utilisation of deliveries by a skilled provider compared to the global averages and some of the clusters in central Kenya have significantly higher utilisations compared to the global mean.

Having established the presence of spatial dependencies; i.e., spatial autocorrelation and heterogeneity, in the utilisation of deliveries assisted by a skilled provider, I now proceed to characterise the relationship between utilisation and its determinants using a spatial model.

3.2.3.3. Geographically Weighted Regression (GWR) for Maternal Health Care Utilisation in Kenya

Geographically weighted regressions allow for the exploration of spatial variations in a regression model. Unlike in traditional regression models where the coefficients are constant across a study area and observations are assumed to be homogenous, geographically weighted regressions allow for heterogeneity of observations that arise from regional and geographical differences (Asamoah, Agardh and Cromley, 2014; Hajarisman and Karyana, 2016; Brunsdon and Comber, 2018; Harris, 2019).

Administrative regions such as provinces and states have been used in past studies to show geographical differences as shown in section 3.2.2.2. The mixed signs of the coefficient for provinces could be a result of provinces representing large areas that are likely to have heterogeneous sets of individuals in terms of socioeconomic and demographic characteristics. The access of individuals to health facilities also varies depending on location as shown in section 2.3. As such, the effect of these characteristics on the utilisation of maternal health care is also bound to differ. This forms the basis of utilising GWR models which use geographical coordinates as an indicator for the location which is more likely to have individuals with more homogenous characteristics. The province variable used earlier to indicate the location of the observation is excluded in the GWR analysis in favour of the geographical coordinates which are more precise indicators of location.

Figures B4.1 – B4.4 in appendix B show the average distribution of some of the covariates used in the GWR analysis except for marital status and place of residence. The average level of education for mothers in most of the clusters is primary education (44.91% of the clusters) and secondary education (45.98% of the clusters). On a lesser scale are clusters with an average of less than primary education (5.19%) and only 3.92% of the clusters have high average levels of education (higher than secondary education). Most of the clusters with low levels of education (lower than primary are located in the north and north-eastern areas of the country which are considered as Arid and Semi-Arid Lands (ASAL) which are highly disadvantaged in terms of education due to the nomadic way of life in these areas in search of pasture (Commission on Revenue Allocation, 2012; Kenya National Bureau of Statistics, 2018). The highest proportion of clusters has households in the middle of the asset index distribution (33.40% of clusters are in the third asset quintile) followed by 20.87%, 17.90%, 17.84% and 9.99% of the clusters at quintiles 4,5,2 and 1, respectively. Same as in the case of education, the poorest of the clusters are mostly in the north and north-eastern parts of the country and are thus disadvantaged for the same reasons discussed above in the case of education. The clusters in these areas also have the highest distance to cover to reach the nearest health facility offering maternal health care and as such, this further makes an already tough situation worse; i.e., the mothers have to contend with barriers to utilisation of maternal health care from both the demand and supply-side.

While the average mother's age at the time a child is born and the average number of children born to a mother do not seem to display any discernible patterns across the study space, a substantial proportion of the clusters (24.41%) on average have mothers who are in the lowest age quintile (15-22 years) and have 2-3 children (32.6% of the clusters). Most of the clusters (62.08%) are closest to a level two health facility. This is expected since level two health facilities make up the largest proportion of health facilities as shown in figure 2.2. Most of the clusters (45.86%) also do not have an alternative supply of health facilities within a five km radius; i.e., there is either 0 or 1 health facility within the 5 km radius prescribed by the Ministry of Health to consider a health facility as being accessible (Ministry of Health, 2014).

Given these observed differences across clusters, it is expected that the effect of these covariates on the outcome variables is bound to be different depending on the underlying cluster characteristics which differ depending on the location. GWR models, therefore, serve a twofold purpose. The first is to determine whether there is spatial non-stationarity in the factors that explain the outcome variables; i.e., does the standard regression model which assumes homogeneity of observations explain the relationship between the covariates and the outcomes well, and second, to determine the covariates whose effect on the outcome varies spatially.

The estimation of the GWR models is accomplished in several steps. First, a standard regression also referred to as a global model, is estimated. This model is similar to the logit model estimated in section 3.2.2.2 but excludes the province variable. The global model assumes that the associations between the outcomes and covariates in question do not vary spatially.

$$y = \beta_0 + \sum_{k}^{\rho-1} \beta_k x_k + \varepsilon \tag{3.6}$$

Where:

- y is the outcome variable; i.e., at least one ANC visit to a skilled provider, delivery by a skilled provider and first PNC check from a skilled provider within two days after delivery
- β_0 is the intercept
- β_k is the coefficient for the k^{th} covariate; i.e., mother's education levels, wealth, place of residence, mother's age, parity, marital status, distance to the nearest health facility, size of nearest health facility, alternative supply of health facilities
- ε is the random error
- $\boldsymbol{\rho}$ is the number of regression coefficients to be estimated

Local regressions are then estimated for each of the geographical coordinates. The local regression estimates n*ρ number of coefficients; i.e., ρ coefficients for each of the n locations. The number of clusters with observations relevant to this chapter is 1581. The model is represented as:

$$y_i = \beta_{0i} + \sum_{k}^{\rho-1} \beta_{ki} x_{ki} + \varepsilon_i \tag{3.7}$$

where x_{ki} is the value of k^{th} covariate of location i

The local regression is estimated over a specific bandwidth/ distance from each geographical coordinate. The bandwidth is calibrated to minimise:

$$\sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq i}(B)\right)^2 \tag{3.8}$$

where:

- y_i is the fitted value of the outcome variable from the global regression
- $\hat{y}_{\neq i}(B)$ is the fitted value of the outcome variable from the local regression excluding observations which are at coordinate *i*

The optimal bandwidth is estimated at 0.02863 for all the outcomes under consideration.[14] This is the proportion of nearest observations used per geographical coordinate to estimate the local regression. This translates to approximately 595 observations of the 20,873 available observations being used to estimate the local regressions for ANC and delivery services and 593 of the 20,740 observations used to estimate the PNC services local regressions at each geographical coordinate. Tables 3.3.1 - 3.3.3 present a summary of the local regression coefficients and compare them to the global regression coefficients.[15]

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14 Estimated on Stata using gwr package (Pearce, 1998; StataCorp, 2021). Computations were performed using facilities provided by the University of Cape Town's ICTS High Performance Computing team: hpc.uct.ac.za

15 Estimated on RStudio using spgwr package (Bivand and Yu, 2022).

*The local regressions estimate n*ρ number of coefficients; i.e., ρ coefficients for each of the n locations. This represents 1581*12 coefficients. This would be cumbersome to report. I therefore present the summary of the coefficients which include the range of coefficients, the 1st and 3rd quartiles and the median from the local regression and the global regression coefficients.*

The signs of the coefficients in the global model remain the same as in the regression in table 3.1. The local coefficients show variation with coefficients ranging from negative to positive except for coefficients for years of mother's education which are consistently positive for all three outcomes. The variation in the local coefficients alludes to the possibility that spatial non-stationarity might exist in the factors that explain the utilisation of maternal health care as the coefficient estimates vary depending on the location of the cluster across the study space. To ascertain this, Monte Carlo simulations are used to determine which, if any, of the variables display statistically significant differences in the local regression coefficients as compared to the global regression coefficients. The simulations assign observations to a different geographical coordinate and measure how this affects the local regression coefficients. The hypotheses being evaluated are:

> *H_0: there are no statistically significant differences between the coefficients from the global and local regression; i.e., the coefficients of the covariates explaining outcomes are constant across a geographical location.*
>
> *H_a: there are statistically significant differences between the coefficients from the global and local regression; i.e., the coefficients of the covariates explaining outcomes vary depending on geographical location.* *(3.9)*

Table 3.4 presents the results of the Monte Carlo simulation testing for spatial non-stationarity of the variables which affect maternal health care utilisation.[16] All the covariates considered display spatial non-stationarity for at least one of the outcomes except for the covariate representing marital status.

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16 Estimated in RStudio using GWmodel package (Lu *et al.*, 2014; Gollini *et al.*, 2015; RStudio Team, 2020).

Table 3.3.1: Summary of coefficients for local and global regressions using geographically weighted regression for the outcome measuring attendance of at least one ANC visit to a skilled provider

	Local regression coefficients					**Global regression coefficients**
	Min.	*1st Quartile*	*Median*	*3rd Quartile*	*Max.*	
Intercept	-1.5828	-1.0527	-0.9126	-0.7488	-0.0839	-0.9895
Mother's years of education	0.0287	0.0737	0.0869	0.0961	0.1293	0.0965
Household asset index	-0.0361	0.0067	0.0218	0.0380	0.1391	0.0237
Place of residence (Omitted category: Urban)						
Rural	-0.7439	-0.2351	-0.1302	0.0097	0.5504	-0.1392
Mother's age at child's birth	0.0283	0.0624	0.0703	0.0778	0.1119	0.0700
Number of children	-0.2182	-0.0923	-0.0564	-0.0313	0.0366	-0.0652
Marital status (Omitted category: Single/not living together)						
Married/ living together	-0.4274	-0.6500	-0.4950	-0.3553	-0.1204	-0.4918
Size of nearest health facility (Omitted category: Level 2)						
Level 3	-0.4274	-0.1067	-0.0106	0.0755	0.8635	-0.0597
Level 4	-0.4721	-0.0488	0.0237	0.1678	0.7244	0.0446
Level 5	-1.4553	0.2382	0.3780	0.5037	0.8691	0.4485
Alternative supply of health facilities	-0.0170	-0.0035	0.0026	0.0132	0.0507	0.0036
Distance to the nearest health facility	-0.0467	-0.0120	-0.0053	0.0022	0.0298	-0.0087

Table 3.3.2: Summary of coefficients for local and global regressions using geographically weighted regression for the outcome measuring delivery assisted by a skilled provider

	Local regression coefficients					***Global regression coefficients***
	Min.	*1st Quartile*	*Median*	*3rd Quartile*	*Max.*	
Intercept	-2.80571	-1.90971	-1.43418	-0.74041	0.760351	-1.1424
Mother's years of education	0.064653	0.144125	0.165067	0.179586	0.216519	0.1567
Household asset index	0.012541	0.117969	0.192094	0.271606	0.623003	0.1865
Place of residence (Omitted category: Urban)						
Rural	-2.19194	-0.64525	-0.41404	-0.2232	0.102262	-0.6737
Mother's age at child's birth	-0.00404	0.026856	0.0399	0.061357	0.163521	0.0447
Number of children	-0.70871	-0.31173	-0.18958	-0.16623	-0.10537	-0.2181
Marital status (Omitted category: Single/not living together)						
Married/ living together	-0.42947	-0.04003	0.074251	0.199648	0.659717	0.0551
Size of nearest health facility (Omitted category: Level 2)						
Level 3	-0.61883	0.110196	0.246202	0.435624	0.917065	0.2367
Level 4	-1.2173	0.177445	0.331073	0.537879	1.015911	0.2992
Level 5	-7.01892	0.378279	0.604396	0.955847	14.50597	0.7431
Level 6	-4.57623	-0.23181	0.237001	4.34516	18.19502	-0.0774
Alternative supply of health facilities	-0.06223	-0.00498	0.021853	0.044508	0.999656	0.0108
Distance to the nearest health facility	-0.07304	-0.02305	-0.00926	0.004729	0.079176	-0.0108

Table 3.3.3: Summary of coefficients for local and global regressions using geographically weighted regression for the outcome measuring the first PNC check done within two days after birth by a skilled provider

	Local regression coefficients					**Global regression coefficients**
	Min.	*1st Quartile*	*Median*	*3rd Quartile*	*Max.*	
Intercept	-3.9363	-2.8323	-2.4469	-2.1247	-1.5261	-2.5808
Mother's years of education	0.0093	0.0659	0.0785	0.0932	0.1571	0.0921
Household asset index	-0.0372	-0.0053	0.0059	0.0198	0.0657	0.0064
Place of residence (Omitted category: Urban)						
Rural	-1.0174	-0.3101	-0.2418	-0.1244	0.4981	-0.2160
Mother's age at child's birth	0.0002	0.0271	0.0331	0.0415	0.0833	0.0348
Number of children	-0.1931	-0.0975	-0.0728	-0.0476	0.0356	-0.0779
Marital status (Omitted category: Single/not living together)						
Married/ living together	-0.8036	-0.3938	-0.2517	-0.0929	0.3248	-0.2241
Size of nearest health facility (Omitted category: Level 2)						
Level 3	-0.3509	-0.1170	-0.0226	0.0997	0.4082	-0.0538
Level 4	-1.2029	-0.1146	0.0424	0.2550	0.6947	0.0237
Level 5	-1.2157	0.0631	0.2403	0.3600	5.1356	0.2487
Level 6	-0.3135	0.0797	0.1833	0.2790	1.4549	0.1710
Alternative supply of health facilities	-0.3100	-0.0031	0.0067	0.0109	0.0441	0.0068
Distance to the nearest health facility	-0.1704	-0.0096	0.0017	0.0185	0.0845	-0.0013

Table 3.4: p-values of spatial non-stationarity tests using Monte Carlo simulations

	At least one ANC visit to a skilled provider	***Delivery assisted by a skilled provider***	***First PNC check from a skilled provider***
Intercept	0.31	0.00	0.72
Mother's years of education	0.00	0.00	0.32
Household asset index	0.04	0.00	0.01
Place of residence (Omitted category: Urban)			
Rural	0.86	0.00	0.49
Mother's age at child's birth	0.33	0.00	0.27
Number of children	0.02	0.00	0.10
Marital status (Omitted category: Single/not living together)			
Married/ living together	0.22	0.12	0.79
Size of nearest health facility (Omitted category: Level 2)			
Level 3	0.01	0.00	0.09
Level 4	0.01	0.01	0.17
Level 5	0.68	0.11	0.31
Level 6	-	0.11	0.99
Alternative supply of health facilities	0.67	0.00	0.10
Distance to the nearest health facility	0.00	0.00	0.89

Given the results of the Monte Carlo simulations, figures B5.1-B5.9 in appendix B are plotted to illustrate the spatial distribution of the coefficients for the local regressions of the variables that display statistically significant differences from the global regression coefficients. Since most of the covariates do not display the same patterns across the country for the three outcomes, correlation matrices figures B6.1-B6.3 in appendix B are also included to explore the relationship between the GWR coefficients and the underlying cluster characteristics.[17] Due to the categorical nature of the place of residence and health facility level variables, correlations

[17] *Plotted using a Stata user written command heatplot (Jann, 2019).*

will not suffice and, therefore, the GWR coefficient data for the categorical variables are overlaid on a choropleth map showing the probability of finding a health facility within a 5 km radius to aid in the interpretation of the observed GWR coefficients.[18]

The increase in the probability of utilising maternal health care is highest in the clusters where mothers on average have lower years of education, mothers deliver children at a younger age and have a lower number of alternative supply of health facilities. The largest reductions in the probability of utilising maternal health care are associated with clusters where mothers have relatively more children and rural clusters in areas with a low density of health facilities. As expected, the higher the probability of finding a level 3 or level 4 health facility within a 5 km radius of a woman's dwelling, the more likely they are to utilise it compared to a level 2 health facility. Some of the coefficients, however, display an unexpected trend. The effect of wealth offers mixed results with the effect on ANC services being highest for clusters with the lowest wealth as would be expected but highest for clusters with the lowest wealth for PNC services. The distance covariate also displays the expected effect on delivery by a skilled provider with the largest decreases in the probability of utilisation in the clusters which are furthest from a health facility. However, it displays an unexpected effect on the utilisation of ANC services. The level 4 health facilities show a curious result in the north-eastern parts of the country where areas with a low density of level 4 health facilities have high coefficients for utilisation of ANC services. These results are further discussed in the next section.

3.3. Discussion of Results

Using data from the DHS 2003, 2008/09 and 2014 surveys, we have seen that the utilisation of maternal health care services has increased across the surveys. In comparing the utilisation between successive surveys, the increase is statistically significant with the increase in the utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider being the highest between the 2008/09 and 2014 surveys. The period between the 2008/09 and 2014 DHS surveys was characterised by the inauguration of the free maternal care program which made utilisation of ANC, maternity and PNC services free in public health facilities. The FMC program thus reduced the cost barrier to accessing these services and led to an influx of women seeking these services. This spells progress in the fight against child

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18 Stata user-written commands spgrid used to generate the underlying grid and spkde used to calculate the probability density function (Pisati, 2009, 2011).

mortality since the uptake of more maternal health care services in health facilities is encouraged to ensure improvements in maternal and child health outcomes.

More educated women are more likely to use maternal health care. Education makes women more aware of their needs and the importance of accessing maternal health care in a health facility. More education enables women to get higher-paying jobs and therefore, they can afford to live in areas with better social amenities. Education also improves a woman's standing at home thus giving them decision-making powers on whether to seek maternal health care and where they will seek it. More educated women are also more likely to be aware of programs aimed at improving maternal and child health (Ahmed *et al.*, 2010; Arthur, 2012; Kenya National Bureau of Statistics *et al.*, 2015; Bobo, Yesuf and Woldie, 2017). Higher utilisation of maternal health care is also associated with higher wealth levels. Wealthier people are better placed to cover the direct and indirect costs associated with maternal health care utilisation such as money paid at the health facility for consultation, admission, drugs and transport to the health facility. Wealthier people are also more likely to be insured which increases the scope of health facilities that they can utilise (Ahmed *et al.*, 2010; De Allegri *et al.*, 2011; Zere *et al.*, 2011; Arthur, 2012; Dutta *et al.*, 2018).

Women in rural areas are less likely to use maternal health care compared to women in urban areas. This can be explained by, among other things, the low density of health facilities in rural areas thus necessitating travel over long distances to access these services. Distance to transport networks is also higher in rural areas which further impedes the utilisation of maternal health care (Rosero-Bixby, 2004; Penfold *et al.*, 2007; McLaren, Ardington and Leibbrandt, 2014). In the Kenyan context, most of the health facilities in rural areas are level 2 facilities; i.e., dispensaries which are operational and open only during the day and as such, deliveries happening at night are either done at home or if possible, health facilities in the nearest urban area which are open for 24 hours. The levels of poverty in rural areas are also comparatively higher as compared to urban areas. This further compounds the utilisation problem since wealth offers an added advantage in terms of utilisation (Dutta *et al.*, 2018).

The likelihood of utilising maternal health care increases as the mother's age increases. This can be explained by the risk of complications increasing with the increase in the age of the mother. Older women are more prone to birth complications, pre-term deliveries and prolonged labour which puts the lives of both the mother and child at risk and necessitates closer monitoring of both mother and child before, during and after delivery (Magadi, Diamond and

Madise, 2001; Lambon-Quayefio and Owoo, 2014). The more the number of children born to a woman, the higher the self-confidence that the woman gains in the birthing process especially if previous births were without complications. This, therefore, might explain why women who have had four or more births have lower utilisation of maternal health care compared to women with less than four children (Boah, Mahama and Ayamga, 2018). The likelihood of utilising maternal health care is lower for women who are married/living with a partner compared to their counterparts who are single/living alone. These results are statistically significant for ANC and PNC services. The DHS 2014 survey found that 6% of women failed to access healthcare as a result of not getting permission from their partners/spouses (Kenya National Bureau of Statistics and ICF International, 2015).

The utilisation of deliveries assisted by a skilled provider decreases with increasing distances from health facilities. The further away an individual lives away from the health facility, the higher the time and monetary cost associated with accessing maternal health care services. This is especially worse for poor women who have to contend with the higher transport costs associated with longer distances to health facilities. At the same time, deliveries are a time-sensitive event therefore distance to the nearest health facility is of paramount importance (Aliy and Mariam, 2012; McLaren, Ardington and Leibbrandt, 2014; Hodge *et al.*, 2015, 2016). The size of the health facility was found to be significant in explaining the utilisation of deliveries by a skilled provider. The likelihood of a woman being delivered by a skilled provider increases when the nearest health facility is of a higher level. The higher the facility level, the longer the operational hours, the higher the bed capacity and the higher the availability of skilled health care providers available. This reduces overcrowding and delays and ensures quality care can be provided (Ganle *et al.*, 2014; Mariita, 2019). A higher alternative supply of health facilities also increases the likelihood of a woman having a delivery assisted by a health provider and receiving PNC within two days after delivery by a skilled provider. A higher alternative supply implies more health facilities in the vicinity of an individual from which women seeking maternal health care can choose from.

The distribution of the covariates explaining the utilisation of maternal health care varies across Kenya thus presenting the possibility that their effect on the outcomes will vary depending on the location. One indicator of this possibility is the divergent signs of the coefficients of the GWR local regression estimates from positive to negative for covariates which present a strictly positive/negative coefficient in a standard global regression model. While the coefficients of the global model maintain the same sign as in the previous analysis using the logit regression model, the local coefficients range from negative to positive except for the coefficient for the variables measuring the mother's years of education. The Monte Carlo simulations show the presence of spatial non-stationarity in all but one of the factors that explain the utilisation of maternal health care. Only the effect of marital status does not show spatial non-stationarity for all three outcomes under consideration. This means that the global model does estimate the effect of marital status on maternal health outcomes well. The effect of level 5 and 6 health facilities also do not display spatial non-stationarity compared to level 2 health facilities, possibly due to the small number of these facilities offering maternal health care in Kenya; i.e., only three level 6 health facilities and sixteen level 5 health facilities were offering maternal health care services as of 2015.

Most of the clusters which display high coefficients for mothers' education and wealth are located in the north and north-eastern parts of Kenya. These are areas which are arid and semi-arid lands (ASAL). As such, these areas tend to be marginalised due to low attendance at schools and have higher poverty levels (Kenya National Bureau of Statistics, 2018). Therefore, being more educated in such areas offers a woman a higher advantage in the utilisation of maternal health care. This is similar to results by Ohonba, Ngepah and Simo-Kengne (2019) who found that the effect of maternal education on child health outcomes was higher in South Africa for sub-populations which have higher educational deficits; i.e., Black people and coloureds. Higher education coefficients are also associated with clusters which have wealthier households, older mothers, fewer children per woman and a higher alternative supply of health facilities. More educated women in clusters with richer households, therefore, have a double advantage of being aware of the maternal health care services that they require and having the means to mitigate the barriers that are associated with utilisation such as cost and distance. Wealthier women can also afford to live in areas with enough amenities thus reducing the distance between them and the facilities where they need to seek maternal health care. More educated women are also expected to have fewer children due to having information on the dangers posed by having more children and thus they would be more open to utilising family planning to manage their family sizes (Liu and Raftery, 2020).

The negative effect of a higher number of children on the probability of utilising maternal health care is further exacerbated in clusters where women on average deliver at an older age and for clusters which are further away from health facilities. This fits the expectation that older women are more likely to have more children. The negative effect of distance is especially higher in rural areas which are normally disadvantaged in terms of accessibility due to low density. As expected, for cluster-level variables, clusters with higher distances to the nearest health facility have a higher reduction in the probability of utilisation of maternal health care, a result of higher costs, both time and monetary, that are required to overcome the distance barrier. The clusters with the highest effect of the covariate alternative supply of health facilities also have the lowest distances to the nearest health facility thus augmenting the positive effect of the alternative health facilities. The increase in the probability of utilisation of level 3 and 4 health facilities compared to level 2 health facilities is higher for clusters in areas where the probability of finding a level 3 or 4 health facility is also higher. However, there exist clusters where living close to these higher-level health facilities compared to level two health facilities reduces the probability of utilising the higher-level facilities and an exploration of the reasons why this might be the case would be of added value. Women in rural areas are less likely to utilize maternal health care, especially in clusters with women with lower average levels of education, where mothers deliver at a younger age and with a lower alternative supply of health facilities.

CHAPTER FOUR: INEQUALITY IN MATERNAL HEALTH CARE UTILISATION IN KENYA

4.1. Introduction

Research shows that high inequalities exist in the utilisation of maternal health care, which often fails to reach the poor.[19] Inequality in utilisation may arise from differences in service provision—such as long distances to health facilities, a lack of transport, long waiting times, and low service quality which limit access, particularly in spatially remote areas. In addition, socioeconomic, demographic and cultural factors influence the take-up of maternal health care utilisation. For example, a lack of education may limit awareness and a lack of economic empowerment may limit a woman's decision-making and ability to seek quality maternal health care (Ahmed *et al.*, 2010; Fleurbaey and Schokkaert, 2011; Kim *et al.*, 2016).

To address inequalities in the utilisation of health care stemming from socio-economic factors, one of the interventions that have been employed by governments around the world is the reduction or removal of user fees. In Kenya, free maternal care was introduced in public health facilities in June 2013, to encourage women to seek care in health facilities during pregnancy, delivery and up to 6 weeks after birth. However, this measure does not automatically imply that utilization will increase, as other barriers persist (Ganle *et al.*, 2014; McKinnon *et al.*, 2015; Haider *et al.*, 2017; Santas, Celik and Eryurt, 2017; Fenny *et al.*, 2019). Particularly, access to quality care is a major determinant of whether women seek maternal health care, and differences in access may be key to understanding inequality in service utilisation. This aspect of analysis has majorly been missing from existing analyses, which mainly focus on socioeconomic and demographic characteristics.

Using three rounds of Demographic and Health Surveys (DHS) collected in 2003, 2008/09 and 2014, I quantify the extent of inequality in the utilisation of maternal health care, track its evolution over time, and investigate key drivers that contribute to inequality in the utilisation of maternal health care between the poor and non-poor in Kenya. Specifically, I first descriptively compare differences in service utilisation between poor and non-poor groups,

19 Equality is categorised into horizontal and vertical equality. Vertical equality means that individuals with different health needs are treated differently according to their level of need. Factors that lead to vertical equality include age, disability and level of health. Horizontal equality implies that individuals with the same needs are treated the same way regardless of their socioeconomic status. I focus on horizontal inequality in this chapter.

defined in terms of relative asset wealth, and contrast utilisation rates before and after the removal of user fees. Second, I employ an Oaxaca-Blinder type decomposition analysis using recentered influence function (RIF) regressions to assess the drivers of inequality in the utilisation of maternal health care. Going beyond the demand-side focus of existing studies, I combine the DHS data with information on the availability and characteristics of health facilities, which allows me to account for supply-side factors in the decomposition analysis.

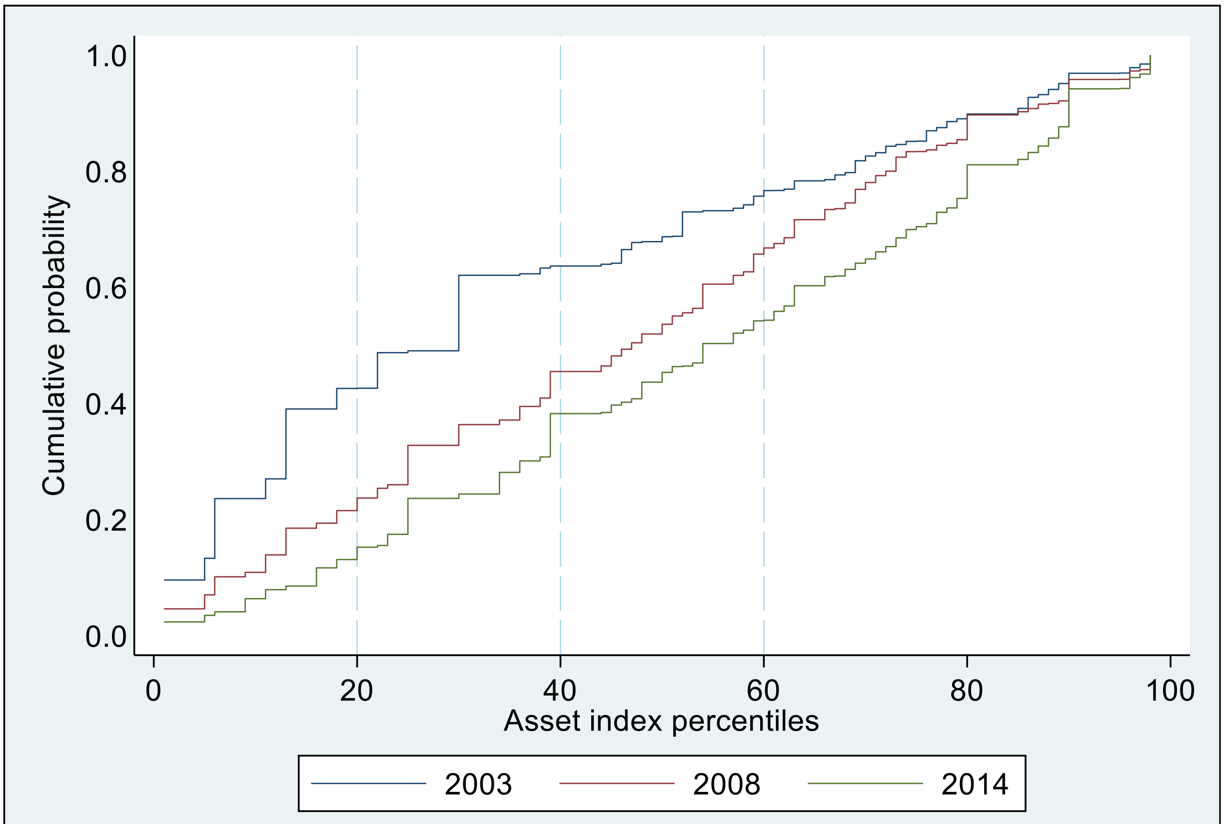
4.2. Methodology and Results

4.2.1. Definition of Asset Poverty

The relative poverty line is set at a cut-off point which is a percentage α of a set standard (Foster, 1998).[20] This study utilises the asset index to measure a household's socioeconomic situation since the demographic and health surveys (DHS) do not contain data on the incomes of individuals and households. The asset index allows for the ranking of households based on their ownership of private assets and their access to public assets relative to other households. Booysen *et al.*(2008), Filmer and Scott (2012) and Ngo and Christiaensen (2018) use the 40th percentile asset index cut-off point. This is recommended by the World Bank by Filmer and Scott (2012) which found a high correlation in the households classified as the poorest 40% using both per capita expenditures and asset indices. Booysen *et al.* (2008) use the 60th percentile asset index cut-off point to classify the poor and non-poor since Africa is deemed to have higher poverty levels and the asset index does not discriminate well between the poor and non-poor at lower levels due to the clustering of households at the lower end of the asset index distribution. Other studies also use the 20th percentile asset index cut-off point to represent extreme poverty (Oosthuizen, 2008). This study will thus utilise all three cut-off points; i.e., 20th, 40th and 60th percentiles to define the poor and non-poor and compare results based on the different definitions of poverty. Figure 4.1 shows the cumulative distribution function for the asset index across surveys. Asset poverty shows a decrease between the 2003 and 2014 surveys with the proportion of households classified as poor at the 20th, 40th and 60th percentiles, reducing across the surveys.

20 Poverty is defined as either absolute or relative. Absolute poverty refers to a situation in which a household's income is low such that access to basic needs such as food, water, sanitation facilities, health, shelter, education and information is curtailed. The absolute poverty line is fixed. Relative poverty is the deprivation of a household compared to other households and it is prone to changes depending on whether the livelihoods of other households in a particular administrative unit, mostly a country, are improving or worsening.

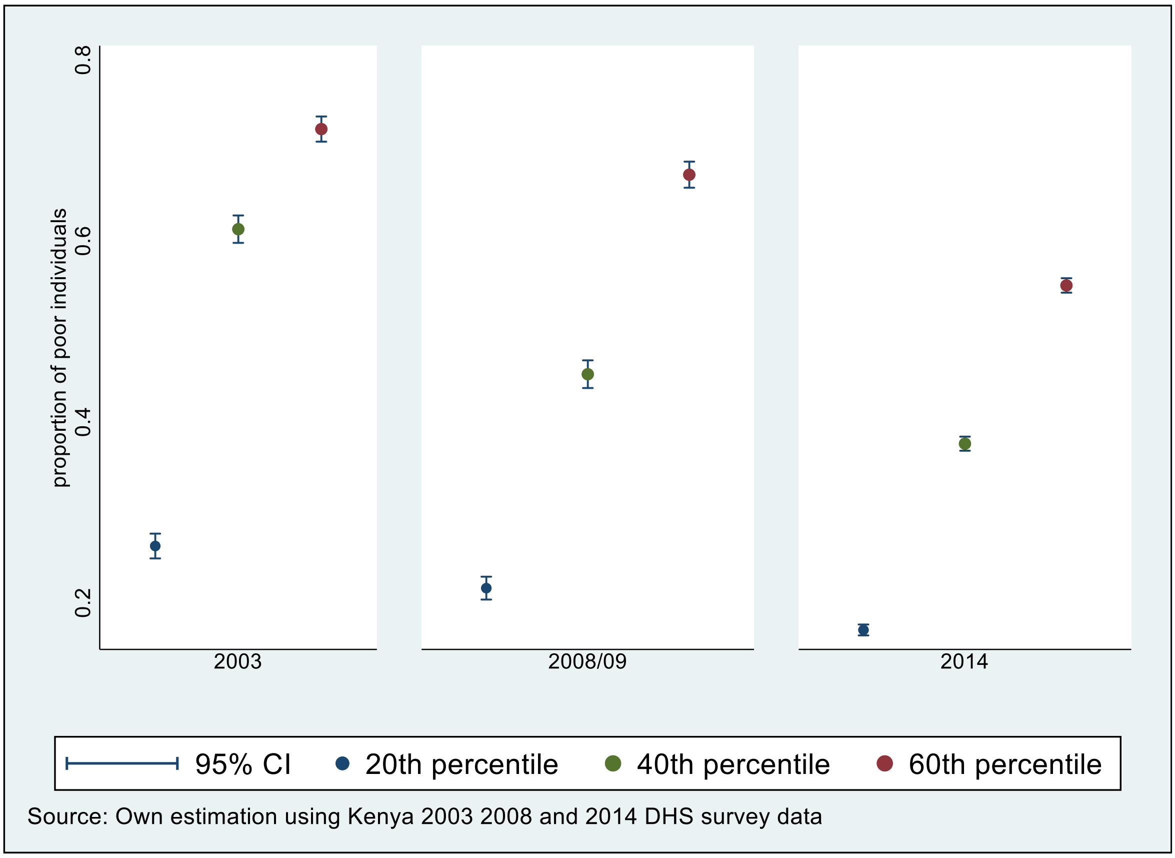
Figure 4.1: Cumulative density functions for household asset index across surveys and the 20th, 40th and 60th percentile cut-off points



Source: Own estimation using Kenya 2003 2008 and 2014 DHS survey data

Figure 4.2 shows the proportion of individual women who came from asset-poor households in 2003, 2008/09 and 2014 surveys using the 20th, 40th and 60th percentile asset index cut-off points. The proportion of the asset poor shows a reduction between 2003 and 2014 surveys at the 20th, 40th and 60th asset index percentiles. This also reinforces the result in figure 4.1 which shows a reduction in the asset index poverty between surveys.

Figure 4.2: Proportion of individuals from poor households over the 20th, 40th and 60th percentile asset index cut-off points across surveys



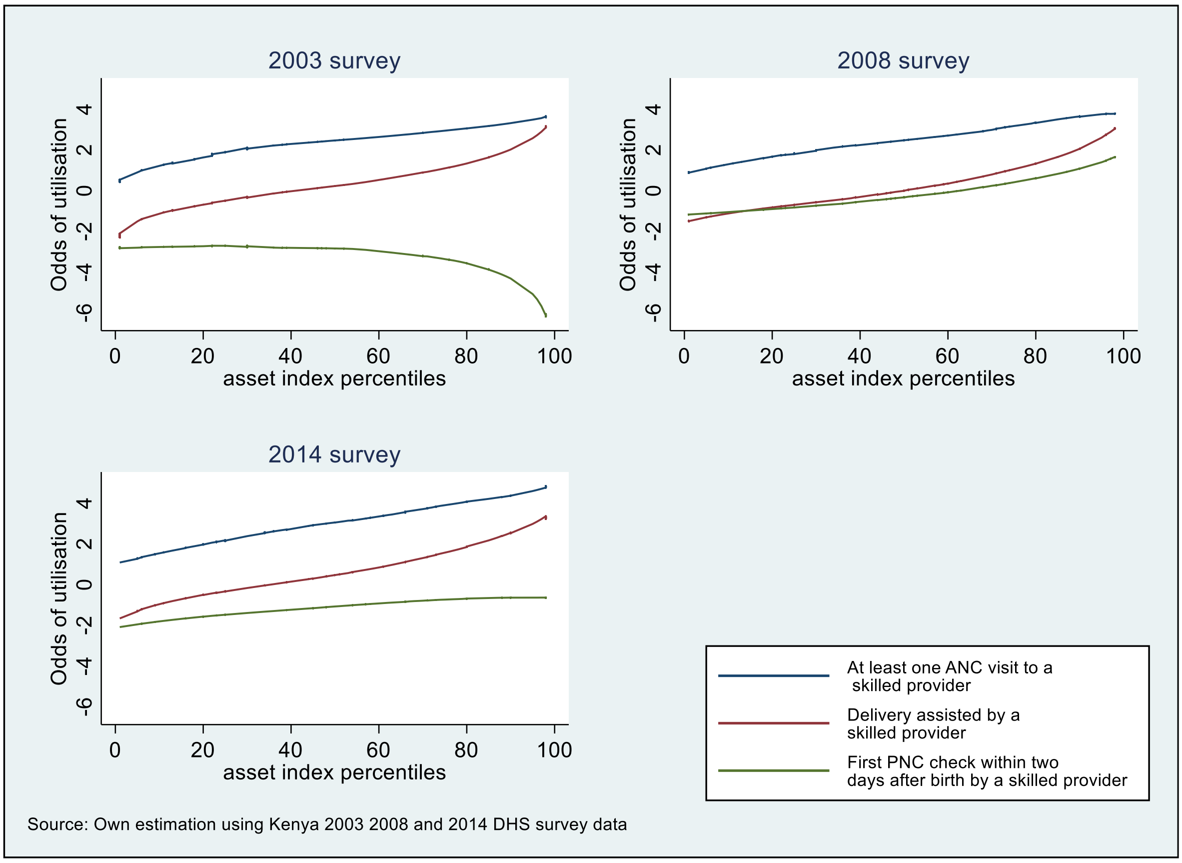
4.2.2. Inequality in the Utilisation of Maternal Health Care in Kenya

4.2.2.1. Determination of Outcomes to Include in Inequality Analysis

First, I determine the variables to include in the analysis of inequality by calculating the odds of the utilisation of maternal health care services under consideration across the asset index distribution. This is achieved by a non-parametric locally weighted regression that predicts the probability of utilising maternal health care across the asset wealth distribution. At each point (x_i, y_i), the log-odds of utilisation are calculated by regressing the binary health outcomes against the asset index using the observations which are within a specified bandwidth. The point (x_i, y_i), is given a higher weight compared to points further away within the bandwidth (Cleveland, 1979; Royston, 1991).

Figure 4.3 shows the smoothed distributions for the odds of utilising maternal health care in the 2003, 2008 and 2014 DHS surveys plotted against the asset index distribution across surveys.

Figure 4.3: Odds of the utilisation of maternal health care in Kenya across the asset index distribution



The odds of the utilisation of the maternal health care in question increase with an increase in the asset index except for the utilisation of PNC services by a skilled provider in the 2003 survey. The anomaly in this distribution might be explained by the fact that the women who utilised this service make up 3.56% of the sample, most of whom are at the lower end of the asset index distribution as shown in figure C1 in appendix C. The odds of having one PNC check within two days after delivery by a skilled provider are lower than zero across the entire asset wealth distribution for the 2003 and 2014 surveys. Given that the odds of getting a PNC check within the first 48 hours is less than zero regardless of where the individual is located on the asset index distribution, this implies that there are no differences in utilisation between the poor and non-poor and subsequently, no inequalities in the utilisation of this maternal health care service. Therefore, the analysis of this maternal health care service will not be included in the subsequent analysis of the trends of inequality in the utilisation of maternal health care across surveys.

Figures C2.1-C2.3 in appendix C show the utilisation of maternal health care across surveys with the asset index divided into two groups; i.e., poor and non-poor, classified using the 20^{th}, 40^{th} and 60^{th} percentile asset index cut-off points. The proportion of utilisation for at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider shows an increase from 2003 to 2008 and finally to the 2014 survey. However, the proportion of utilisation is consistently higher above the asset wealth poverty cut-off points across the surveys. This points to asset wealth offering an advantage in the utilisation of maternal health care.

4.2.2.2. Measurement of Inequality in the Utilisation of Maternal Health Care in Kenya across Surveys

Now that the maternal health outcomes which have inequality have been determined, I proceed to characterise the extent to which the inequality exists over time. The conventional method used to portray inequality is the concentration index which is a bivariate rank-dependent index that shows the relationship between a cumulative health outcome and the cumulative socioeconomic variable of interest; i.e., the asset index, ranked from the lowest to the highest. The concentration index is bounded between -1 and 1. A value of zero implies perfect equality, negative values show that the distribution is skewed toward the lower end of the cumulative distribution of socioeconomic status while positive values show that the distribution is skewed toward the higher end of the cumulative distribution of socioeconomic status (Regidor, 2004; Fleurbaey and Schokkaert, 2011; Kjellsson and Gerdtham, 2013; Ki*m et al*, 2016; Bobo, Yesuf and Woldie, 2017; Haider *et al*, 2017; Nghargbu and Olaniyan, 2017). The concentration index is represented in equation 4.1:

$$C = \frac{2}{n^2 \mu_h} \sum_{i=1}^{n} z_i h_i \tag{4.1}$$

where:

- h is the binary health outcome of interest; i.e., utilisation of at least one ANC visit to a skilled provider and delivery assisted by a skilled provider
- μ_h is the mean of the health outcome
- n is the number of observations
- $\sum_{i=1}^{n} z_i h_i$ is the normalized sum of the weighted health outcome

- $z_i = \frac{(n+1)}{2} - \lambda_i$. n is the number of observations while λ_i is the ranking of the individuals using the asset index with $\lambda_i = 1$ being the richest and λ_i=n being the poorest

The range of the concentration index for binary variables is determined by the mean which is the proportion of times the variable is equal to one; i.e., the proportion of utilisation for a maternal health care service. For binary variables, the range of the concentration index ranges between μ-1 and 1-μ. This implies that the range of the concentration index reduces and tends to zero as the mean of the outcome variable increases. However, this does not necessarily mean that the inequality has reduced. This introduces a challenge when comparing populations with different means as the range of values which the concentration index can take will be different for the different populations. The chapter uses the concentration index stipulated by Wagstaff which makes adjustments when the outcome variable is binary. The Wagstaff index standardises the concentration index by dividing it by the maximum possible value that the concentration index for binary variables can take; i.e., 1-μ, to ensure the concentration index lies within the specified bounds (Wagstaff, 2005; Kjellsson and Gerdtham, 2013; Haide*r et al,* 2017) . The Wagstaff concentration index is represented in equation 4.2:

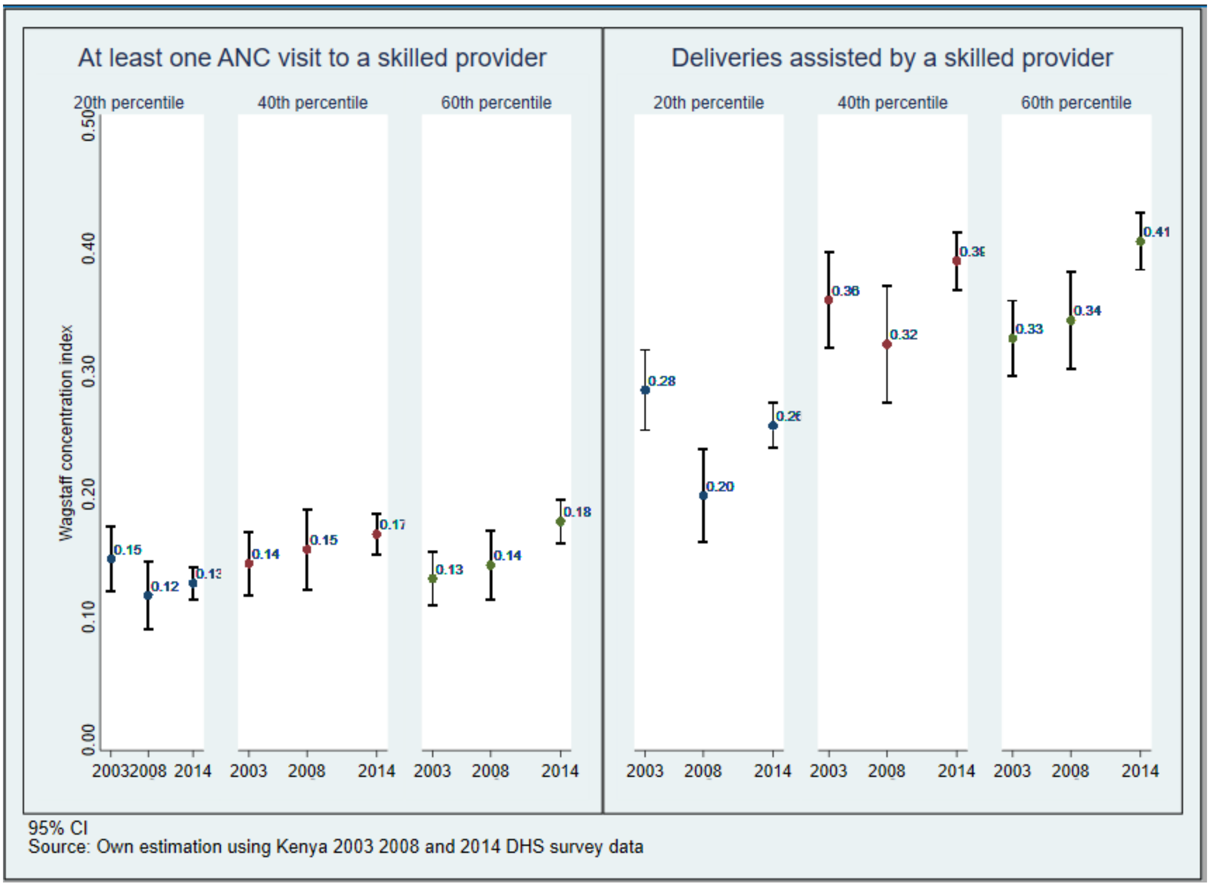
$$W = \frac{2}{n^2(1-\mu_h)\mu_h} \sum_{i=1}^{n} z_i h_i \tag{4.2}$$

where the variables are defined the same as in equation 4.1

However, the Wagstaff index is not devoid of weaknesses. First, it is dependent on value judgments. Therefore, the attribute that is coded zero matters. For example, the codding of health and ill health would then determine whether one is investigating inequality in health or ill health. Secondly, in the event that only the top x% of the population records the presence of an attribute, the Wagstaff index would be fixed at 1. The converse happens when only the bottom z% of the population records the presence of an attribute and the Wagstaff index is fixed at -1. These two scenarios present a case of perfect pro-rich and pro-poor inequalities, respectively, even though this is not the case. However, cases like this are seldom present in real-world data (Erreygers and Van Ourti, 2011; Wagstaff, 2011; Ataguba, 2022).

Inequality indices are calculated to ascertain the presence of inequality in the utilisation of maternal health care. The indices compare inequalities using the asset index cut-off points; i.e., 20th, 40th and 60th percentiles as determined in section 4.2.1. Figure 4.4 presents the Wagstaff concentration indices for the variables of interest across surveys when the cut-off points are set at the 20th, 40th and 60th percentiles, respectively.

Figure 4.4: Wagstaff concentration indices for utilisation of maternal health care over the 20th, 40th and 60th percentile asset index cut-off points across surveys



All the indices presented are positive and statistically significant as indicated in table C1 in appendix C. This indicates the presence of pro-non-poor inequality in the utilization of maternal health care. This confirms the earlier scenario in figures C2.1 - C2.3 which showed higher utilisation of maternal health care among the non-poor as compared to the poor. The inequality is especially high for deliveries assisted by a skilled provider. The trend in inequality shows an increase in inequality in the attendance of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider for the 60th percentile asset index cut-off point. As a robustness check, a comparison is done for the individuals from the bottom 20th and 40th percentiles against the top 40 percentile who are classified as non-poor under all the 3 poverty asset index cut-off points. The inequality is higher at the 20th and 40th percentiles when compared to the top 40th percentile relative to when the comparison is done to the 80th and 60th percentiles, respectively as shown in figure C3. The differences in inequality between the 2003 and 2014 surveys are statistically significant only when comparing individuals in the bottom 40 to the top 40th percentile for both utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider as shown in table C2 in appendix C.

One of the programs used in an attempt to reduce the effect of the cost barrier on the utilisation of maternal health care and make the services more affordable is the reduction/ removal of user fees. Kenya introduced such an intervention in June 2013. Given that the presence of inequality in the utilisation of maternal health care has been confirmed in this section, I now proceed to describe the utilisation of maternal health care before and after the start of the FMC program and examine whether the program had an effect on inequality.

4.2.3. Inequality in the Utilisation of Maternal Health Care in Kenya before and After the Start of the Free Maternal Care Program

4.2.3.1. Determination of Outcomes to Include in Inequality Analysis

The odds of the utilisation of maternal health care across the asset index distribution are estimated using the locally weighted regression described in section 4.2.2.1. Figure 4.5 shows the smoothed distributions for the odds of utilising maternal health care before and after the start of the FMC program plotted against the asset index distribution. The odds of utilising maternal health care increase as asset wealth increases with the pattern of odds of utilisation being similar before and after the start of the FMC program. The odds of having one ANC visit to a skilled provider are higher than zero while the odds of having one PNC check within two days after delivery by a skilled provider are lower than zero across the asset wealth distribution both before and after the start of the FMC program. Therefore, the analysis of these two maternal health care services will not be included in the subsequent analysis of the trends of inequality before and after the start of the FMC program.

Figure 4.5: Odds of the utilisation of maternal health care across the asset index distribution before and after the start of the FMC program

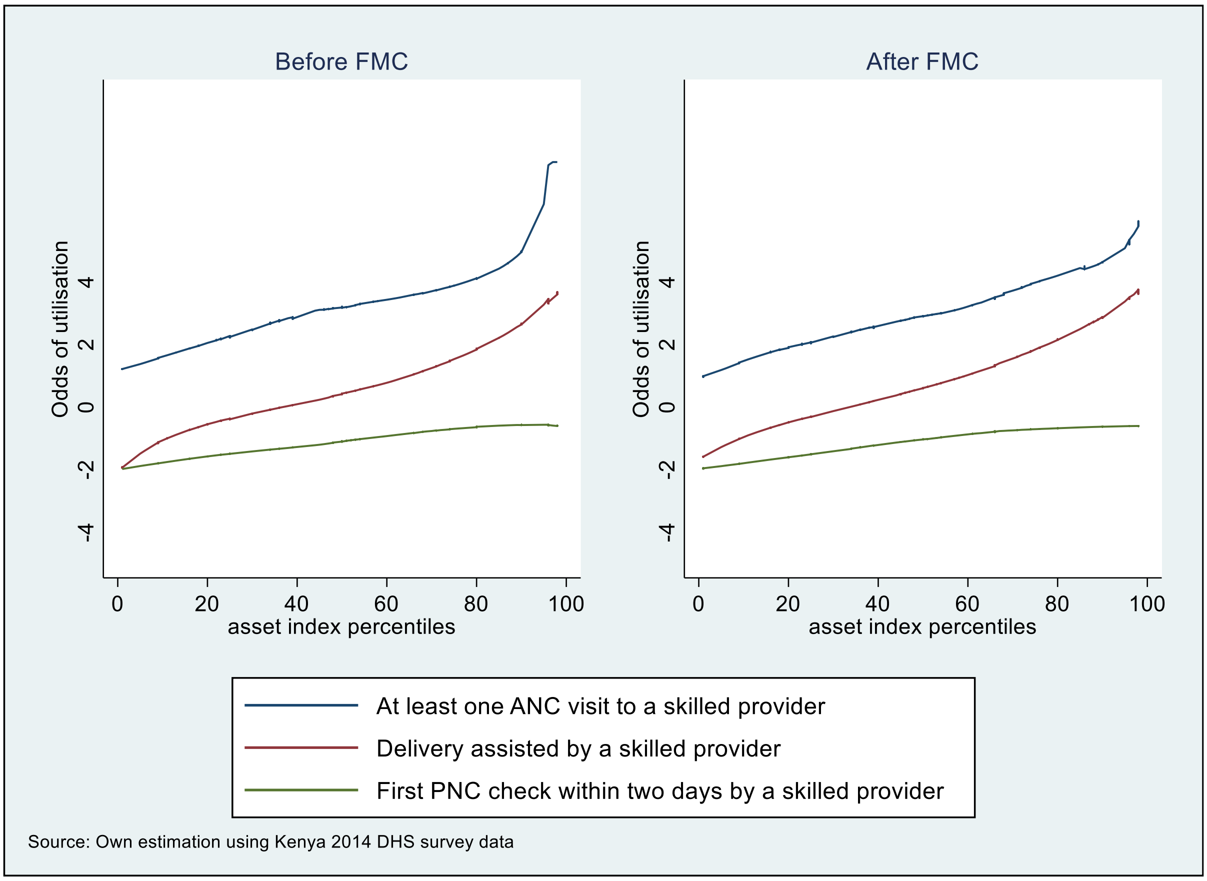
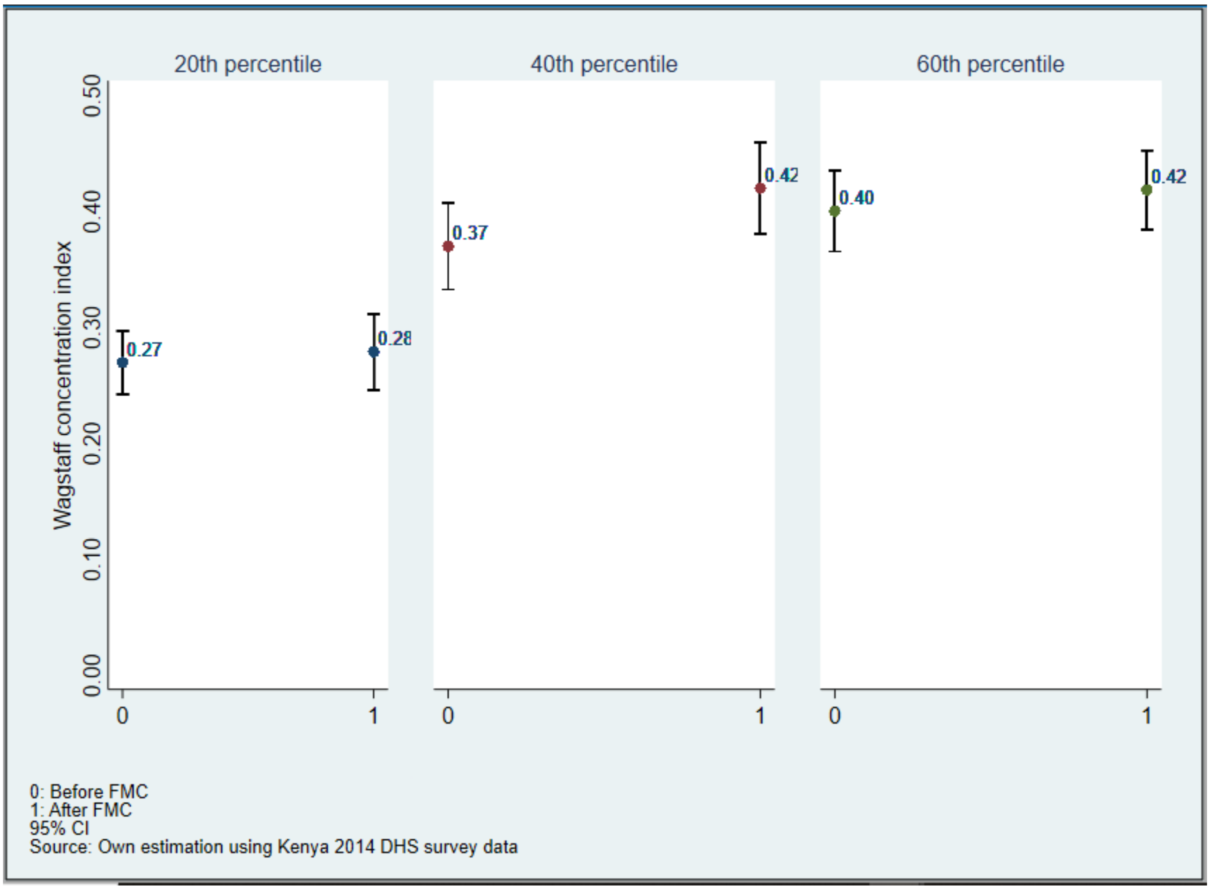


Figure C4 in appendix C shows the utilisation of delivery by a skilled provider of the two asset index groups before and after the start of the FMC program. The proportion of utilisation is higher among the non-poor compared to the poor. While the proportion of utilisation increased after the start of the FMC program across the asset index distribution, the proportion of utilisation is still higher for individuals in the non-poor groups. Now that the maternal health outcomes which have inequality have been determined, I proceed to characterise the extent to which the inequality exists before and after the start of the FMC program.

4.2.3.2. Measurement of Inequality in the Utilisation of Maternal Health Care in Kenya Before and After the Start of the Free Maternal Care Program

This section compares the inequality in the utilisation of delivery assisted by a skilled provider before and after the start of the FMC program. Figure 4.6 shows the calculated Wagstaff indices.

Figure 4.6: Wagstaff concentration indices for utilisation of delivery by a skilled provider over the 20th, 40th and 60th percentile asset index cut-off points before and after the start of the FMC program



The calculated Wagstaff indices are positive and significantly different from zero as shown in table C3 in appendix C indicating inequality does exist with the non-poor having a higher utilisation of delivery assisted by a skilled provider. A robustness check is conducted by calculating inequality when the bottom 20 and 40 percentiles are compared to the top 40 percentile. The inequality is higher than when the comparison is done to the top 80 and top 60 percentiles, respectively as shown in figure C5 and table C4 in appendix C. The reduction or removal of user fees is meant to increase utilisation regardless of socioeconomic status thus improving equality. However, contrary to expectations, the differences in inequality before and after the start of the FMC program are not statistically significant except when comparing the bottom 40 percentile to the top 60 percentile which is statistically significant at 10%. This shows that there are other crucial factors explaining the utilisation of maternal health care apart from the cost which might be discouraging women from accessing maternal health care services. In light of this, I extend the analysis to determine other factors that explain the differences in the utilisation of maternal health care between the poor and non-poor.

4.2.4. Decomposition of Inequality in the Utilization of Maternal Health Care in Kenya Using Recentered Influence Functions (RIF)

Assume that $H \in (a_H, b_H)$ is a health variable; i.e., utilisation of at least one ANC visit to a skilled provider and delivery assisted by a skilled provider, with mean μ_H and probability measure F_H. a_H and b_H are the lower and upper bounds of the variable. Assuming a function $v(F)$ where F is a probability measure for $v(F)$. F_Y is the fractional rank of an individual when ranked according to a socioeconomic variable Y; i.e., the asset index. The functional form for a rank-dependent index is thus given by the joint distribution of H and Y (Firpo, Fortin and Lemieux, 2009; Heckley, Gerdtham and Kjellsson, 2016; Finn and Leibbrandt, 2018; Rios-Avila, 2019b).

$$I = v^{I}(F_H, F_Y) = v^{\omega}(F_H)v^{AC}(F_H, F_Y) \tag{4.3}$$

where:

- $v^{\omega}(F_H)$ is the weighting function for the rank-dependent index
- AC is the absolute concentration index

Suppose a small change in the characteristics of an observation results in the distributional statistic changing from F_H to a new distribution G_H. The function G_H can be defined as:

$$G_H = (1 - \varepsilon)F_H + \varepsilon\delta_h \tag{4.4}$$

where $\varepsilon \in (0,1)$ is the relative change in the population as a result of changing F_H by a quantity δ_h

An influence function measures the effect of an observation on the distributional statistic. An influence function is thus defined as:

$$IF = \frac{\partial v(G_H)}{\partial \varepsilon}\Big|_{\varepsilon \to 0} \tag{4.5}$$

The decomposition is done in two steps. The first step estimates an IF for the rank-dependent index e.g. the mean, quantile etc. The recentered influence function linearizes the rank-dependent index by adding the influence function back to the health variable functional form $\mathrm{v}(\mathrm{F_H})$.

$$\mathrm{RIF}(\mathrm{h};\mathrm{v}) = \mathrm{v}(\mathrm{F_H}) + \big(\mathrm{IF}(\mathrm{h};\mathrm{v})\big) \tag{4.6}$$

$RIF(h; v)$=f (mother's education levels, region of residence, place of residence, mother's age, parity, marital status, distance to the nearest health facility, size of nearest health facility, alternative supply of health facilities)

The decomposition analysis using RIFs allows for the construction of a counterfactual distribution to determine what the outcomes of a subpopulation would be if they had the characteristics of a different subpopulation. Reweighting creates a counterfactual group for the non-poor by giving them similar characteristics to the poor to determine whether significant differences in wealth contribute to inequality. The covariates used for the creation of the counterfactual are the same as the ones used in the estimation of the RIFs (Fortin, Lemieux and Firpo, 2010; Firpo and Pinto, 2011).

$$\mathrm{F}_{\mathrm{Y}^{\mathrm{C}}_{\mathrm{non-poor}}(\mathrm{y})} = \int \mathrm{F}_{\mathrm{Y_{non-poor}}|\mathrm{X_{non-poor}}}(\mathrm{y}|\mathrm{X})\Psi(\mathrm{X})\mathrm{dF}_{\mathrm{X_{non-poor}}} \tag{4.7}$$

where Ψ is the reweighting factor = $\frac{\mathrm{dF}_{\mathrm{X_{non-poor}}}(\mathrm{X})}{\mathrm{dF}_{\mathrm{X_{poor}}}(\mathrm{X})}$

The second step utilises ordinary least squares (OLS) to regress the RIF on individual covariates to determine the marginal effects on the RIF due to a change in the individual covariates (Heckley, Gerdtham and Kjellsson, 2016; Firpo, Fortin and Lemieux, 2018).

$$\mathrm{E}[\mathrm{RIF}(\mathrm{h};\mathrm{v})] = \mathrm{X}\beta \tag{4.8}$$

where the covariates are the same as in the estimation of the RIF.

The expected value of the RIF, $\mathrm{E}[\mathrm{RIF}(\mathrm{h};\mathrm{v})]$, is equal to the expected value of the distributional statistic, $\mathrm{v}(\mathrm{F_H})$ since the expected value of the influence function,($\mathrm{IF}(\mathrm{h};\mathrm{v})$ is equal to zero.

Having described the theoretical framework for the decomposition of inequalities using recentered influence functions, I now proceed to a multivariate framework to determine the factors that explain the inequality in the utilisation of maternal health care between the poor and non-poor in Kenya that was shown to exist in section 4.2.2.2. The decomposition is done while controlling for the other socio-economic and demographic factors that explain the inequality as determined in the framework presented in section 2.4. The mean is decomposed using the recentered influence function which allows for reweighting. The explained/compositional component shows the differences in utilisation arising from the differences in observed characteristics while the unexplained/structural effect encompasses the differences in utilisation that are not explained by the observed characteristics and the effect of other factors which are not included in the decomposition model (Fairlie, 2006; Jann, 2008; Rios-Avila, 2019a). Decomposition of the mean is done while controlling for the mother's education, province of residence, place of residence, mother's age at a child's birth, parity and marital status.[21] Table 4.1 shows the results of the aggregate decomposition of the differences in the utilisation of maternal health care.

[21] *Stata user written command Oaxaca_rif (Rios-Avila, 2021) is used for decomposition of mean differences. The author recommends the use of bootstrap standard errors. However, since bootstrap and svy are not automatically supported together by the command, I replicate the weights from the survey using the user written command bsweights (Kolenikov, 2010). To achieve balanced bootstrap: i.e. same number of replications from each strata, the number of replications recommended for the bsweights command is equal to the least common multiple of the number of primary sampling units in each stratum. However, for the data used in this chapter, that number of replications is too high, (the data used has 92 strata with the lowest number of clusters in a stratum being 8 and the highest being 56. This results in a least common multiple of 80313433200 which is not feasible to run). For all the decomposition analysis in this chapter, I therefore use 1900 replications which is the highest number of replications I can run without an error message from the Stata program.*

Computations were performed using facilities provided by the University of Cape Town's ICTS High Performance Computing team: hpc.uct.ac.za

Table 4.1: Aggregate decomposition of the mean differences in utilisation of maternal health care between the poor and non-poor at different asset index cut-off points using Recentered Influence Functions (RIFs) when controlling for socioeconomic and demographic factors

	ANC by a skilled Provider			***Delivery by a skilled provider***		
	20th percentile	*40th percentile*	*60th percentile*	*20th percentile*	*40th percentile*	*60th percentile*
Non-poor	0.7379***	0.7642***	0.7949***	0.6939***	0.7754***	0.8516***
	(0.0046)	(0.0053)	(0.0063)	(0.0073)	(0.0073)	(0.0073)
Counterfactual	0.6869***	0.6596***	0.6997***	0.4858***	0.4900***	0.6356***
	(0.0129)	(0.0089)	(0.0524)	(0.0211)	(0.0251)	(0.0680)
Poor	0.5702***	0.6207***	0.6424***	0.3113***	0.3958***	0.4565***
	(0.0075)	(0.0053)	(0.0048)	(0.0121)	(0.0099)	(0.0094)
Difference	0.1677***	0.1436***	0.1525***	0.3827***	0.3796***	0.3951***
	(0.0087)	(0.0073)	(0.0077)	(0.0137)	(0.0115)	(0.0120)
Compositional	0.1167***	0.0390***	0.0573	0.1745***	0.0942***	0.1791***
	(0.0127)	(0.0087)	(0.0519)	(0.0208)	(0.0254)	(0.0676)
Structural effect	0.0510***	0.1046***	0.0952*	0.2082***	0.2854***	0.2160***
	(0.0134)	(0.0096)	(0.0518)	(0.0216)	(0.0257)	(0.0684)
Observations	20,783	20,783	20,783	20,783	20,783	20,783

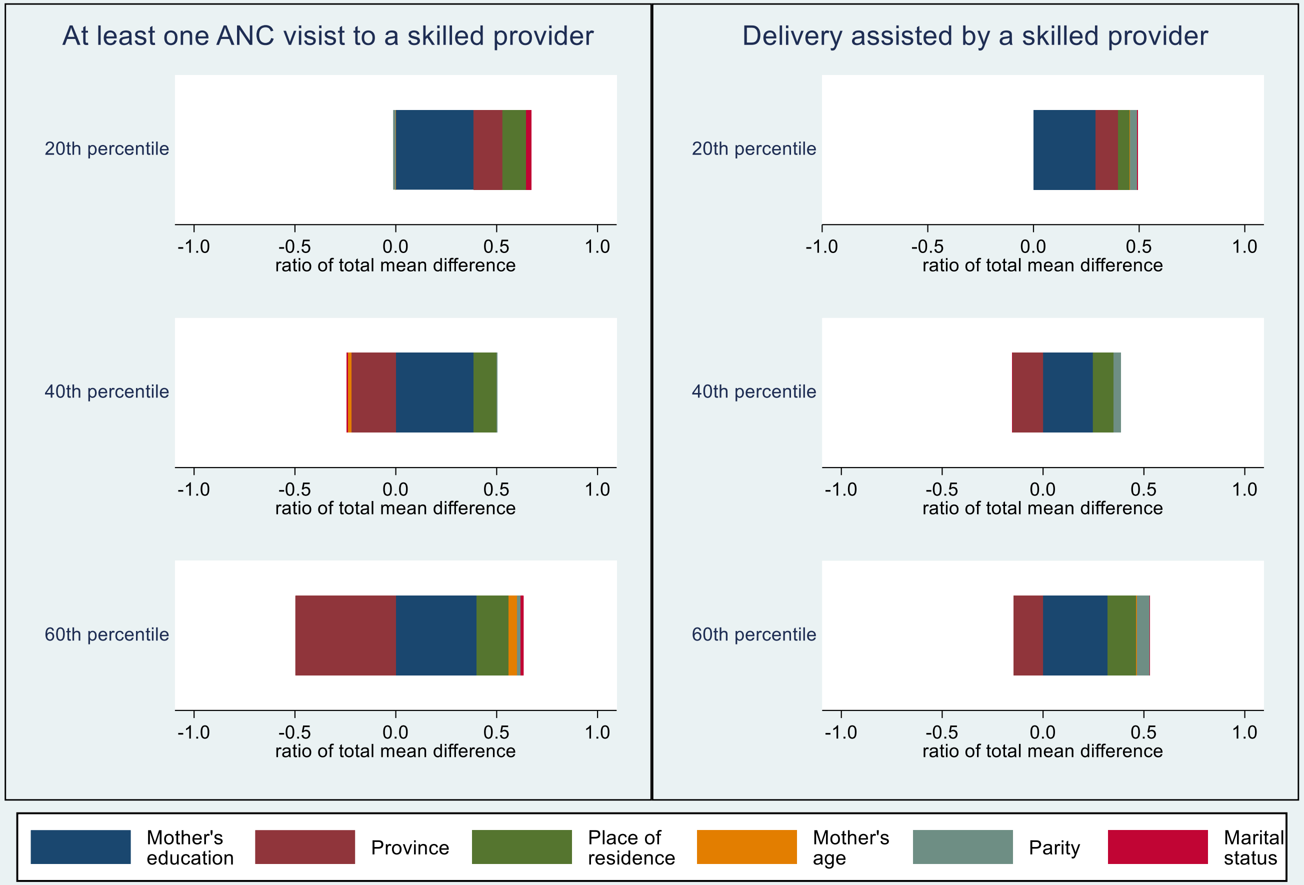
*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The results show that the non-poor have consistently higher utilisation of maternal health care than the poor with the difference in utilisation between the two groups being highly significant. The difference is especially high for the deliveries assisted by a skilled provider. While the utilisation of the non-poor does reduce if they are given the same characteristics as the poor as shown by the counterfactual coefficients, the utilisation is still higher than the poor thus indicating that wealth does offer an advantage in the utilisation of maternal health care. A robustness check is done by decomposing the difference in mean utilisation by the bottom 20 and 40 percentiles to the top 40 percentile. The differences are higher compared to when the comparison is done to the top 80th and 60th percentiles, respectively as shown in Table C5 in appendix C. The non-poor still have significantly higher utilisation of maternal health care compared to the poor. Figure 4.7 shows the detailed decomposition of the contribution of the mother's observable characteristics to the total difference in utilisation of maternal health care between the poor and non-poor with the coefficients and significance levels presented in Table C6 in appendix C.

Maternal level of education is the largest contributor to the mean differences in utilisation of maternal health care between the poor and non-poor in Kenya followed by the province of residence and place of residence. Maternal education and place of residence have positive and statistically significant coefficients. The non-poor are more educated compared to the poor and are more likely to live in urban areas. Province of residence while having a significant effect on inequality presents mixed results in terms of the sign of the coefficients. Parity also has a small positive but statistically significant effect on inequality in the deliveries assisted by a skilled provider. The non-poor are more likely to have fewer children. The specification errors are not significant. Therefore, a linear specification gives a good approximation of the inequality decomposition being investigated in this section. The reweighting error is not statistically significant except when comparing the deliveries assisted by a skilled provider by the bottom 20th percentile poor to the top 40th and 80th percentile non-poor thus indicating that the reweighting procedure replicates the means of the poor group well when creating a counterfactual for the non-poor group.

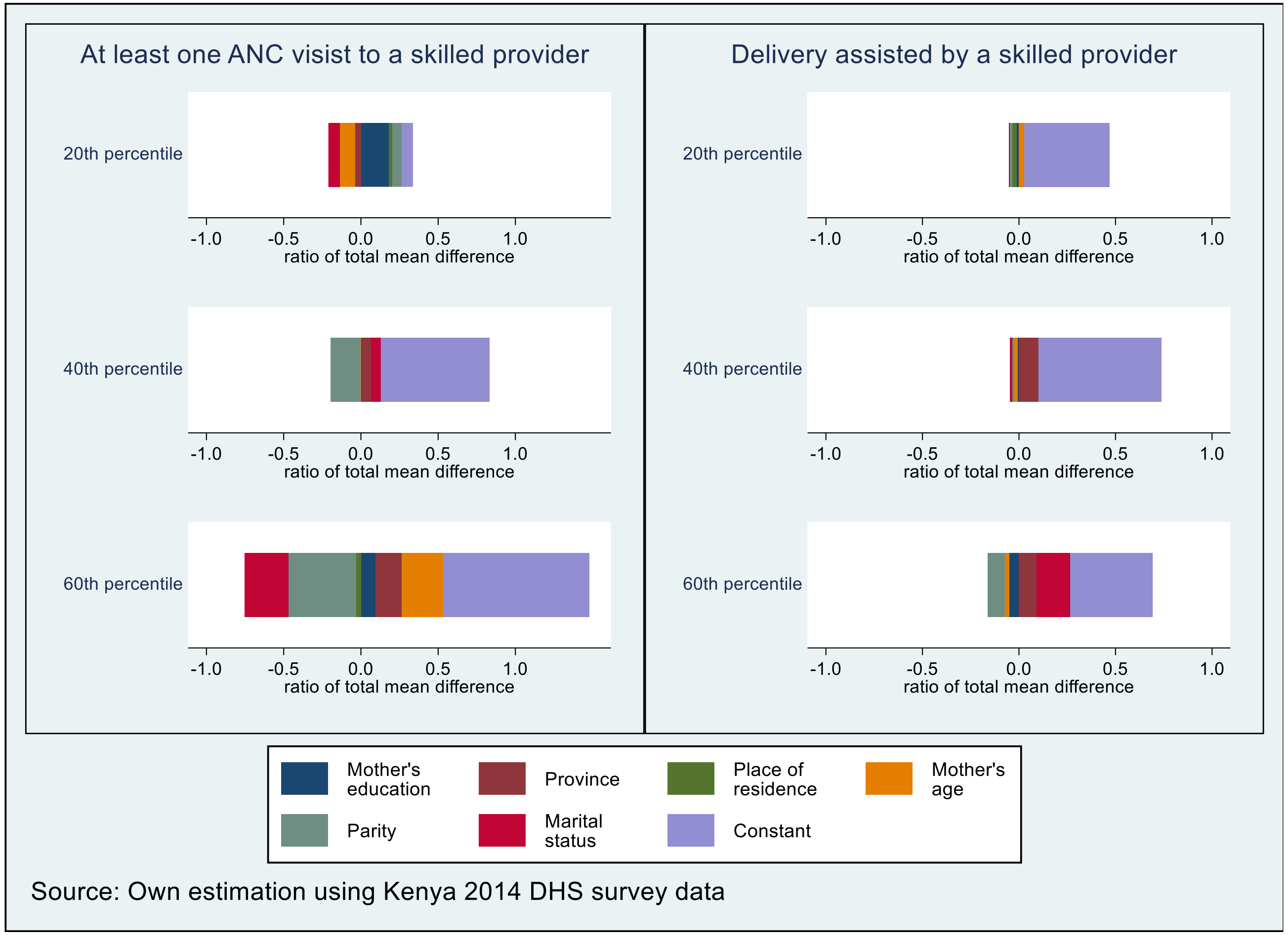
Figure 4.8 shows the detailed decomposition of the contribution of the structural effect to the total difference between the poor and the non-poor. The constant term, which captures other factors that are not included in the model makes the largest component of the structural effect of the total difference in utilisation of maternal health care between the non-poor and the poor except when comparing the mean utilisation of the top 80 percentile to the bottom 20 percentile utilisation of ANC services. Therefore, the current model does not capture all the relevant factors that explain inequality in the utilisation of ANC and delivery services by a skilled provider. Having controlled for the possible relevant factors that explain inequality in the utilisation of maternal health care, there still exist significant differences between the poor and non-poor with the same number of children in the utilisation of ANC services.

Figure 4.7: Detailed decomposition of the contribution of the compositional effect to the total mean difference in utilisation of maternal health care between the poor and non-poor over the 20th, 40th and 60th percentile asset index cut-off points when controlling for socioeconomic and demographic factors



Source: Own estimation using Kenya 2014 DHS survey data

Figure 4.8: Detailed decomposition of the contribution of the structural effect to the total mean difference in utilisation of maternal health care between the poor and non-poor over the 20th, 40th and 60th percentile asset index cut-off points when controlling for socioeconomic and demographic factors



One of the objectives of this chapter is to include supply-side variables in the decomposition model in an attempt to determine the significance of these variables in explaining inequality in the utilisation of maternal health care and thus make the model more robust. Therefore, the decomposition of the mean difference in utilisation of maternal health care between the non-poor and the poor is repeated while including supply-side variables in addition to the socioeconomic and demographic variables that were controlled for earlier. Table 4.2 presents the aggregate decomposition of the mean utilisation of maternal health care when the distance to the nearest health facility, size of the nearest health facility and alternative supply of health facilities within a 5 km radius of an individual are included in the decomposition analysis. The results for the robustness checks are presented in table C7 in appendix C comparing the bottom 20 and 40 percentiles to the top 40 percentile. The results are similar to table 4.1 with the non-poor having a higher utilisation of maternal health care compared to the poor. However, there is no clear direction of change in the compositional effect of the model when compared with the earlier model that controlled only for socioeconomic and demographic characteristics.

Table 4.2: Aggregate decomposition of the mean differences in utilisation of maternal health care between the poor and non-poor at different asset index cut-off points using Recentered Influence Functions (RIFs) when controlling for socioeconomic, demographic and supply-side factors

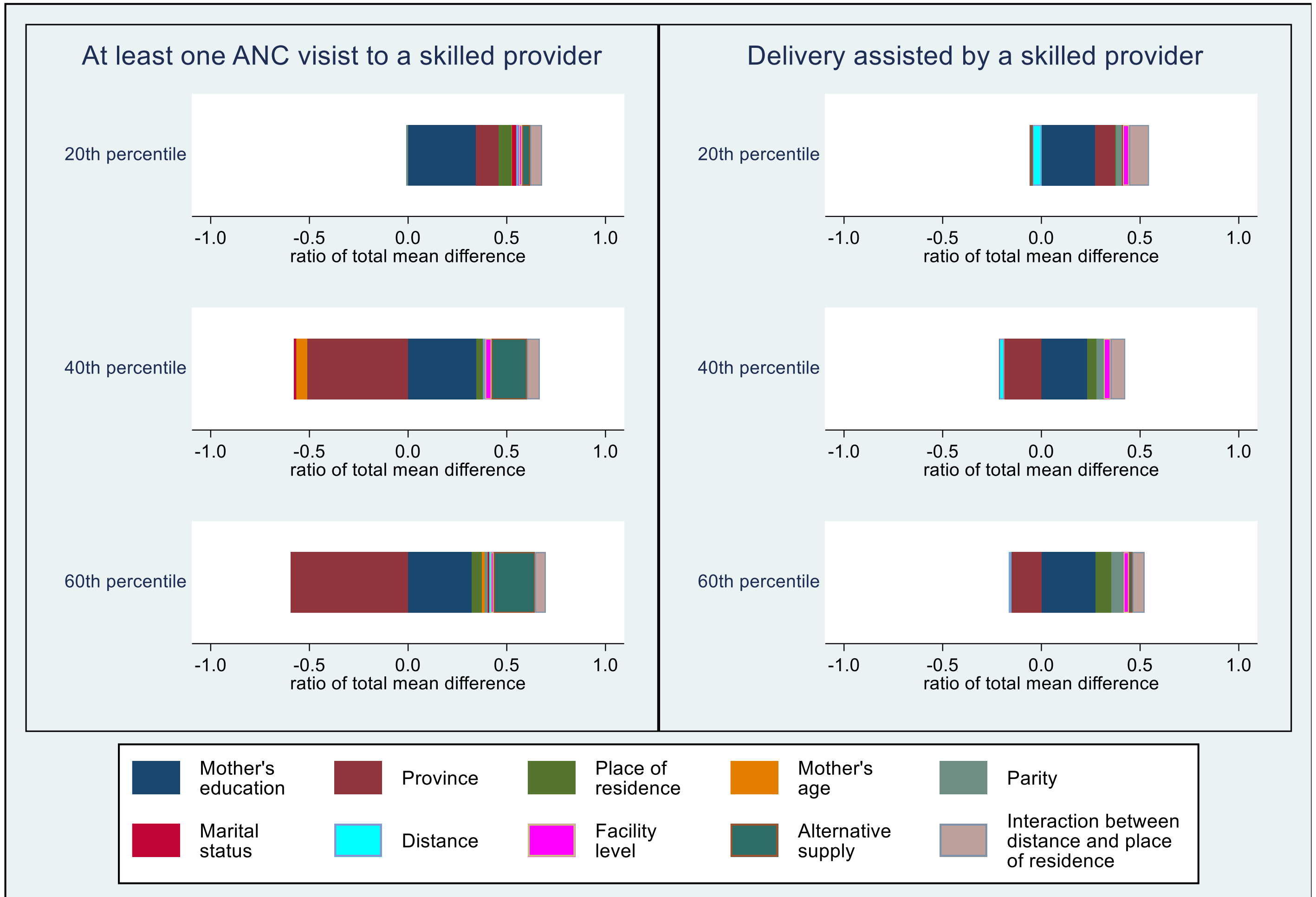
	ANC by a skilled provider			***Delivery assisted by a skilled provider***		
	20th percentile	*40th percentile*	*60th percentile*	*20th percentile*	*40th percentile*	*60th percentile*
Non-poor	0.7379***	0.7642***	0.7949***	0.6939***	0.7754***	0.8516***
	(0.0042)	(0.0052)	(0.0062)	(0.0073)	(0.0074)	(0.0072)
Counterfactual	0.6878***	0.6413***	0.6953***	0.4942***	0.4817***	0.5933***
	(0.0123)	(0.0194)	(0.0394)	(0.0222)	(0.0242)	(0.0616)
Poor	0.5702***	0.6207***	0.6424***	0.3113***	0.3958***	0.4565***
	(0.0074)	(0.0053)	(0.0048)	(0.0124)	(0.0098)	(0.0091)
Difference	0.1677***	0.1436***	0.1525***	0.3827***	0.3796***	0.3951***
	(0.0086)	(0.0073)	(0.0078)	(0.0141)	(0.0118)	(0.0118)
Compositional	0.1176***	0.0207	0.0529	0.1829***	0.0859***	0.1368**
	(0.0121)	(0.0194)	(0.0389)	(0.0215)	(0.0243)	(0.0614)
Structural	0.0501***	0.1229***	0.0996**	0.1997***	0.2937***	0.2583***
	(0.0127)	(0.0198)	(0.0387)	(0.0224)	(0.0248)	(0.0619)
Observations	20783	20783	20783	20783	20783	20783

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Figure 4.9 shows the contribution of the mother's observable characteristics to the compositional component of the total difference in mean utilisation of maternal health care between the poor and non-poor when supply-side variables are included in the decomposition analysis. The coefficients and statistical significance of the detailed decomposition are included in Table C8 in appendix C. Same as before in figure 4.7, the mother's level of education has a substantial contribution to the differences in the utilisation of maternal health care followed by the place of residence. However, while living in rural areas still has a positive effect on inequality, the significance level is dampened by the introduction of supply-side variables. Distance to the nearest health facility is worse for individuals in rural areas as shown by the interaction term. The number of children and facility size have a positive and statistically significant effect on the utilisation of deliveries by a skilled provider. The non-poor are more likely to be more educated, live in urban areas and be closer to health facilities. The non-poor are also more likely to have fewer children and live close to higher-level facilities.

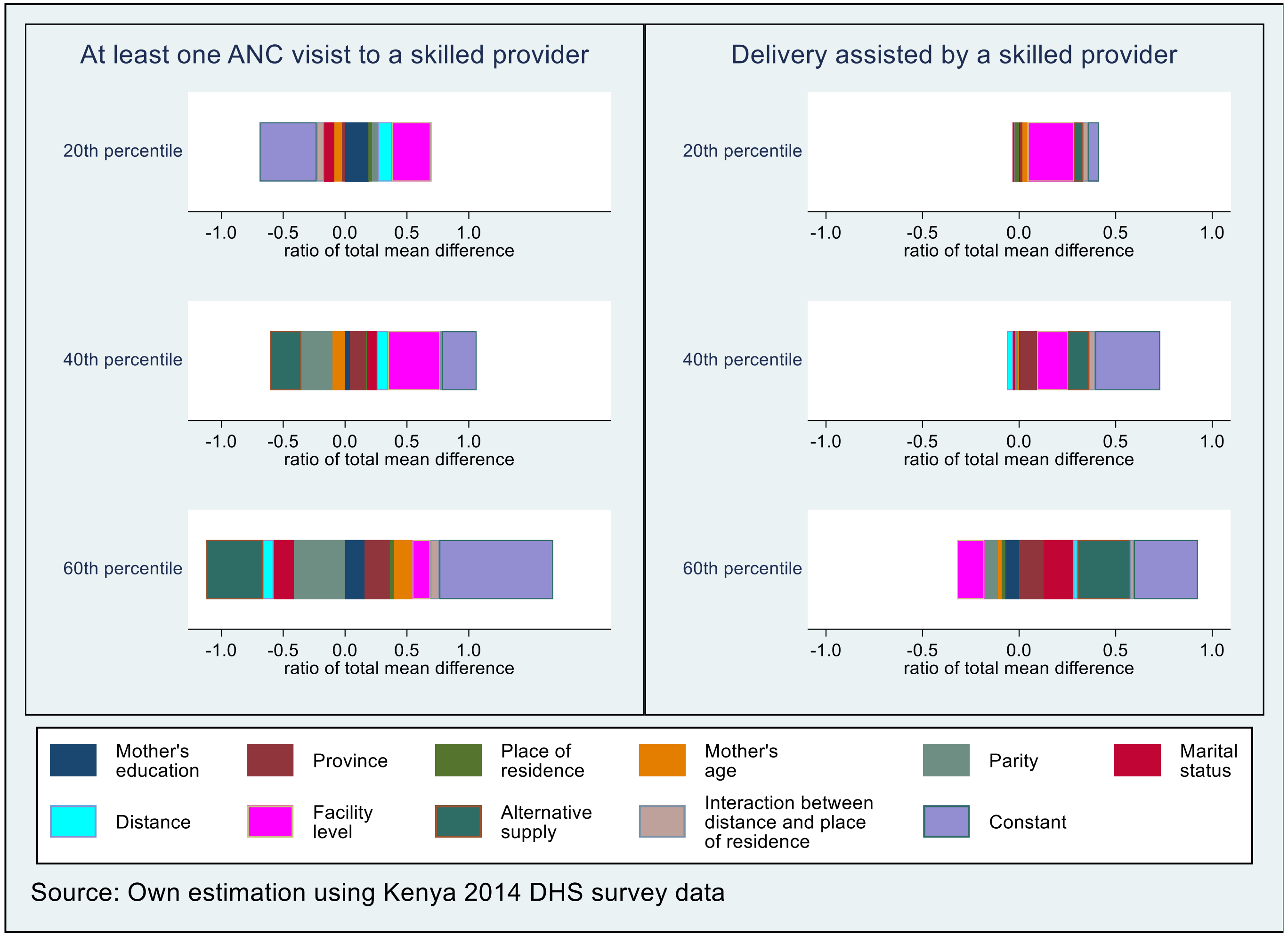
Figure 4.10 shows the contribution of the structural component of the total difference in utilisation of maternal health care between the non-poor and the poor after supply side factors are included in the decomposition model. The structural effect of the differences in the utilisation of maternal health care is higher for the utilisation of at least one ANC visit to a skilled provider. Having controlled for socioeconomic, demographic and supply side factors, there still exist differences in utilisation between the poor and non-poor for women with the same education, the number of children, living close to facilities at the same level and with the same number of health facilities offering maternal health care in their vicinity. The contribution of factors not controlled for in the model as shown by the proportion of the constant to the total mean difference in utilisation of maternal health care between the non-poor and the poor is much smaller compared to when supply-side factors are not controlled for in figure 4.8. Therefore, supply-side factors are important in explaining inequality between the poor and non-poor in Kenya and therefore will be included in the subsequent analysis in this chapter. Having established the importance of supply-side variables, I then proceed to analyse inequality in the utilisation of maternal health care in Kenya before and after the start of the FMC program.

Figure 4.9: Detailed decomposition of the contribution of the compositional effect to the total mean difference in utilisation of maternal health care between the poor and non-poor when controlling for socioeconomic, demographic and supply-side factors



Source: Own estimation using Kenya 2014 DHS survey data

Figure 4.10: Detailed decomposition of the contribution of the structural effect to the total mean difference in utilisation of maternal health care between the poor and non-poor when controlling for socioeconomic, demographic and supply-side variables



4.2.5. Decomposition of Inequality in the Utilisation of Maternal Health Care in Kenya Before and After the Start of the FMC Program using the Recentered Influence Functions

4.2.5.1. Decomposition of the Mean Utilisation

Table 4.3 presents the aggregate decomposition of the mean utilisation of deliveries assisted by a skilled provider before and after the start of the FMC program at the 20th, 40th and 60th percentiles. While the utilisation does increase for both the poor and non-poor groups, the differences remain highly significant even after the introduction of the FMC program in June 2013.

Table 4.3: Aggregate decomposition of the mean differences in deliveries assisted by a skilled provider between the poor and non-poor at different asset index cut-off points using Recentered Influence Functions (RIFs) when controlling for socioeconomic, demographic and supply-side factors

	20th percentile		***40th percentile***		***60th percentile***	
	Before	*After*	*Before*	*After*	*Before*	*After*
Non-poor	0.7027***	0.7507***	0.7716***	0.8359***	0.8512***	0.9044***
	(0.0109)	(0.0097)	(0.0113)	(0.0097)	(0.0124)	(0.0090)
Counterfactual	0.5279***	0.4876***	0.6173***	0.5106***	0.6603***	0.6772***
	(0.0371)	(0.0407)	(0.0202)	(0.0346)	(0.0484)	(0.0973)
Poor	0.3081***	0.3739***	0.4122***	0.4598***	0.4642***	0.5209***
	(0.0184)	(0.0207)	(0.0150)	(0.0150)	(0.0129)	(0.0131)
Difference	0.3945***	0.3767***	0.3594***	0.3761***	0.3871***	0.3834***
	(0.0204)	(0.0228)	(0.0187)	(0.0177)	(0.0173)	(0.0160)
Compositional effect	0.2198***	0.1136***	0.2052***	0.0508	0.1961***	0.1562
	(0.0376)	(0.0376)	(0.0200)	(0.0345)	(0.0476)	(0.0966)
Structural effect	0.1748***	0.2631***	0.1542***	0.3253***	0.1909***	0.2272**
	(0.0377)	(0.0418)	(0.0223)	(0.0364)	(0.0494)	(0.0983)
Observations	5,582	4,867	5,582	4,867	5,582	4,867

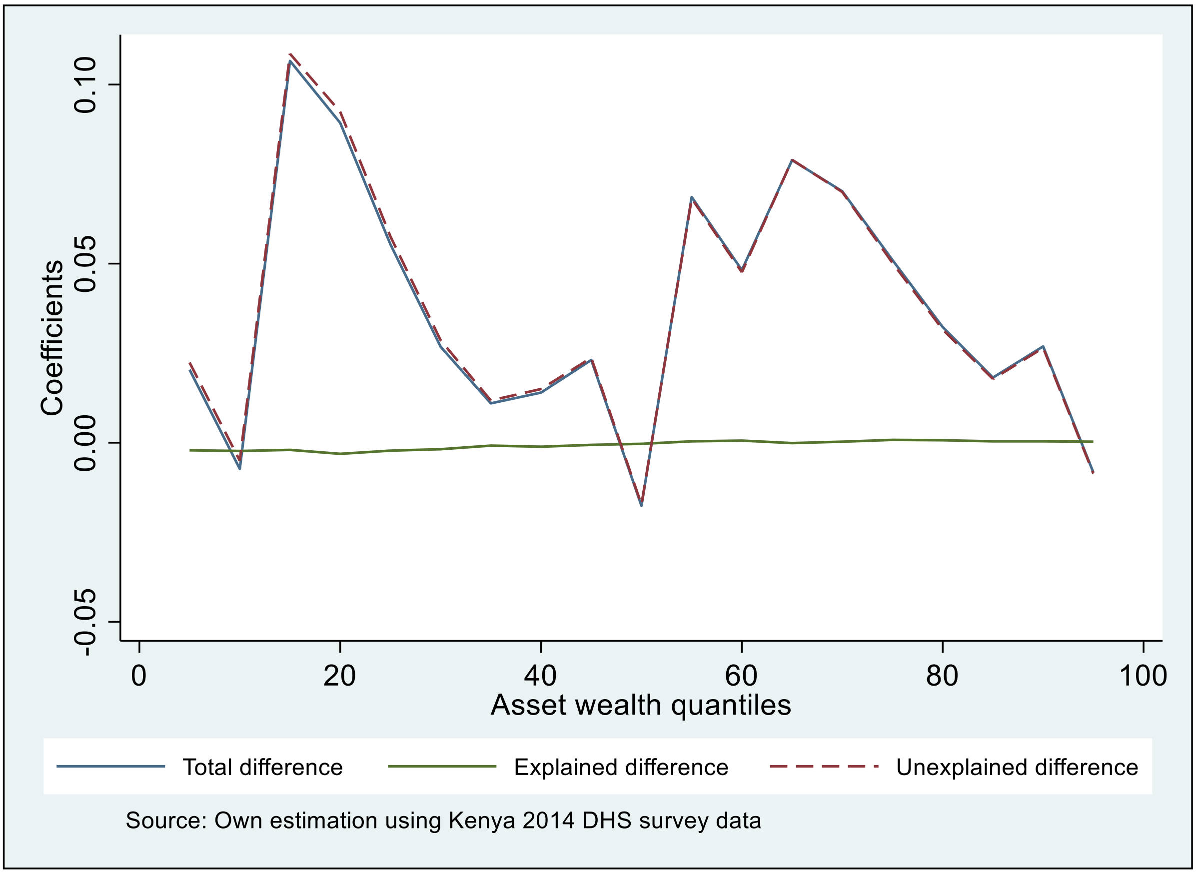
*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

4.2.5.2. Decomposition of the Mean Utilisation across the Asset Index Distribution before and after the start of the FMC program

One advantage that has been cited for using RIFs over the standard Oaxaca-Blinder decomposition is the allowance to decompose other distributional statistics apart from the mean e.g. quantiles (Rios-Avila, 2019b). This section seeks to utilise this advantage to decompose the mean differences in the utilisation of delivery by a skilled provider before and after the start of the FMC program across the asset index distribution. The binary outcome variable is converted into a continuous variable by calculating the mean of the outcome variable at each quantile on the asset index distribution.

Figure 4.11 presents the results of the decomposition of the mean utilisation of deliveries assisted by a skilled provider along the asset index quantiles with the detailed aggregate decomposition presented in Table C9.

Figure 4.11: Quantile decomposition of the total mean difference in utilisation of delivery assisted by a skilled provider before and after the start of the FMC program across the asset wealth quantiles



The results display a positive increase in mean utilisation after the start of the FMC program. The compositional effects of the difference are not statistically significant. This is expected since the DHS data used for analysis is for the 16 months before and after the start of the FMC program. Therefore, the covariates used in the decomposition are not likely to have changed much to explain the differences in utilisation between the two periods. While the largest increase in mean utilisation is at the 15th percentile, significant differences are also observed towards the upper end of the asset index distribution.

4.3. Discussion of Results

The utilisation of maternal health care has been shown to improve maternal and child health outcomes. However, high inequalities exist due to barriers that disadvantage some sections of society due to differences in socioeconomic and demographic characteristics. Another contributor to these high inequalities is differences in access to health facilities and skilled providers. This chapter, therefore, endeavoured to determine whether inequality does exist in the utilisation of maternal health care between the poor and non-poor in Kenya and if so, what drives this inequality. It also aimed at introducing supply-side factors to the analysis of inequality of maternal health care, which is primarily missing, especially in studies utilising DHS data. The variables introduced are distance to the nearest health facility, size of the nearest health facility to indicate the quality of the health facility and alternative supply of health facilities within a 5 km radius of an individual to account for the fact that individuals do not always visit the health facility closest to them.

The household asset index is used to rank individuals and classify them into poor and non-poor categories. The asset index shows a decline in asset poverty from the 2003, to the 2008/09 and ultimately to the 2014 survey. The probability of utilising maternal health care increases with an increase in household asset wealth. The Wagstaff indices calculated show the presence of inequality which favours the non-poor. Inequality is especially higher in the utilisation of deliveries by a skilled provider. This is similar to the findings by Fenny *et al.* (2019) which showed higher inequality exists in the utilisation of deliveries assisted by a skilled provider compared to other maternal health care services.

Reduction/removal of user fees has been used by governments to remove the cost barrier to the utilisation of health care services. Kenya introduced free maternal care on 1st June 2013 which made utilisation of antenatal care, deliveries and postnatal care in public health facilities free. The expectation is that all women would now be able to access maternal health care thus improving maternal and child health outcomes. However, the results show that while utilisation increased, the non-poor still have significantly higher utilisation of maternal health care compared to the poor after the start of the FMC program with the differences in inequality between the two periods not being statistically significant. The largest increase in utilisation is observed at the 15th percentile with substantial increases observed toward the upper end of the asset index distribution. Santas, Celik and Eryurt (2017) found comparable results in Turkey where inequalities were still present even with the introduction of a health transformation program in 2003 which sought to provide equal access to health services. Therefore, while the removal of user fees is an important program, it might not achieve the desired results if it is not augmented with other programs that reduce/remove other barriers to the utilisation of maternal health care e.g. provision and equipping of more health facilities and employing more skilled providers in these facilities to improve access to quality maternal health care.

A decomposition of the factors that drive inequality shows the same results as portrayed by the Wagstaff concentration indices; i.e., inequality favouring the non-poor does exist. The creation of a counterfactual that gives the non-poor the characteristics of the poor such that the only difference between the two groups is the asset wealth shows the utilisation of maternal health care would still be higher for the non-poor group. This indicates that the asset wealth does offer great advantages in the choice of women to seek maternal health care. The mother's education level explains a significant proportion of the differences in the utilisation of both antenatal care and deliveries by a skilled provider. Table C10 in appendix C shows the non-poor are more educated; i.e., have secondary education or higher, compared to the poor. Higher education levels imply that women are more aware of their health care needs and any interventions that the government has put in place to lighten the burden of seeking maternal health care. More educated women are also more likely to have better jobs, earn better and therefore be better placed to foot the direct and indirect costs associated with seeking maternal health care. They are also more likely to live close to social amenities such as hospitals thus easing the process of seeking maternal health care.

Place of residence is also shown to be an important determinant of inequality. Rural areas tend to have a higher proportion of poor individuals as shown in Table C10 in appendix C. They also have a lower density of health facilities compared to urban areas and therefore have poor accessibility. The coefficient for the explained component of the interaction of the distance and place of residence variable shows that the rural areas are more likely to have individuals living further away from health facilities thus creating an additional barrier to utilisation.

While the same supply-side factors affect both the non-poor and the poor, the situation is much more dire for the poor who have to travel relatively long distances to health facilities and have lesser means of mitigating the barriers brought about by supply-side factors e.g. higher travel costs, higher time costs etc. A higher proportion of women with high parity are poor. Women with more children are also more likely not to deliver in health facilities. This is especially likely if the previous births were without complications.

The proportion of the differences in utilisation that are not explained by the covariates controlled for in the decomposition is also quite substantial. While the study endeavoured to control for as many covariates as possible by including supply-side variables, some of the reasons given by women not seeking maternal health care in health facilities cannot be controlled for. For example, in the Kenya DHS 2014 survey, some women cited the reluctance to go to health facilities alone as one of the reasons for not seeking health care in health facilities. However, the proportion of the inequality that is explained by factors not included in the model did reduce after the introduction of supply-side variables.

The utilisation of maternal health care increased for both the poor and non-poor after the start of the FMC program. However, the difference in utilisation between the two groups is still statistically significant. This could be explained by the fact that the data collection for the data used in this study started within a year of the start of the FMC program. Therefore, the analysis only captures the short-term effect of the policy. Another possibility is that wealth is not a substitute for money. Therefore, while an individual could be coming from a non-poor household in terms of assets, monetary wealth is needed to access and utilise health facilities. Therefore, low income could mean that an individual still cannot access services even when they are free. The compositional effect of the decomposition of the utilisation of deliveries assisted by a skilled provider before and after the start of the FMC program across the asset index quantiles is not statistically significant. The covariates controlled for in the decomposition are not likely to have changed substantially within the 16 months before and after the start of the FMC program.

CHAPTER FIVE: IMPACT OF FREE MATERNAL CARE ON UTILISATION OF MATERNAL HEALTH CARE SERVICES AND NEONATAL MORTALITY IN KENYA

5.1. Introduction

The utilisation of maternal health care has been touted as one of the mechanisms through which maternal and child health outcomes can be improved. The World Health Organisation (2015), recommends that a woman makes at least 4 antenatal care visits to a skilled provider, gets assisted during delivery by a skilled provider and receives the first post-natal visit from a skilled provider within two days after delivery. However, these targets are rarely met due to a wide array of factors that limit access to skilled providers. Some of the barriers cited by women as impeding access to health care are the prohibitive cost of seeking care and long distances to health facilities (Kenya National Bureau of Statistics *et al.*, 2015). According to Lang'at and Mwanri (2015), more than half the deliveries being done in Kenya happened without the assistance of a skilled birth attendant thus contributing to the high maternal mortality rates in Kenya.

Kenya enacted a free maternal care policy for public health facilities in June 2013. The policy was meant to address the economic barriers that prevent mothers from utilizing maternal health care at health facilities. It has been shown that most poor mothers were not able to seek these services due to financial constraints. The policy was meant to eliminate this hurdle. The policy also removed user fees charged for antenatal care and postnatal care up to six weeks after birth and any referrals arising from pregnancy-related complications. After the enactment of this policy, public health facilities reported a high increase in the number of deliveries in hospitals with some hospitals reporting as much as a 100% increase by July 2013. Private hospitals also reported a reduction in the number of women seeking maternal care immediately after the program was enacted. However, the proportion of women seeking maternal care in private hospitals went up after the program had been running for some time due to quality issues in public hospitals (Bourbonnais, 2013; Lang'at and Mwanri, 2015; Koon *et al.*, 2017; Njuguna, Kamau and Muruka, 2017; Tama *et al.*, 2017). Previous studies have shown that maternal and child health outcomes improve after the reduction or removal of user fees. This has been attributed to more women utilising maternal health care services which were previously not affordable. However, other factors have been shown to determine utilisation and consequently, uptake of free maternal health care. Therefore, making services free without a more inclusive approach to addressing other barriers to utilisation dampens the impact of such interventions (McKinnon *et al.*, 2015; Lamichhane, Sharma and Mahal, 2017; Njuguna, Kamau and Muruka, 2017; Bhatt *et al.*, 2018; Gitobu, Gichangi and Mwanda, 2018).

In this chapter, I, therefore, seek to determine how the utilisation of maternal health care and levels of neonatal mortality after the start of the FMC program compare to the levels before the start of the program. I will also be seeking to determine how the changes in the utilisation of maternal health care arising from free maternal care had an impact on the levels of neonatal mortality in Kenya. While the effect of free maternal care in Kenya has been studied (Njuguna, Kamau and Muruka, 2017; Tama *et al.*, 2017; Gitobu, Gichangi and Mwanda, 2018), I will seek to improve on these studies in the following ways. First, I use data from the Demographic and Health Surveys (DHS) which is collected from all the counties in Kenya and is nationally representative. This will contrast with previous studies in Kenya which used only a small sample of counties or health facilities in their analysis. Secondly, the 2014 Kenya DHS contains data for births that occurred before and after the start of the free maternal care program. This allows for the measurement of the differences in maternal health outcomes that can be attributed to the free maternal care program

5.2. Methodology and Results

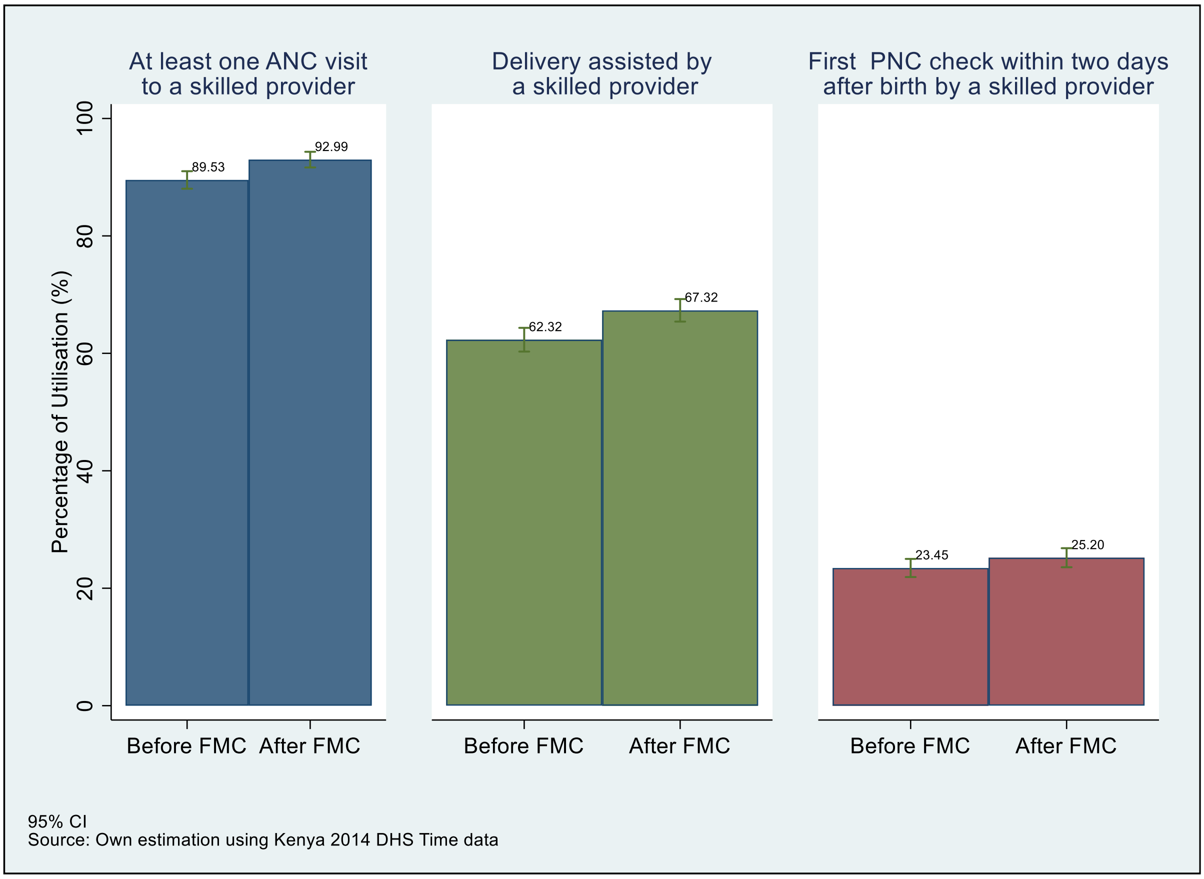
5.2.1. Review of the Utilisation of Maternal Health Care Services and Levels of Neonatal Mortality in Kenya before and After the Start of the FMC Program

Since the Kenya DHS 2014 survey has data for births that occurred in the periods before and after the start of the free maternal care program, this allows for the use of the difference-in-differences method of estimation as used by McKinnon *et al.* (2015), Chama-Chiliba and Koch (2016) and Lamichhane, Sharma and Mahal (2017) to estimate the impact of government interventions reducing or removing user cost on maternal and child health outcomes. The free maternal care program was only applicable to public health facilities, therefore, the children delivered in public health facilities after the start of the program will be the treated units. The control group are the children delivered at private health facilities and homes and other places apart from health facilities after the start of the FMC program. The program was implemented on 1st June 2013 and the data available in the KDHS 2014 after the program started is for 16 months, therefore the time dimension can be represented as [22]:

$$t = \begin{cases} t_0 \ for\ the\ 16\ months\ before\ 1st\ June\ 2013 \\ t_1\ for\ the\ 16\ months\ after\ 1st\ June\ 2013 \end{cases} \qquad (5.1)$$

The maternal health care services under consideration are at least one ANC visit to a skilled provider, delivery assisted by a skilled provider and the first PNC check being done by a skilled provider within two days after delivery. Figure 5.1 shows the utilization of maternal health care services before and after the start of the free maternal care program.

Figure 5.1: Utilisation of maternal health care before and after the start of the free maternal care program



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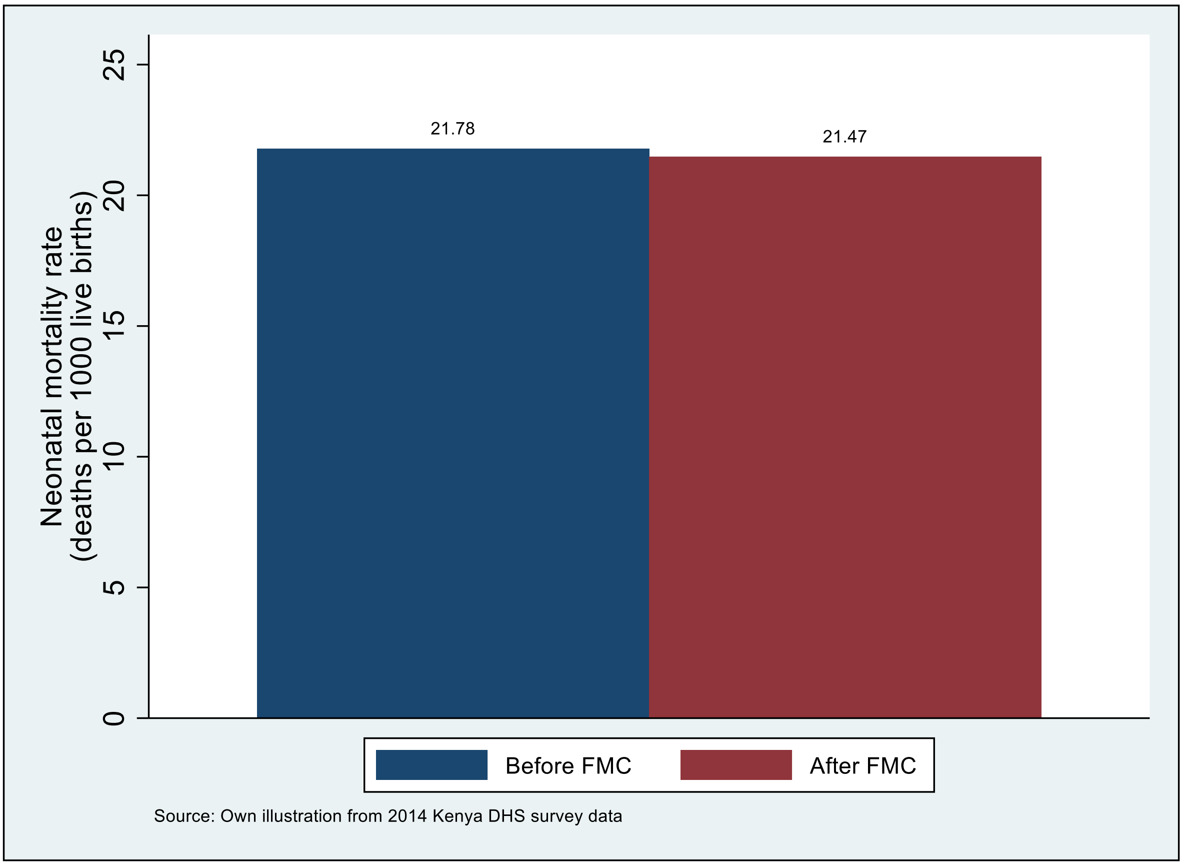
[22] *For the variable representing at least one ANC visit to a skilled provider, the period before FMC refers to children delivered 8 months before the start of the FMC program and the period after are the children delivered 9 to 16 months after the start of the FMC program. The exclusion of the first 8 months after the start of the FMC program is meant to take into account that the mothers who delivered within the first 8 months of the program might have made an ANC visit before 1st June 2013.*

The utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider after the start of the FMC program is higher and statistically different compared to before the start of the program. This indicates a positive effect of FMC which was inaugurated to encourage women to seek maternal health care services in health facilities. The FMC program was meant to increase the utilisation of maternal health care services and in turn, reduce mortality levels for women and children after delivery. Figure 5.2 presents the neonatal mortality rates before and after the start of the FMC program. The neonatal mortality rate reduced from 21.78 per 1000 live births before the start of the FMC program to 21.47 per 1000 live births after the start of the FMC program. The reduction in neonatal mortality was however not statistically significant.

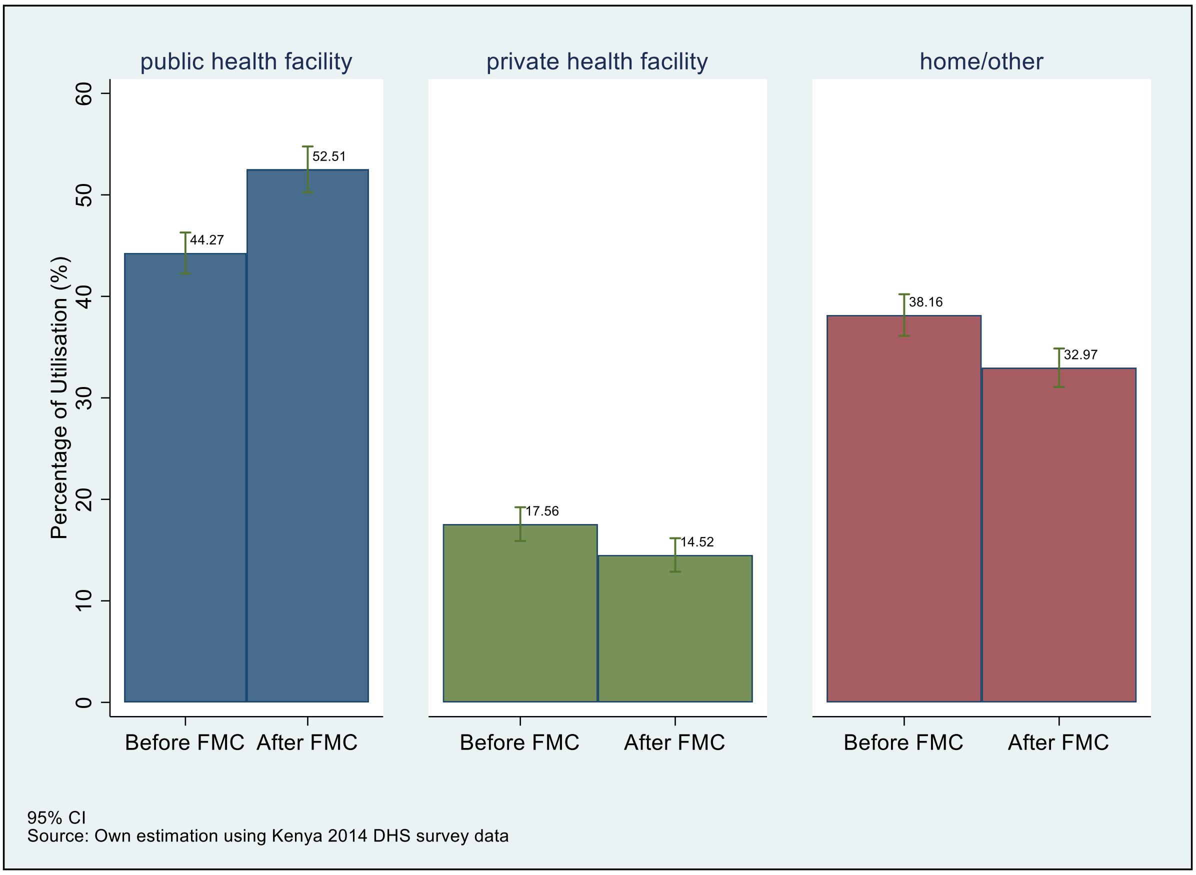
Figure 5.2: Neonatal mortality before and after the start of the FMC program



Data on the location where ANC services were sought was missing for 56.70% of the children who were delivered in this period. The variable measuring whether a woman had delivery assisted by a skilled provider is highly correlated to the place of delivery which is utilised as a treatment variable in this chapter. This violates the unconfoundedness assumption expected in treatment assignment; i.e., that the treatment assignment is independent of potential outcomes

(Imbens and Rubin, 2015), and as such, it cannot be utilised as an outcome variable. The data on the timing of the first PNC check by a skilled provider makes it impossible to determine the exact location where the service was sought; i.e., those who sought the first PNC check in a health facility are not classified into public and private facilities and as such will not serve the purposes of this chapter. Therefore, I will only seek to determine the impact of free deliveries in public health facilities on neonatal mortality. Figure 5.3 presents the proportion of children delivered in public health facilities, private health facilities and those not delivered in health facilities.

Figure 5.3: Place of delivery before and after the start of the FMC program



The figure shows an increase in the proportion of deliveries in public health facilities after the start of the FMC program and a reduction in deliveries in private health facilities and at home/other places. The increase in deliveries in public health facilities and the decrease in deliveries at home/other places are statistically significant at a 5% level of significance. This indicates a positive effect of the program in achieving one of its objectives which was to increase facility based deliveries and reduce deliveries done at home/other places without the assistance of a skilled provider. Having reviewed the changes in maternal and child health outcomes and the place of delivery before and after the start of the FMC program, I now move to assess whether the changes in neonatal mortality within this period can be attributed to the FMC program.

5.2.2. Are the Characteristics of Children Who Were Delivered Not Delivered in Health Facilities and those Delivered in Private Health Facilities Homogenous or Heterogeneous?

I utilise covariates which have been shown as being key factors determining the utilisation of maternal health care for analysis. These variables are the mother's education, household wealth, region of residence, place of residence, mother's age, parity level and marital status (Chama-Chiliba and Koch, 2016; Lamichhane, Sharma and Mahal, 2017; Bhat*t et al*, 2018). The chapter will also introduce supply-side variables, namely, distance to the nearest public health facility, facility level of the nearest public health facility and alternative supply of public health facilities within a 5 km radius of an individual. The variables are as defined in table A8 in chapter two. In addition, the chapter will have a variable measuring time periods (0 being February 2012 to May 2013 and 1 being June 2013 to September 2014), a treatment variable (1 being children delivered in public health facilities and zero otherwise) and a variable measuring the birth interval (1 being 33 months or more between births and 0 otherwise)23.

This section aims to determine how characteristics of the children who were not delivered in health facilities and those delivered in private health facilities will be included as the control group for children delivered in public health facilities. If the characteristics of the children in the two groups are not significantly different, then they will be included as a control group together and matched to those delivered in public health facilities in one equation. Otherwise, each group will be matched to the children delivered in public health facilities on its own thus necessitating the estimation of two separate equations. Table D1 in appendix D presents the means of the individual, household and cluster characteristics of children born at home/other places and those in private health facilities and a measure of how significantly different the means between the two groups are. With the exception of children born to women between 15-19 and 30-39 years, with all marital status, in the 3rd household asset index quintile, living close to a level 6 public health facility and the alternative supply of health facilities, the differences

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23 Pre-birth interval in introduced in this chapter since it has been shown to influence neonatal mortality which was not considered in the analysis done in the previous chapters.

in the other covariates of interest are significantly different between children delivered at home/other places and those delivered in private health facilities. As such, introducing the two groups in one equation as the control group would give biased results since the children delivered in public health facilities will be compared to a heterogeneous control group. In light of these results, the characteristics of the children not delivered in health facilities and those delivered in private health facilities will be included as two separate control groups as opposed to introducing them as one combined group.

5.2.3. Is Matching Necessary?

The difference-in-differences estimation requires the characteristics of the treatment and control group to be similar before the start of the program. However, since the data used is observational, randomisation is not always assured and as such, selection bias in the use of the FMC program could have existed. To ascertain this, the mean differences of the pre-treatment covariates for the two groups are tested for significance. Table D2 in appendix D presents the two-sample t-test for pre-treatment characteristics of children delivered in public health facilities, private health facilities and at home/other places which are potentially related to the outcome variable; i.e., neonatal mortality and the treatment variable; i.e., delivering in a public health facility.

For the children delivered at home/other places and those delivered in public health facilities, only children born 33 months or more after the previous sibling, born to women with primary education, those living in Coast, Eastern and Western Provinces and living close to a level 6 public health facility have no statistically significant differences in the characteristics. On the other hand, only first-born children, children born to women with secondary education, living in the Rift Valley and North eastern provinces, between 20-29 and 40-49 years of age at the time a child was born, in all marital statuses and living close to level 3, 4 and 6 health facilities and alternative supply of health facilities displayed no statistically significant differences between children delivered in private and public health facilities. This indicates substantial differences between the children delivered in public facilities compared to those not delivered in health facilities and those who were delivered in private health facilities. Basing estimation on this data would result in a bias of the inference of the causal effect of delivering in a public health facility on neonatal mortality and estimates with lower confidence intervals. Matching mitigates this by adjusting the difference in covariate means before the difference-in-differences is applied to ensure that the treatment and control groups are comparable (Stuart *et al.*, 2014; Imbens and Rubin, 2015).

5.2.4. Covariate Selection for Propensity Score Matching (PSM)

The chapter utilises 11 variables acting as covariates which have been adopted from the literature. PSM does not necessarily require using all these variables for matching. Covariates to be included in the model for propensity score matching are going to be determined using the procedure set out in Imbens and Rubin (2015). These will be the covariates that increase the probability of an individual utilising the free maternal care program. Logit models are estimated to determine how the addition of a covariate affects the likelihood ratio statistic. In each step, the variable which results in the highest increase in the likelihood ratio statistic is picked and included in the baseline model. The variables that do not result in a significant difference in the likelihood ratio statistic are dropped from subsequent steps. The process is then repeated iteratively for the remaining variables until all the variables that should be included in the propensity score specification are identified. The variable measuring the birth interval between successive births will be included in the matching process since it has been shown to have an effect on neonatal mortality (World Health Organisation, 2005).

Tables D3 and D4 in appendix D show the iterative steps and the likelihood statistics at each step combined with the significance levels for each likelihood statistic. Table D3 shows that 8 out of 10 variables are selected to be used for propensity score matching for the children who were not delivered in health facilities to those delivered in public health facilities. These variables are the mother's education, household asset wealth, region of residence, place of residence, mother's age at child's birth, mother's parity, distance to the nearest public health facility and size of the nearest public health facility. On the other hand, 5 variables are selected to be utilised in matching the children delivered in private health facilities to those delivered in public health facilities as shown in table D4. These variables are the mother's education, household asset wealth, region of residence, place of residence and distance to the nearest public health facility. I now proceed to the estimation of the model.

5.2.5. Matching Difference-in-differences

The matching difference-in-differences (MDID) is then implemented in three steps. First, MDID utilises the covariates selected in section 5.2.4 to create a counterfactual for children delivered in public health facilities after the start of the FMC program to children delivered in public health facilities before the start of the FMC program and to children delivered in private health facilities and at home and other places, both before and after the start of the FMC program using kernel matching. This is done since the data being used is not panel data, thus the matching creates a pseudo-panel from cross-sectional data. Secondly, the differences in outcomes between the treatment and control groups for the pseudo panels created by kernel matching in the first step are estimated, both before and after the start of the free maternal care program. The differences are calculated while controlling for variables that explain the outcome variable and the treatment variable.

> *neonatal mortality status =f (mother's education levels, household asset wealth, region of residence, place of residence, mother's age, mother's parity, pre-birth interval, mother's marital status, distance to the nearest health facility, size of nearest health facility, alternative supply of health facilities)* (5.2)

Lastly, the difference between the pre-program and post-program differences is estimated (Blundell and Dias, 2009).

The MDID estimator is thus estimated as[24]:

$$\widehat{\alpha}^{\mathrm{MDID}} = \sum_{i \in T_1} \left\{ \left[y_{it_1} - \sum_{j \in T_0} \widetilde{w}_{ijt_0}^{T} \; y_{it_0} \right] - \left[\sum_{j \in C_1} \widetilde{w}_{ijt_1}^{C} \, y_{it_1} - \sum_{j \in C_0} \widetilde{w}_{ijt_0}^{C} \, y_{it_0} \right] \right\} w_i \tag{5.3}$$

where:

- t_0 is the period before a policy intervention; i.e., before the free maternal care program started in June 2013
- t_1 is the period after a policy intervention; i.e., after the free maternal care program started in June 2013
- T_0 is the treatment group at time t_0 ; i.e., the children delivered at public health facilities before the start of the FMC program

[24] The diff command on Stata by allows for these three steps to be run concurrently (Villa, 2016)

- T_1 is the treatment group at time t_1 ; i.e., the children delivered at public health facilities after the start of the FMC program
- C_0 is the control group at time t_0 ; i.e., the children delivered at private health facilities or homes and other places before the start of the FMC program
- C_1 is the control group at time t_1 ; i.e., the children delivered at private health facilities or homes and other places after the start of the FMC program
- $\widetilde{w}_{ij}$ is the weight of control observation j for treated observation i
- w_i is the weight for the reconstruction of the outcome distribution for the treated sample.

The characteristics of children delivered in private health facilities and those delivered at home/other places were found to be heterogeneous in section 5.2.2. As such, the matching to children born in public health facilities will be done separately. Tables 5.1 and 5.2 present the MDID estimation results measuring the average treatment effect that deliveries in a public health facility had on neonatal mortality when compared with deliveries at home/other places and deliveries in a private health facility. The first column presents the results of the estimation on the unmatched sample while the second column presents the result of the same estimation on the sample matched using kernel matching. Common support is enforced with the kernel matching to ensure that for each unit in the treated group, there is a unit in the control group with the same/similar propensity score. A thin or lack of common support results in increased bias and variance of the estimator (Lechner and Strittmatter, 2019).

Table 5.1: Difference-in-differences estimation results with deliveries at home and other places apart from health facilities as the control group and deliveries in public health facilities as the treatment group

	Unmatched Sample	***Matched Sample***
Before		
Home/ Others (C)	0.038	0.046
Public health facility (T)	0.027	0.018
Difference before FMC (T-C)	-0.011	-0.027**
	(0.009)	(0.011)
After		
Home/ Others (C)	0.027	0.020
Public health facility (T)	0.028	0.019
Difference after FMC (T-C)	0.001	-0.002
	(0.006)	(0.007)
Difference-in-differences	0.002	0.026**
	(0.008)	(0.013)
Number of observations	9197	9185

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table 5.1 shows the results of the difference-in-differences estimation for children who were not delivered in health facilities and those who were delivered in public health facilities. For both the matched and unmatched samples, neonatal mortality is higher for children who are not born in health facilities before the start of the FMC program. However, the differences are only statistically different for the matched sample. After the start of the program, the differences in neonatal mortality are not statistically significant for both the matched and unmatched samples. The magnitude of the first differences and the difference-in-difference estimates are higher for the matched samples. The difference-in-differences estimator shows an increase in neonatal mortality with the increase being statistically significant for the matched sample. The mean differences with matching are expected to present a more accurate picture since matching reduces the differences between the treatment and control groups thus making the groups comparable. The difference-in-differences estimate for the matched sample shows an increase in the average neonatal mortality by 2.6% after the start of the FMC program.

The results in table 5.2 show conflicting results with and without propensity score matching for the mean differences before the start of the FMC program. The neonatal mortality is higher for the children born in public health facilities for the unmatched sample while it is higher for children born in private health facilities for the matched sample before the start of the FMC program. After the start of the FMC program, the average neonatal mortality is lower for the children born in private health facilities, both for the unmatched and matched samples. The difference-in-differences estimate shows an increase in the average neonatal mortality after the start of the FMC program for both the unmatched and matched samples. However, the first differences and the difference-in-differences estimates are not statistically significant.

Table 5.2: Difference-in-Differences estimation results with deliveries in private health facilities as the control group and deliveries in public health facilities as the treatment group

	Unmatched sample	***Matched sample***
Before		
Private health facility (C)	0.051	0.027
Public health facility (T)	0.056	0.021
Difference before FMC (T-C)	0.006	-0.006
	(0.007)	(0.009)
After		
Private health facility (C)	0.060	0.022
Public health facility (T)	0.056	0.021
Difference after FMC (T-C)	0.004	-0.001
	(0.011)	(0.009)
Difference-in-differences	0.009	0.006
	(0.014)	(0.013)
Number of observations	5896	5761

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

5.2.6. Does Matching Improve Covariate Balance?

Table D5 in appendix D shows the statistical significance of the mean differences between the children delivered in public health facilities compared to those not delivered in health facilities and those delivered in private health facilities after propensity score matching is enforced with common support. For most of the covariates under consideration, the difference in covariate means is not statistically significant. After matching the children who were not delivered in health facilities and those delivered in public health facilities, firstborn children, children born within 33 months of the previous sibling, born to women with primary education, between 30-39 years at the time the child is born, with all marital statuses and living close to public level 5 health facility remain unbalanced at a 10% level of significance. With respect to characteristics of children delivered in private and public health facilities, all characteristics are balanced after matching except for children born to women living in the coast province and in the 15-19 year age bracket at the time the child is born. As such, while matching does not eliminate all the differences between the treatment and control groups, it significantly reduces the mean differences between them making the groups more comparable. Therefore, combining matching with the difference-in-differences estimation is necessary (Blundell and Dias, 2009).

5.3 Discussion of Results

The FMC program was implemented in June 2013 via a presidential directive. It made antenatal care, deliveries and postnatal care in public health facilities free. This was meant to encourage more women to seek these services in public health facilities rather than at home and from other unskilled providers. The objective was to reduce mortality among women and children since health facilities are equipped with skilled health providers; i.e., doctors and nurses who are trained to deal with any eventualities arising before, during and after delivery.

The proportion of women who made one ANC visit to a skilled provider and delivered in a health facility rose after the start of the FMC program. There was also an increase in women who sought delivery services in public health facilities. At the same time, the proportion of deliveries at private health facilities, homes and other places reduced. This result is similar to findings by Njuguna, Kamau and Muruka (2017) and Lamichhane, Sharma and Mahal (2017) who found women were more likely to switch to seeking maternal health care in facilities offering free maternal health care. This indicates that the program made progress in achieving one of its objectives which was to reduce the proportion of women who were not seeking maternal health care services in health facilities. The reduction in the proportion of women seeking delivery services in private health facilities indicates the desire of more women to utilise the free services provided by the government as opposed to those provided by private entities at a fee. A comparison of the neonatal mortality rates before and after the start of the FMC program shows a reduction in neonatal mortality. However, this reduction is not statistically significant. The individual characteristics of women and their access to health facilities are of core importance in explaining child health outcomes. While reducing the cost at the point of service is important, the impact is dampened if the women cannot access the facility or they are not aware of the government intervention making the service free.

The matching difference-in-differences preliminaries show that a sizeable proportion of the mean differences of covariates without matching are statistically significant when comparing the characteristics of children delivered in public health facilities with those delivered at home/other places and in private health facilities. When matching is implemented with common support, the balance in the characteristics between the groups improves thus making the groups much more similar as compared to when matching had not been implemented.

The matching difference-in-differences estimation shows that in comparing deliveries not done in health facilities and those done in public health facilities, the first differences and the difference-in-differences estimates are not statistically significant for the unmatched samples. However, for the matched sample, the first differences are statistically significant before the start of the FMC program. After the start of the FMC program, the level goes down for the children born away from health facilities and increases for deliveries done in public health facilities. This indicates that neonatal mortality which was quite high at home and other places might have reduced due to more women seeking maternal health care in public health facilities after the FMC program was implemented. Neonatal mortality increased by 2.6% between the two periods; i.e., before and after the start of the FMC program. While this is an unexpected result, it calls to question the dynamics behind the factors that determine neonatal mortality that could have resulted in this increase when the expectation would be a decrease in neonatal mortality. The matching difference-in-differences coefficient for deliveries in public and private health facilities is not statistically significant. This indicates that the chance of survival of a child beyond thirty days after birth does not depend on the type of health facility where they are born.

One of the factors which could have contributed to this increase in neonatal mortality would be that the FMC program came into being via a presidential directive on the 1st of June 2013. This resulted in a surge of women seeking maternal health care services in public health facilities. Some hospitals reported a 100% increase in the deliveries being done in the period after the start of the FMC program. While this increase showed a positive response to the program, health facilities were not fully equipped to handle this increase. Some public health facilities were understaffed and lacked the necessary supplies. As such, while more women sought to deliver in health facilities, the quality of services rendered might have dampened the achievement of the initial objective of the FMC program to reduce mortality rates among children (Bourbonnais, 2013; Wamalwa, 2015).

The chapter does a difference-in-differences estimation to analyse the impact of the FMC program on neonatal mortality. The socioeconomic and demographic data used for this analysis was sourced from the Kenya DHS 2014 survey. Data collection for this survey started 11 months after the start of the FMC program. Given that there might have been a lag before the program was fully implemented, this analysis might not fully capture the full impact of the FMC program. The chapter also does not analyse the impact of ANC and PNC services on neonatal mortality due to data shortcomings as indicated in section 5.2.1. Since these services are theorised as explaining the chances of survival of both mother and child before and after delivery, the chapter does not cover the whole scope of services that would explain neonatal mortality before and after the start of the FMC program.

CHAPTER SIX: CONCLUSION, RECOMMENDATIONS AND AREAS FOR FURTHER STUDY

6.1. Summary of Findings and Contributions of the Thesis

In this thesis, I endeavoured to contribute by exploring important issues around maternal and child health outcomes in Kenya. In the second chapter, I introduced supply-side factors to DHS data which primarily collects information on individuals and households. This is important in increasing the robustness of the models assessing the factors which explain the utilisation of maternal health care and the inequalities that are observed in the utilisation of these services. The asset index is calculated using a pooled set of assets from the 2003, 2008/09 and 2014 DHS surveys to allow for comparability of asset poverty across surveys. As spelt out in the chapter, the UC PCA has a couple of advantages over other indices. The calculated asset index shows a steady decline in asset poverty from 2003 to 2008 and ultimately to the 2014 DHS survey. I then map the health facilities offering maternal health care in Kenya as of 2015. The mapping displays a clustering of health facilities in the western, central and southeastern parts of Kenya. The clustering of health facilities is shown to follow the population density in that, areas with high population density have a higher density of health facilities offering maternal health care services. While increasing health facilities is desirable, especially in areas which are currently underserved such as the northern parts of the country, the government also must make considerations for the per capita costs in terms of human resources, equipment and monetary costs that would arise from such a venture.

In chapter three, I examine the trends in the utilization of maternal health care in Kenya across three DHS surveys; i.e., 2003, 2008/09 and 2013 surveys. An analysis of the factors affecting maternal and child health outcomes is then done using a logit regression model when supply-side factors are controlled for. The utilization of maternal health care is found to increase with increases in maternal education, household wealth, maternal age at birth of the child, facility level of the nearest health facility and alternative supply of health facilities. Lower utilization is found for married women compared to their single counterparts, women in rural areas compared to their urban counterparts and women living much further from a health facility offering maternal health care. The chapter also shows the presence of spatial dependencies in the utilization of maternal health care, in that areas with high utilization of maternal health care are more likely to be surrounded by areas with similarly high utilization and vice versa. All the covariates used except for marital status display statistically significant variations in the coefficients depending on the location of the individual. This means that the effect of various covariates is not constant across the study space. Therefore, the use of geographically weighted regression models allows for spatial dependency and spatial non-stationarity of covariates to be accounted for, thus resulting in correct standard error estimates and consequently correct inferences. Ignoring spatial dependency, especially spatial autocorrelation biases the analysis towards rejecting the null hypothesis.

In the fourth chapter, an analysis of inequality in the utilization of maternal health care services is undertaken using the Wagstaff concentration index which is more appropriate for binary variables, unlike the standard concentration index. High levels of inequality are found to exist in the utilisation of maternal health care. This inequality is especially severe for the utilisation of deliveries by a skilled provider. It is therefore more likely that the poor do not have the resources to mitigate the disadvantages that exist in the utilisation of maternal health care such as long distances to health facilities. A decomposition of the factors contributing to the inequality between the non-poor and the poor in terms of utilization of maternal health care services is done using recentered influence functions which allow for reweighting and creation of counterfactuals. Through this analysis, I show that maternal education is the most significant determinant of this inequality. The non-poor are also found to have higher utilisation of maternal health care than the poor even if they have the same characteristics, thus implying that wealth does offer an advantage in utilisation.

The free maternal care program was implemented to encourage the utilization of maternal health care in health facilities and curb the high maternal and child mortality rates therefore I go on to assess the effect of this program on inequality. Even with the introduction of the FMC program in 2013, inequality remains which points to other factors hampering the utilization of maternal health care, especially among the poor. While utilisation of maternal health care increased across the asset index distribution after the introduction of the FMC program, the increase was highest at the 15th asset index percentile with substantial differences also observed towards the upper end of the asset index distribution. However, the effect on inequality was not statistically significant. While such programs are meant to level the playing field for all regardless of their wealth levels, other barriers to utilisation such as accessibility costs, do exist. If these are not mitigated when the direct costs to utilisation are reduced or removed, these will dampen the effect of such policies. That said, the data used in my analysis was collected soon after the start of the program (16 months) and the full effects of the program might not have been fully achieved by the time the data was collected.

In the fifth chapter, I examine more formally the impact of the program on the utilization of maternal health care services and levels of neonatal mortality. This is an improvement on previous studies since I use a nationally representative sample for the impact analysis. I include in the sample only those children who were born within 16 months of the start of the FMC program in order to take into account the fact that data collection for the DHS 2014 survey began within a year of the start of the FMC program. Therefore, only 16 months within the inauguration of the FMC program are accounted for. The program evaluation using the matching difference-in-differences method of estimation shows a significant increase in the utilisation of maternal health care after the start of the program. However, a comparison of the neonatal mortality levels of the children born in public health facilities and those born at home shows an overall significant increase in the levels of neonatal mortality in Kenya after the introduction of the program.

This paradox could have stemmed from an increase in health facility attendance by women after the services were made free without a commensurate increase in resources such as personnel and equipment. Overworked health practitioners provide a fertile ground for errors to be made. At the same time, women who are willing to seek maternal health care from health facilities might shy away from it to avoid the inconvenience of long waiting times at the health facility and the possibility that they might not receive adequate and quality health care. All these factors negate the benefits of removing user fees. A comparison of neonatal mortality for children born in public and private health facilities shows no significant differences after the start of the program. This points to the possibility that the type of facility, whether public or private, does not have an implication on neonatal mortality.

6.2. Recommendations from the thesis

One of the main contributions I make in this thesis is to introduce supply-side factors into the analysis of maternal and child health outcomes alongside the socioeconomic and demographic variables that are traditionally drawn from DHS surveys. These supply-side variables have been shown in previous studies to be significant determinants of maternal health care utilisation and consequently, maternal and child health outcomes. I also show that some of the effects of inequality that are attributed to the place of residence stem from the supply side, especially from the distance to the health facility. I achieve this objective by introducing distance to the nearest health facility variable and alternative supply of health facilities variables to measure accessibility costs and the size of the nearest health facility to measure the quality of the nearest health facility. However, some shortcomings remain in this regard. The provision of household-level geographical data would enable the calculation of household-level supply-side variables which are expected to be more precise than the cluster-level supply-side variables which have been utilised in this thesis. Additionally, the collection of names of health facilities where the women who delivered at health facilities would allow for a more accurate calculation of the distance to health facilities rather than the assumption made in this thesis that the women would visit the nearest health facility.

The running theme in this thesis is the importance of maternal education levels on maternal health care utilisation and inequality in utilisation between the poor and non-poor. While the government has made great strides in improving education levels in Kenya - for example by introducing tuition-free primary education in 2003 and tuition-free day secondary education in 2008 - a substantial proportion of the population, especially the poor were still not educated as of 2014. The government should ramp up information sessions for women of childbearing age on the importance of utilising maternal health care before, during and after delivery. The information should be tailored such that it can be understood by everyone, regardless of their education level.

I also show that great strides have been made in improving maternal and child health outcomes. The introduction of the FMC program in 2013 led to significant increases in deliveries in public health care facilities where the program was first implemented. However, more needs to be done in the fight to further improve these outcomes. One of the challenges that has been shown to exist is the accessibility of health facilities. While the Ministry of Health defines a health facility as being accessible if it is within 5km of an individual's dwelling, some of the clusters interviewed in the DHS 2014 survey were more than 90 km away from a public health facility offering maternal health care. Distance to the nearest health facility is more of a challenge in clusters which have on average poorer households and in rural areas. Most individuals live close to level 2 facilities which are not operational for 24 hours. Therefore, even if the services being provided in public health facilities have no direct cost, the indirect cost from travel and time costs are still a barrier to utilisation. Investing in more health facilities with adequate personnel, equipment and operational hours would go a long way in improving the utilization of maternal health care services.

The government of Kenya introduced the Linda Mama initiative in 2016 which expanded free maternal care to low-cost private and health-based facilities (Orangi *et al.*, 2021). An analysis of the impact of this program on the utilisation of maternal health care, inequality and neonatal mortality is of interest. The Kenya DHS 2022 survey is currently underway and therefore would form a good basis for such a study.[25]

I also recommend that the presence of spatial dependency be explored before deciding on whether to utilise global models for analysis. In case of spatial non-stationarity is present, appropriate spatial models can then be utilized for analysis.

[25] *As of August 2022*

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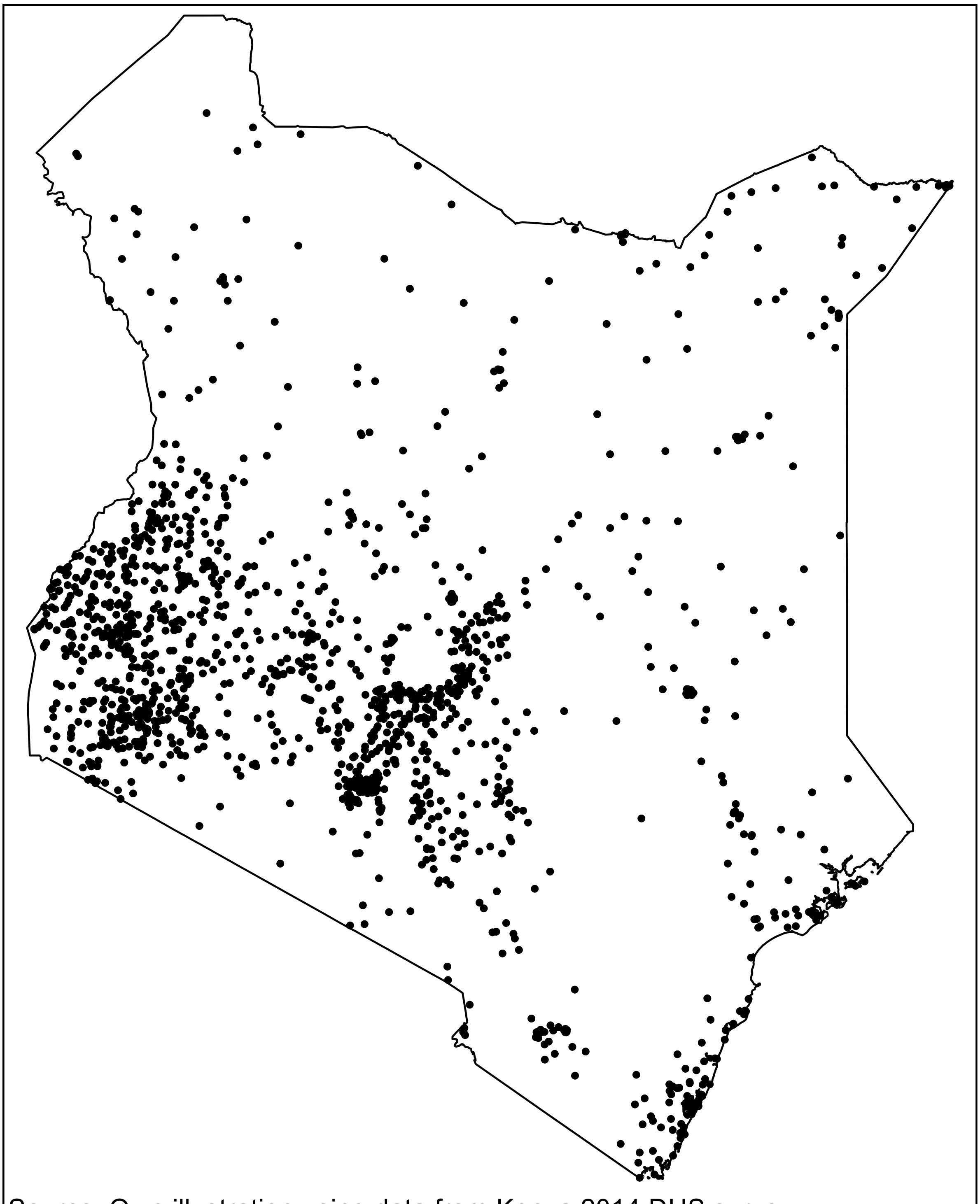
APPENDICES

Appendix A: Chapter Two

Table A1: Overview of DHS Surveys Collected in Kenya

Survey		***DHS 2003***	***DHS 2008/09***	***DHS 2014***
No. of clusters interviewed	*Rural*	*271*	*267*	*995*
	Urban	*129*	*133*	*617*
Household Sample Size		*8561*	*9057*	*36430*
No. of Observations for Individual Women		*8195*	*8444*	*31079*
No. of observations for children born to interviewed women		*22074*	*22534*	*83591*

Figure A1: Clusters interviewed in the DHS Kenya 2014 survey



Source: Own illustration using data from Kenya 2014 DHS survey

Table A2: Assets and characteristics showing a household's private assets and access to basic services included in calculating the index

Private assets		
Radio, television, refrigerator, bicycle, motorcycle, car/truck, telephone/mobile phone, solar panels, land, number of rooms for sleeping		
Access to basic services		
Electricity		
Drinking water sources	*Improved water sources*	*piped water into dwelling or plot, public tap, tube wells, boreholes, protected wells, protected springs, rainwater,*
	Unimproved water sources	*unprotected well, unprotected spring, surface water, others*
Type of toilet facility	*Improved sanitation*	*Flush toilet connected to a piped sewer system, septic system, pit latrine or somewhere else, pit latrine with slab, ventilated improved pit latrine, composting toilet.*
	Unimproved sanitation	*flush to do not know where, pit latrine without a slab, no facility, composting toilet, bucket toilet, hanging toilet/latrine, others*
Main floor material	*Improved floor material*	*tablet/wood plank, palm/bamboo, parquet, polished wood, vinyl, asphalt strips, ceramic tiles, cement, carpet*
	Unimproved floor material	*earth, mud, dung, sand, others*
Main roof material	*Improved roof*	*Corrugated iron, asbestos sheets, concrete, tiles*
	Unimproved roof	*grass, thatch, palm leaf, makuti, tin cans, others, no roof*
Type of cooking fuel	*Clean fuel*	*electricity, liquefied petroleum gas (LPG), natural gas,*
	Solid fuel	*coal, lignite, charcoal, firewood, straw/shrub/grass, agricultural crop, dung, no food cooked in the household, other*

Table A3: Percentage of household owning assets considered in the calculation of the uncentered principal component index

Private assets	***2003***	***2008/09***	***2014***
Radio	*72.91%*	*71.25%*	*62.72%*
Television	*21.69%*	*28.62%*	*27.35%*
Refrigerator	*6.27%*	*8.39%*	*4.64%*
Bicycle	*26.56%*	*28.42%*	*20.17%*
Motorcycle	*0.82%*	*2.11%*	*7.58%*
Car/truck	*6.07%*	*7.04%*	*3.97%*
Telephone/mobile phone	*16.08%*	*60.16%*	*81.66%*
Solar	*3.08%*	*4.76 %*	*10.47%*
Land	*59.39%*	*76.63%*	*72.35%*
Average no. of rooms for sleeping	*1.91*	*1.83*	*1.74*
Access to basic services			
Improved water	*60.51%*	*66.77%*	*67.64%*
Improved sanitation	*22.26%*	*50.38%*	*47.65%*
Improved floor	*41.56%*	*45.36%*	*43.98%*
Improved roof	*75.54%*	*78.20%*	*81.77%*
Clean cooking fuel	*23.55%*	*17.91%*	*13.48%*
Electricity	*20.08%*	*24.96%*	*26.91%*

Table A4: Asset weight from factor analysis, principal components analysis and uncentered principal components analysis

	Factor analysis	***Principal components analysis***	***Uncentered principal components***
Private assets			
Radio	0.2943	0.1694	0.1212
Television	0.6982	0.3598	0.2389
Refrigerator	0.4344	0.2392	0.5371
Bicycle	-0.0366	-0.0191	0.1214
Motorcycle	0.0907	0.0545	0.2199
Car/truck	0.3227	0.1818	0.5388
Telephone/mobile phone	0.4614	0.2584	0.1252
Solar	0.0390	0.0248	0.1638
Land	-0.3306	-0.1827	0.0849
No. of rooms for sleeping	0.0021	0.0040	0.1074
Access to basic services			
Improved water	0.4562	0.2574	0.1232
Improved sanitation	0.6076	0.3279	0.1581
Improved floor	0.7487	0.3854	0.1739
Improved roof	0.4049	0.2293	0.1133
Clean cooking fuel	0.6316	0.3320	0.2908
Electricity	0.8119	0.4030	0.2394

Table A5: Cronbach's alpha and Feldt test results for assets and characteristics showing a household's access to basic services available for each DHS survey

Private assets	***Include in the calculation of the asset index***	
	Cronbach's alpha	*Feldt statistic*
Radio	Yes	Yes
Television	Yes	Yes
Refrigerator	Yes	Yes
Bicycle	No	No
Motorcycle	No	No
Car/truck	No	No
Telephone/mobile phone	Yes	Yes
Solar	No	No
Land	No	No
No. of rooms for sleeping	No	No
Access to basic services		
Improved water	Yes	Yes
Improved sanitation	Yes	Yes
Improved floor	Yes	Yes
Improved roof	Yes	Yes
Clean cooking fuel	Yes	Yes
Electricity	Yes	Yes

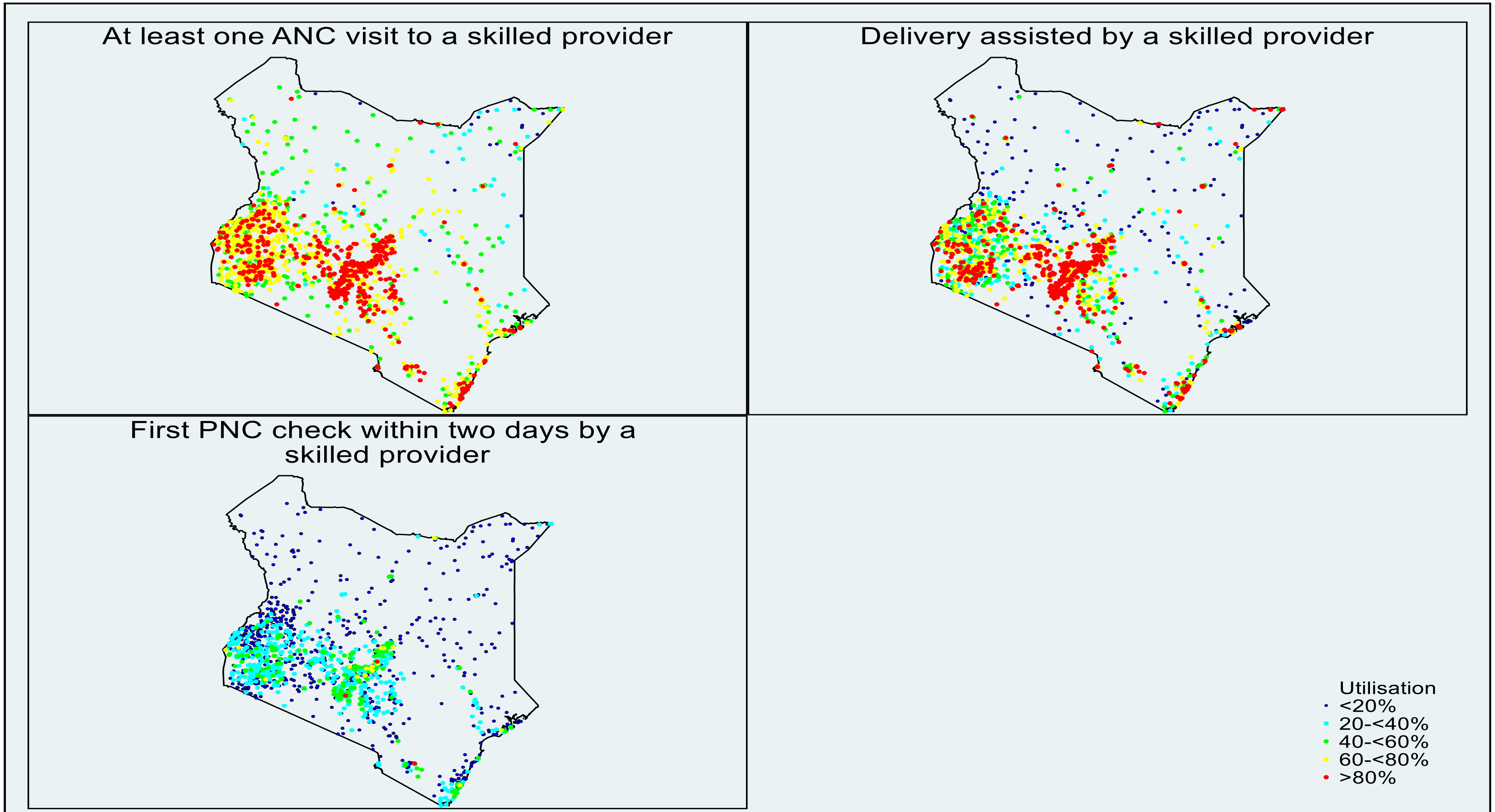
Table A6: Uncentered principal components index weights

	weights
Radio	*0.1385*
Tv	*0.2885*
Fridge	*0.6995*
Phone	*0.1456*
Improved water	*0.1486*
Improved floor	*0.2146*
Improved sanitation	*0.1949*
Improved roof	*0.1320*
Clean fuel	*0.4034*
Electricity	*0.3174*

Table A7: Proximity of DHS clusters in 2014 to health facilities offering maternal health care services

Distance	***Antenatal care***	***Maternity services***	***Postnatal care***
At most five kms	*1060 (77.14%)*	*940 (59.46%)*	*970 (61.35%)*
More than five kms	*521 (32.95%)*	*641 (40.54%)*	*611 (38.65%)*
Total	*1581*	*1581*	*1581*

Figure A2: Average utilisation of maternal health care in the clusters interviewed in the Kenya 2014 DHS survey



Source: Own illustration using data from Kenya 2014 DHS survey

Table A8: Variable Definition

Variables	***Definition***
Outcome Variables	
ANC by a skilled provider	It refers to ANC being provided by either a doctor or a nurse. It is measured by a binary variable with 1 representing at least 1 visit from a skilled provider and 0 otherwise.
Delivered by a skilled provider	It refers to a woman being assisted during delivery by a doctor or a nurse. It is measured by a binary variable with 1 representing deliveries done by a skilled provider and zero otherwise.
First postnatal check by a skilled provider	It refers to a woman receiving PNC within two days after delivery from a doctor or nurse. Measured by a binary variable where 0 represents no postnatal care or first postnatal check after 2 days and 1 represents receiving the first postnatal check within two days after delivery by a skilled provider.
Individual (mother) level variables	
Mother's education	Measured by a categorical variable with 0 =no education, 1 = primary education, 2 = secondary education and 3 = higher than secondary education
Province of residence	Measured by a categorical variable with 0==Nairobi, 1=Central, 2=Coast, 3=Eastern, 4=Nyanza, 5=Rift valley, 6=Western and 7=North eastern province
Age of the mother at the child's birth	Measures the age of the mother at the time a child was born. Represented by a discrete variable. Ranges between 15 and 49 years.

Parity	Measures the number of children that have ever been born to a woman. Measured by a binary variable with 0 = less than four children and 1 = four or more children
Marital status	Measured by a binary variable with 1 =women who are married or living with a partner and 0 = women living alone.
Household-level variables	
Wealth	Measured by an asset index that is represented by a discrete variable with 0 = 1st quintile, 1=2nd quintile, 2=3rd quintile, 3=4th quintile and 4=5th quintile.
Cluster level variables	
Place of residence	Measured by a binary variable with 0 =urban dwellers and 1 = rural dwellers.
Distance	It measures how far a DHS cluster is from the nearest health facility in kilometres. It is represented by a continuous variable.
Size of health facility	It is represented by a discrete variable measuring the level of the nearest health facility where 0=level 2, 1=level 3, 2=level 4, 3=level 5 and 4=level 6.
Alternative supply	It is measured by the number of health facilities within a 5 km radius of the cluster.

Appendix B: Chapter Three

Table B1: Utilisation statistics

Utilisation	***Freq.***	***Percent***
No utilisation	*3097*	*15.92*
Used one service	*6488*	*33.36*
Used two services	*6586*	*33.86*
Used three services	*3279*	*16.86*
Weighted Total	*19450*	*100*

Table B2: Descriptive statistics

Variable	***Obs***	***Mean***	***Std. err.***	***Min***	***Max***
Individual-level characteristics	14820				
Mother's Education					
No education	2762	0.0974	0.0047	0	1
Primary	7765	0.5441	0.0081	0	1
Secondary	3189	0.2615	0.0062	0	1
Higher	1104	0.0969	0.0058	0	1
Region of residence					
Nairobi	428	0.1154	0.0079	0	1
Central	1188	0.1051	0.0044	0	1
Coast	1826	0.1014	0.0050	0	1
Eastern	2279	0.1271	0.0055	0	1
Nyanza	2069	0.1377	0.0055	0	1
Rift Valley	4714	0.2767	0.0075	0	1
Western	1398	0.1108	0.0053	0	1
North Eastern	918	0.0258	0.0023	0	1
Mother's age at child's birth					
15-19 years	1580	0.1075	0.0036	0	1
20-29 years	8280	0.5740	0.0064	0	1
30-39 years	4284	0.2787	0.0054	0	1
40-49 years	676	0.0398	0.0020	0	1
Parity		.	.	.	.
Low Parity	8846	0.6524	0.0062	0	1
High Parity	5974	0.3476	0.0062	0	1
Marital Status					
Not Married/Not living together	2586	0.1849	0.0041	0	1
Married or living together	12234	0.8151	0.0041	0	1
Household-level characteristics					
Wealth	14294				
1st asset quintile	3444	0.1729	0.0064	0	1
2nd asset quintile	3339	0.2205	0.0057	0	1

3rd asset quintile	3393	0.2181	0.0057	0	1
4th asset quintile	2710	0.2016	0.0068	0	1
5th asset quintile	1408	0.1869	0.0091	0	1
Cluster level characteristics					
Place of residence	1581				
Urban	613	0.4381	0.0069	0	1
Rural	968	0.5619	0.0069	0	1
Health facilities offering antenatal care					
Distance	1581	4.2774	0.1299	0.0887	91.73
Size					
Level 2	951	0.5906	0.0167	0	1
Level 3	384	0.2566	0.0151	0	1
Level 4	217	0.1319	0.0109	0	1
Level 5	29	0.0209	0.0052	0	1
Alternative supply	1581	7.8289	0.3566	0	69
Health facilities offering Maternity					
Distance	1581	5.5514	0.1608	0.1392	91.73
Size					
Level 2	693	0.3793	0.0131	0	1
Level 3	514	0.3635	0.0157	0	1
Level 4	326	0.2127	0.0136	0	1
Level 5	38	0.0335	0.0070	0	1
Level 6	10	0.0109	0.0038	0	1
Alternative supply	1581	3.2244	0.1391	0	29
Health facilities offering postnatal care					
Distance	1579	6.0847	0.1942	0.1324	154.534
Size					
Level 2	851	0.5096	0.0164	0	1
Level 3	458	0.3181	0.0159	0	1
Level 4	226	0.1362	0.0109	0	1
Level 5	35	0.0284	0.0065	0	1
Level 6	9	0.0078	0.0026	0	1
Alternative supply	1579	4.9026	0.2782	0	40

Figure B1.1: Moran scatterplot (At least one ANC visit to a skilled provider)

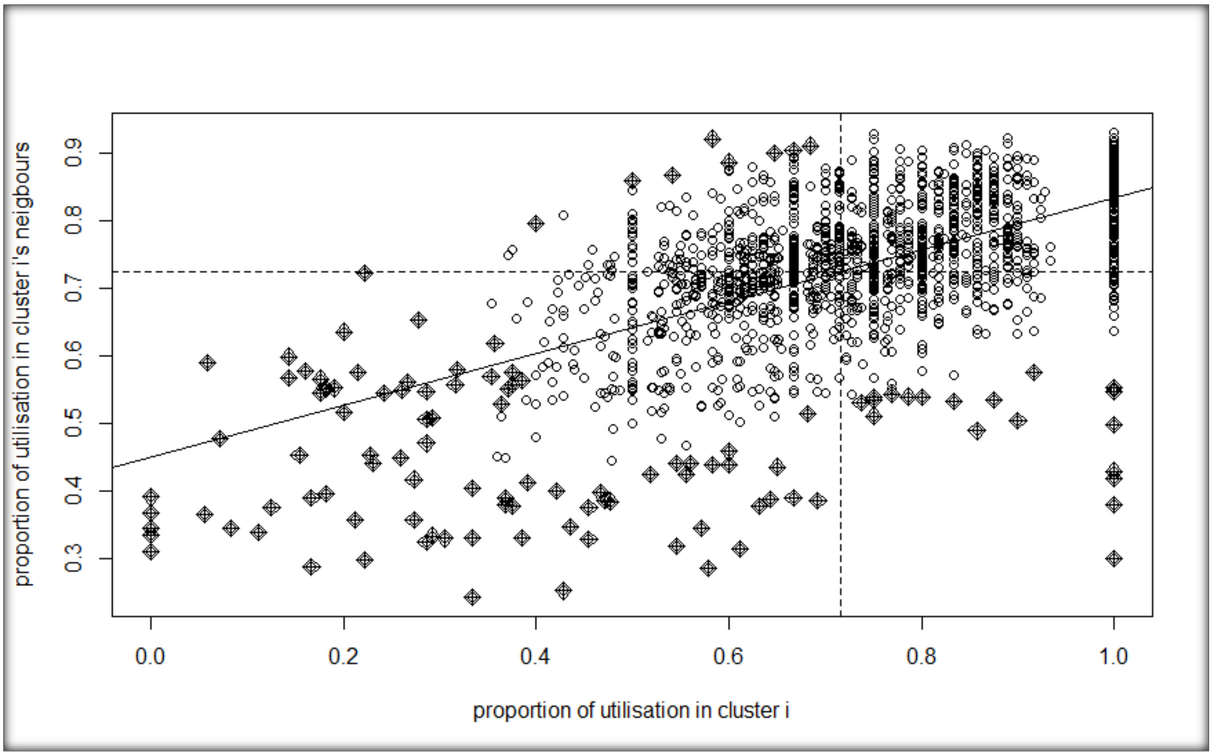


Figure B1.2: Moran scatterplot (Deliveries assisted by a skilled provider)

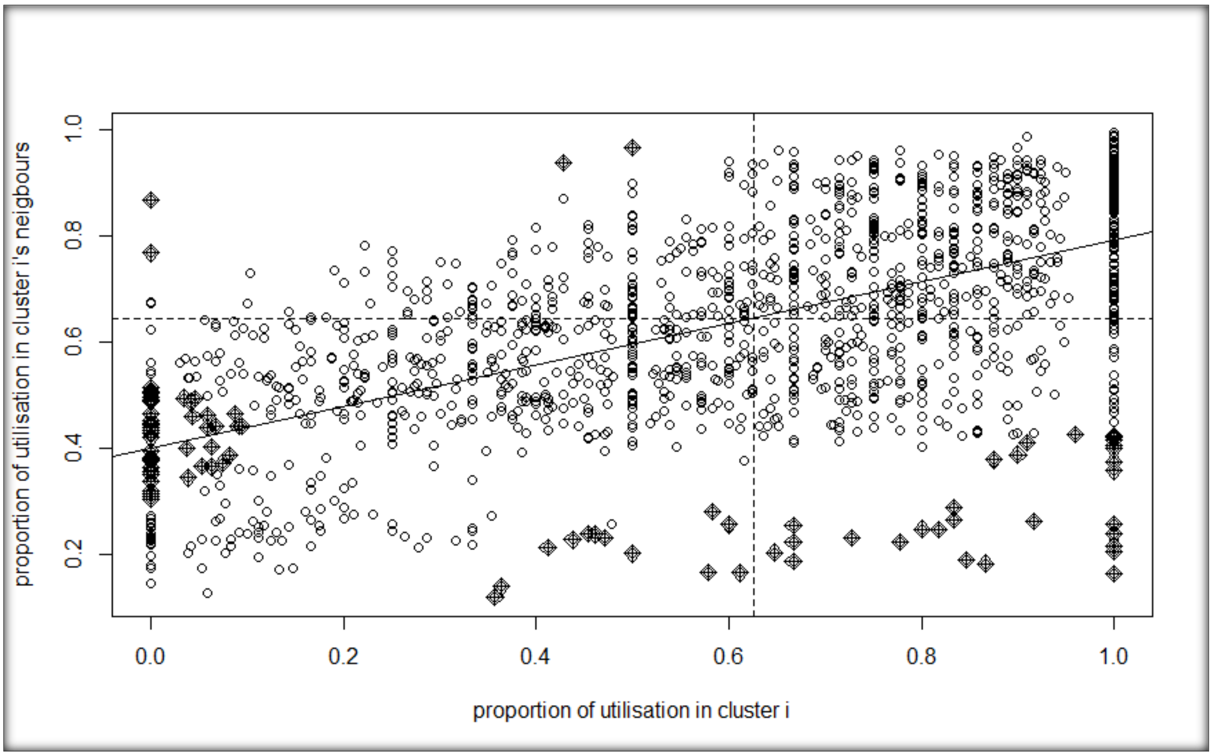


Figure B1.3: Moran scatterplot (At least one ANC visit to a skilled provider)

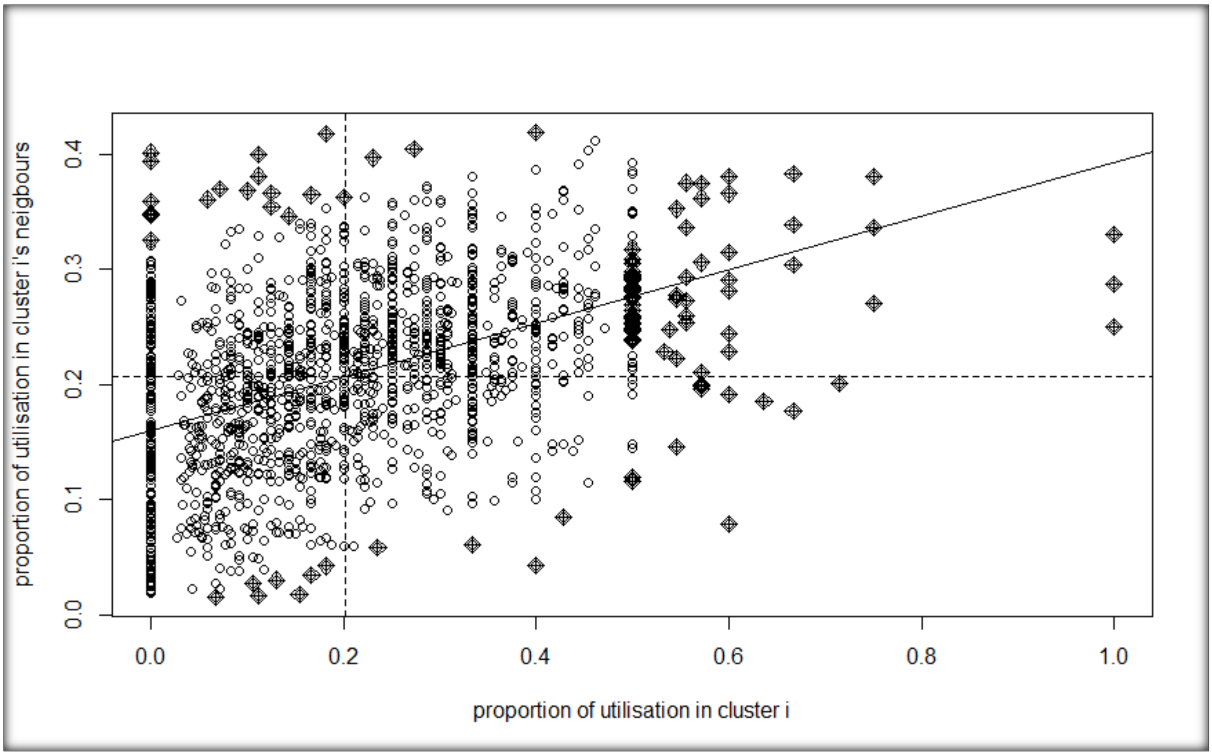


Figure B2.1: Local Moran value groups (ANC by a skilled provider)

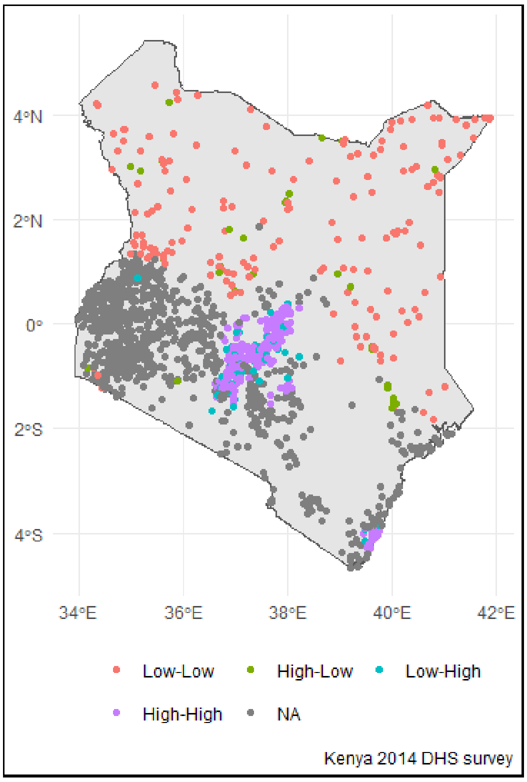


Figure B2.2: Local Moran value groups (Delivery assisted by a skilled provider)

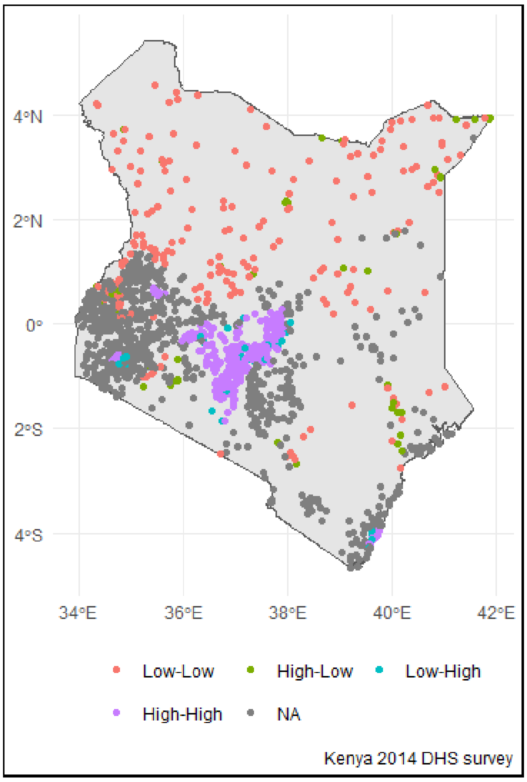


Figure B2.3: Local Moran value groups (PNC by a skilled provider)

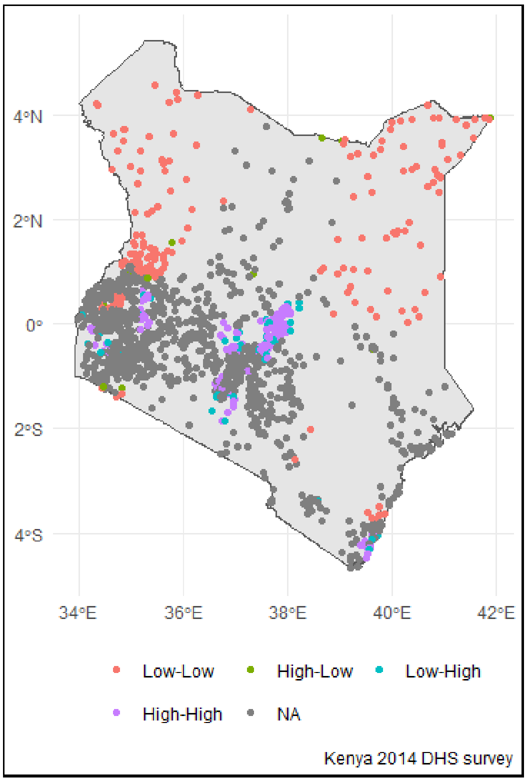


Figure B3.1: Geographically weighted mean utilisation (ANC by a skilled provider)

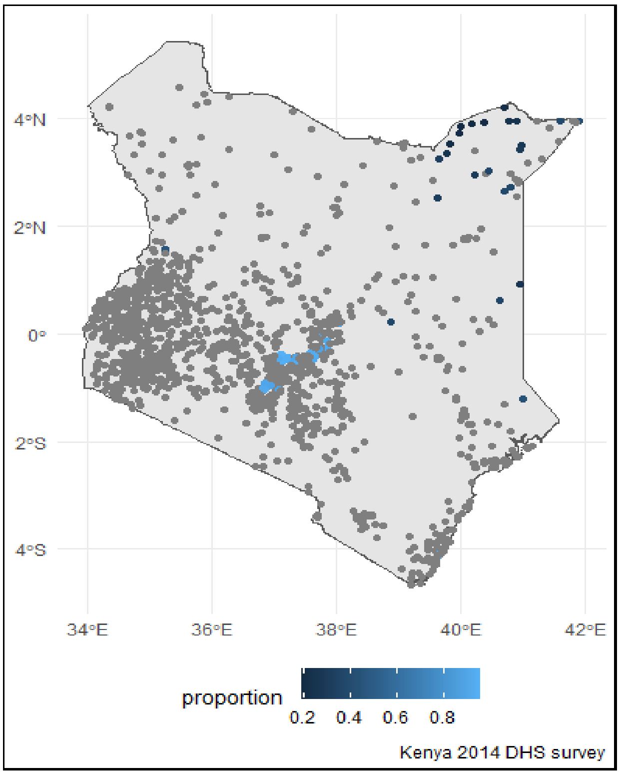


Figure B3.2: Geographically weighted mean utilisation (Delivery assisted by a skilled provider)

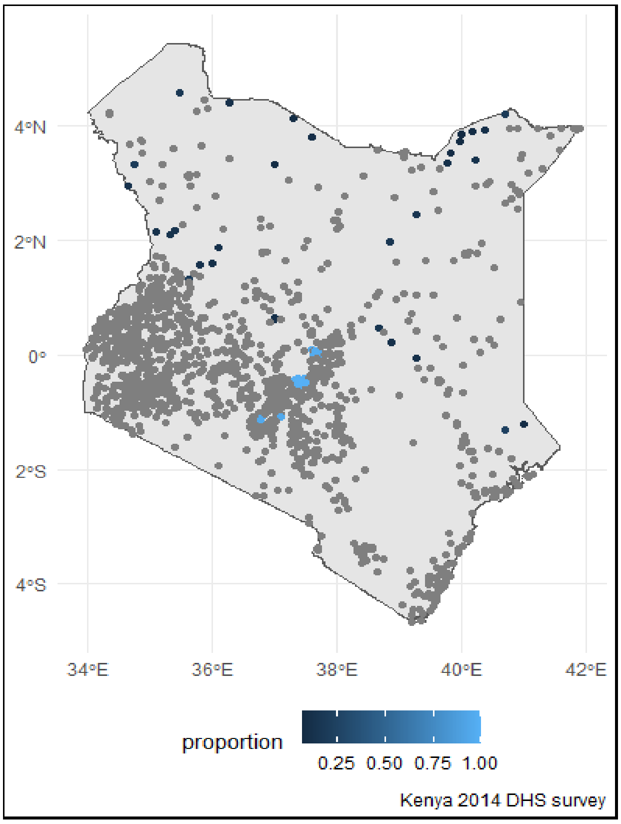


Figure B3.3: Geographically weighted mean utilisation (PNC by a skilled provider)

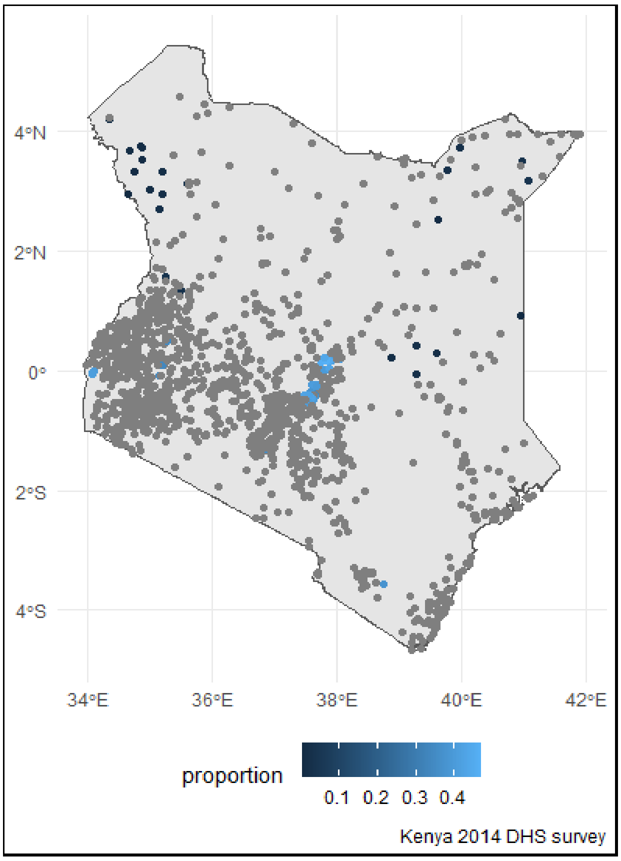


Figure B4.1: Average cluster characteristics

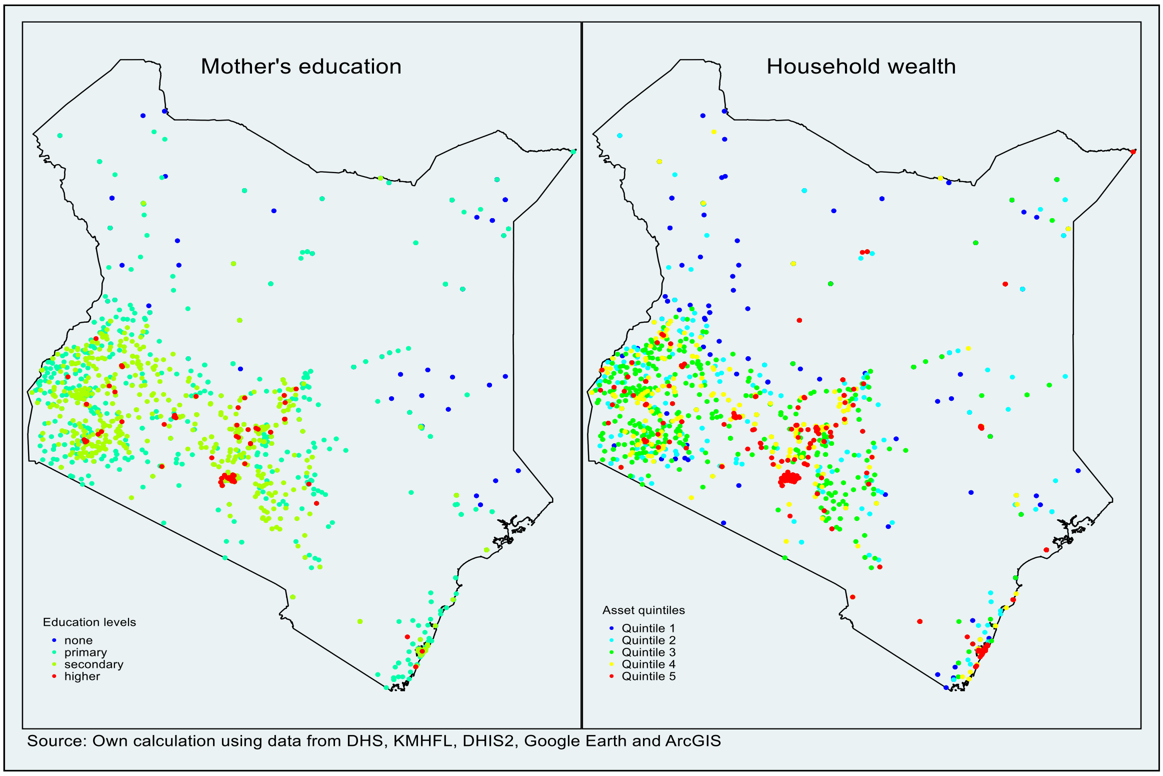


Figure B4.2: Average cluster characteristics

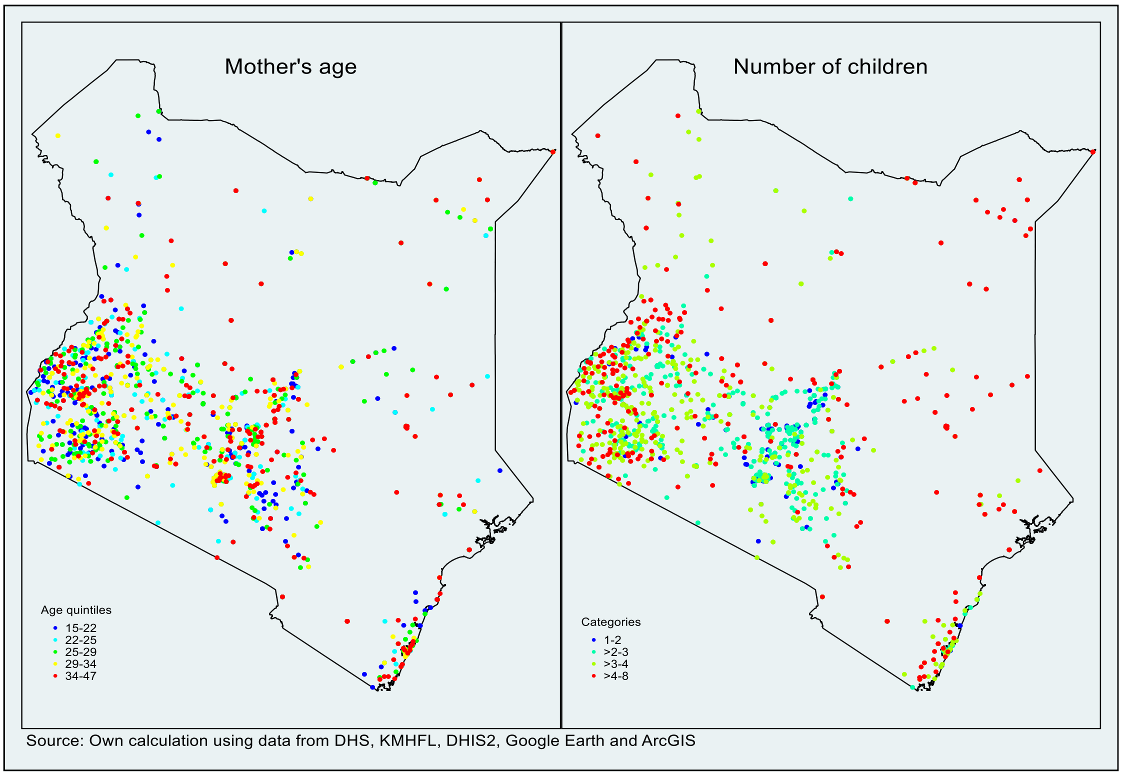
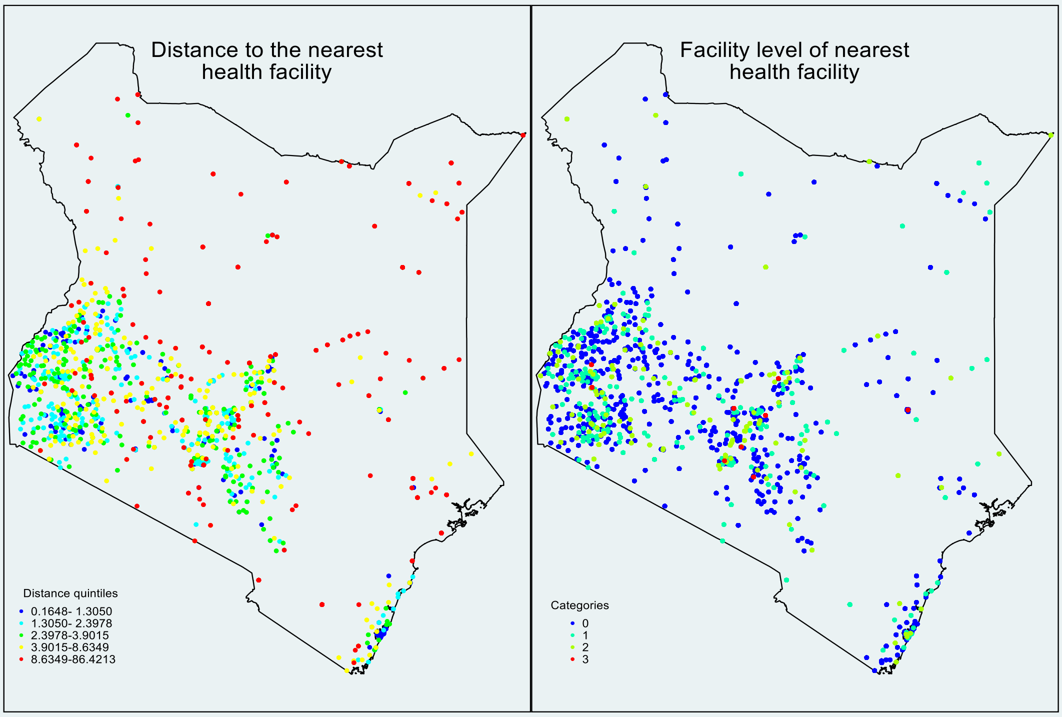
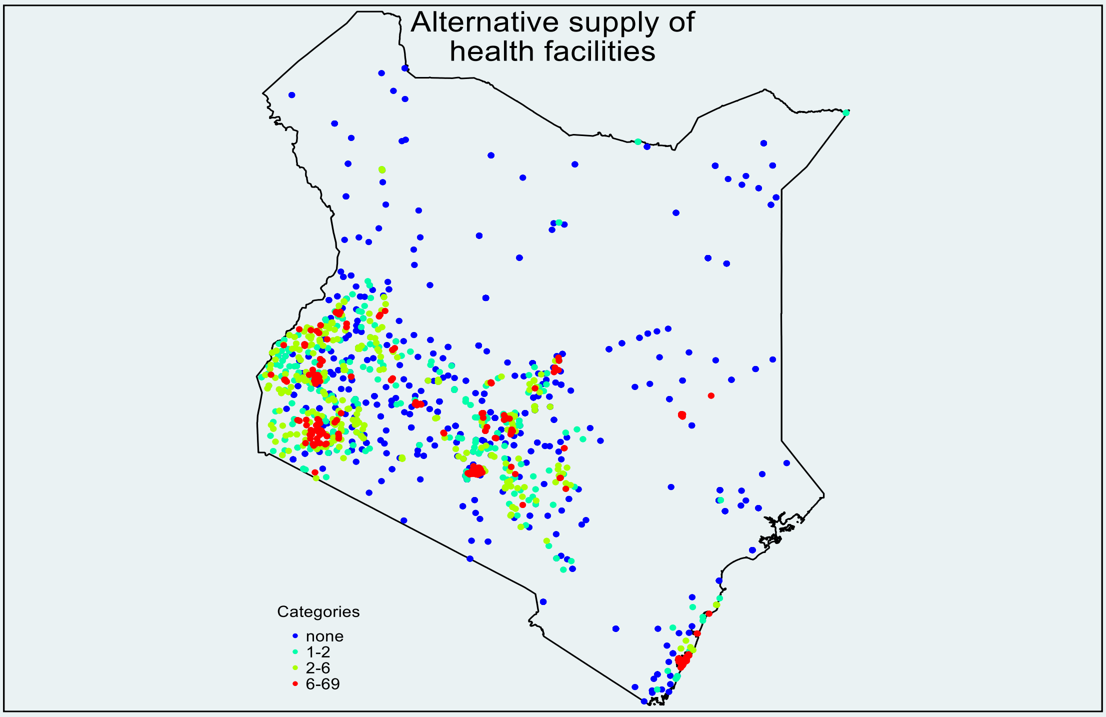


Figure B4.3: Average cluster characteristics



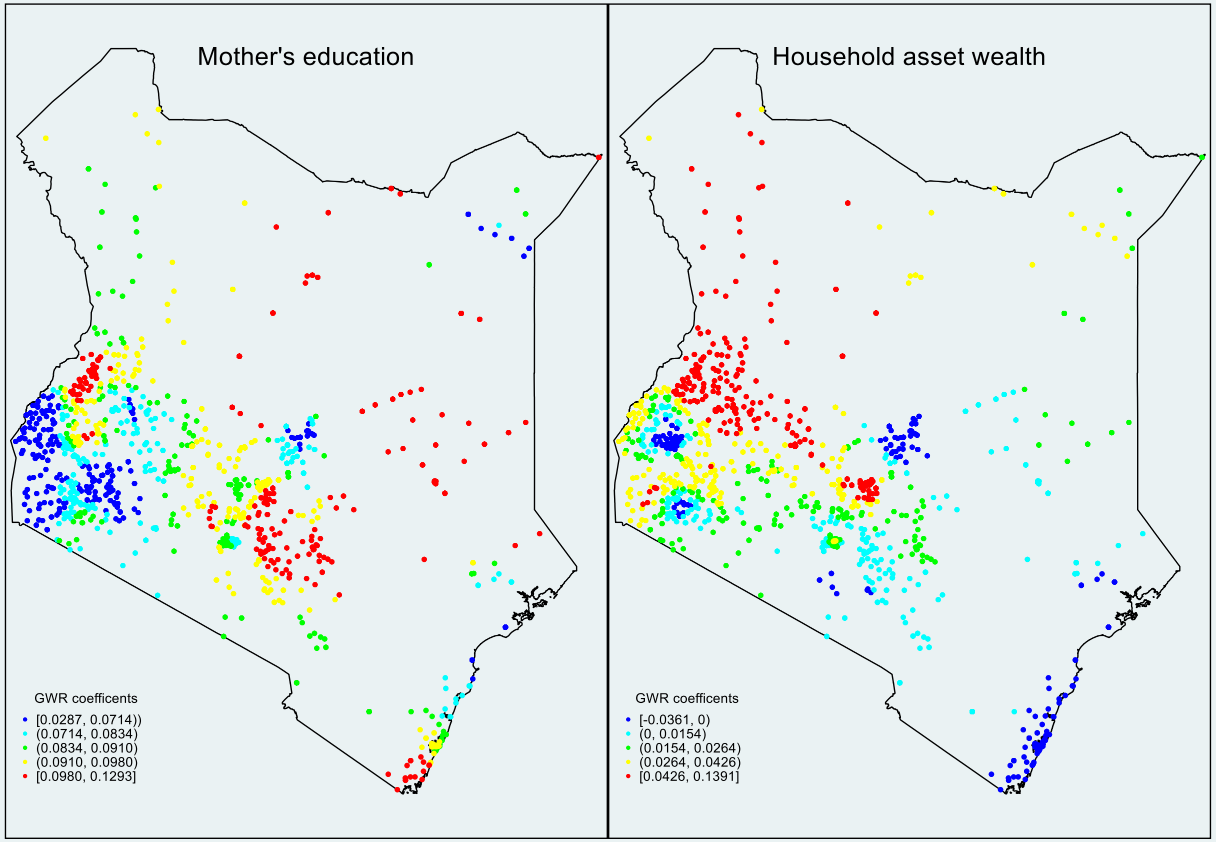
Source: Own calculation using data from DHS, KMHFL, DHIS2, Google Earth and ArcGIS

Figure B4.4: Average cluster characteristics



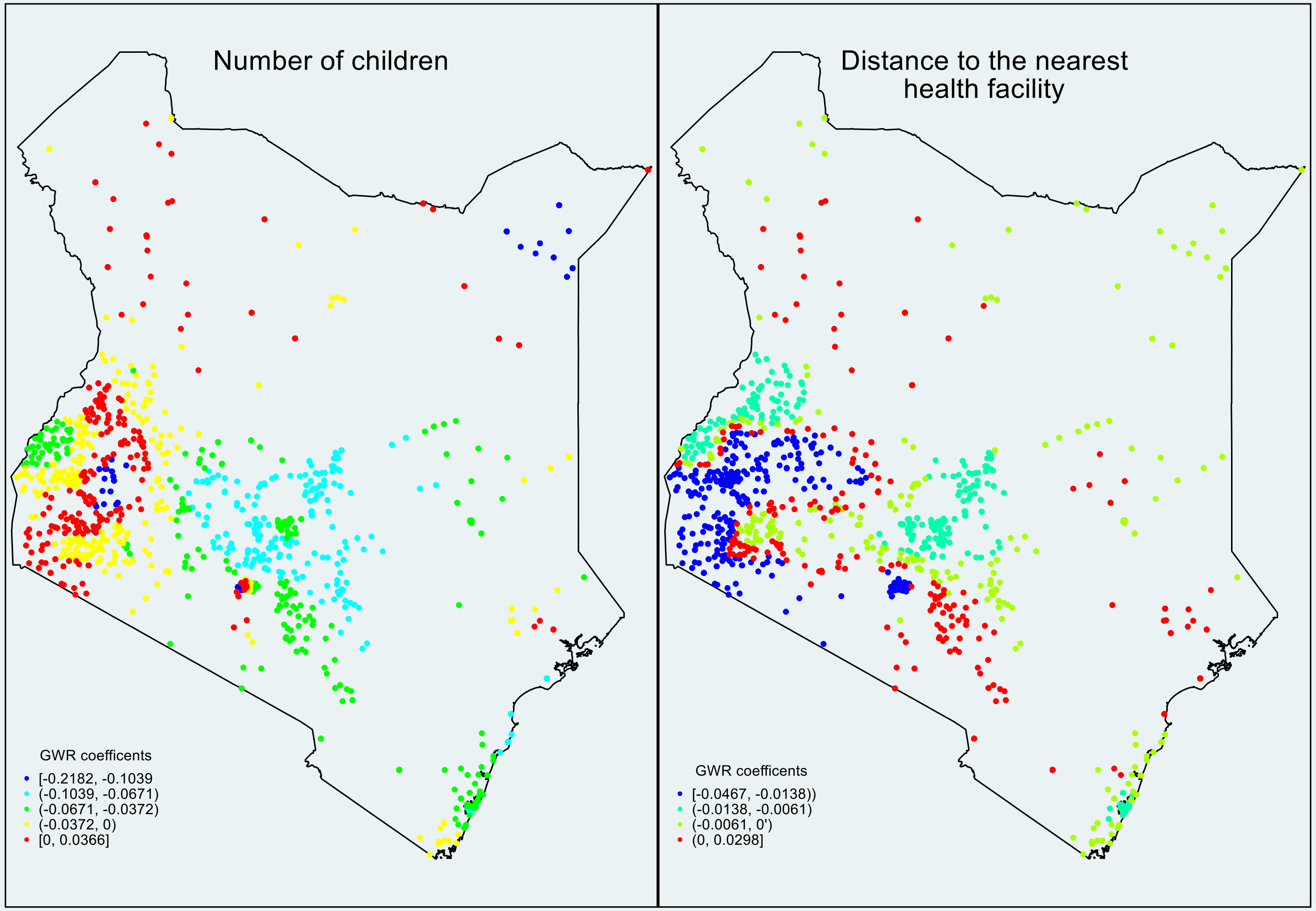
Source: Own calculation using data from DHS, KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.1: Spatial distribution of the effects of education and household asset wealth on utilisation of at least one ANC visit to a skilled provider



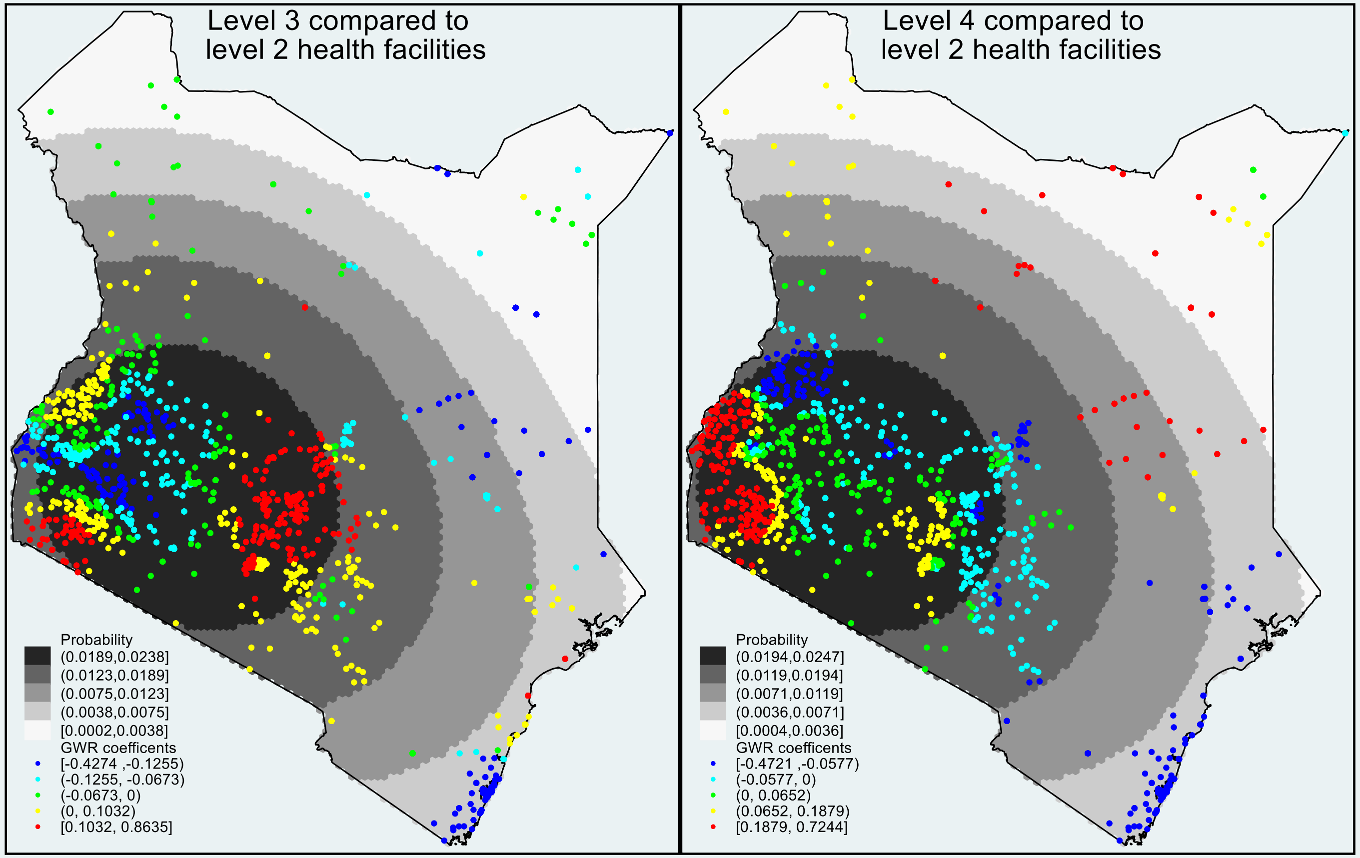
Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.2: Spatial distribution of the effects of the number of children and distance to the nearest health facility on utilisation of at least one ANC visit to a skilled provider



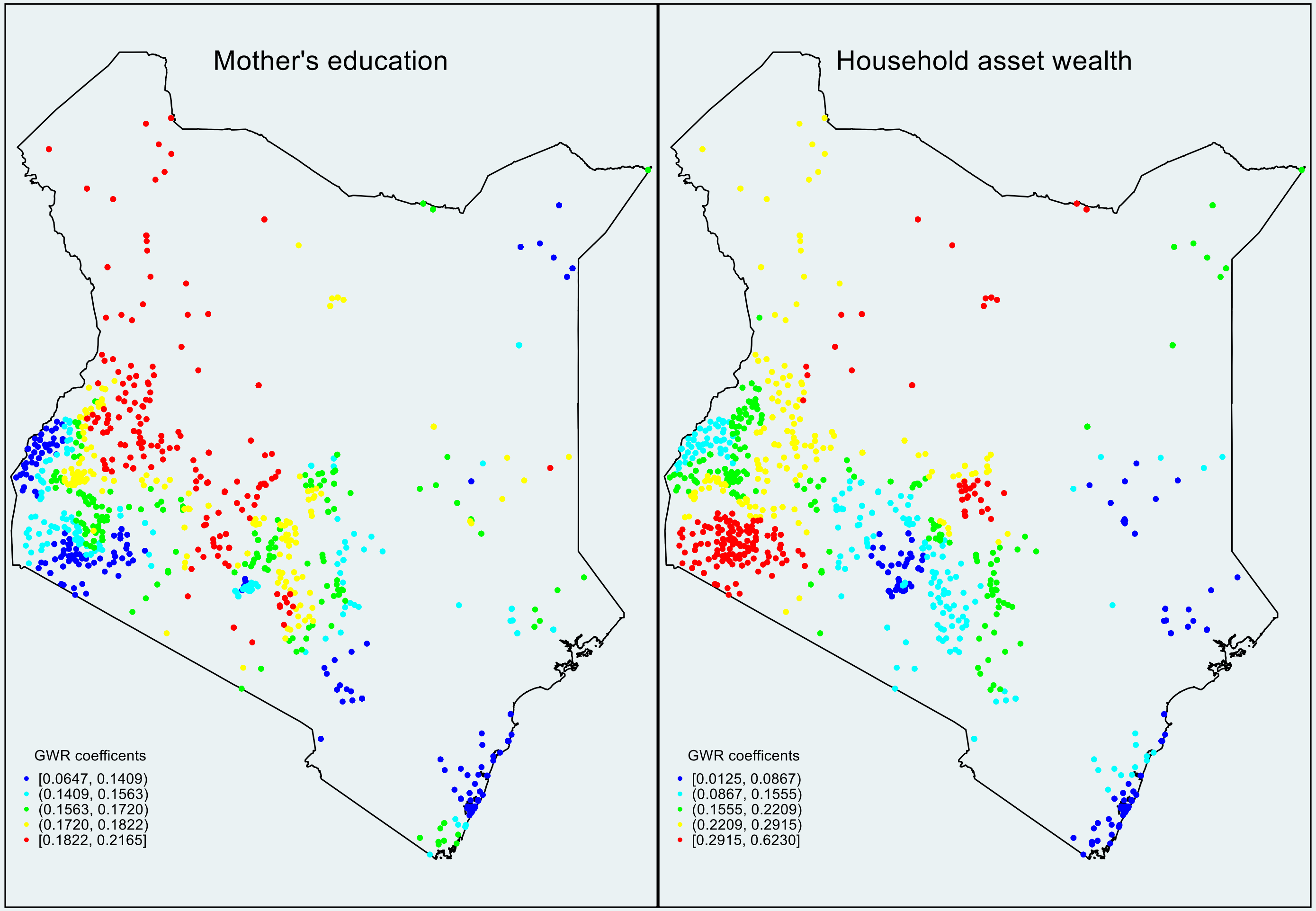
Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.3: Spatial distribution of the effects of proximity to level 3 and level 4 compared to level 2 health facilities on utilisation of at least one ANC visit to a skilled provider



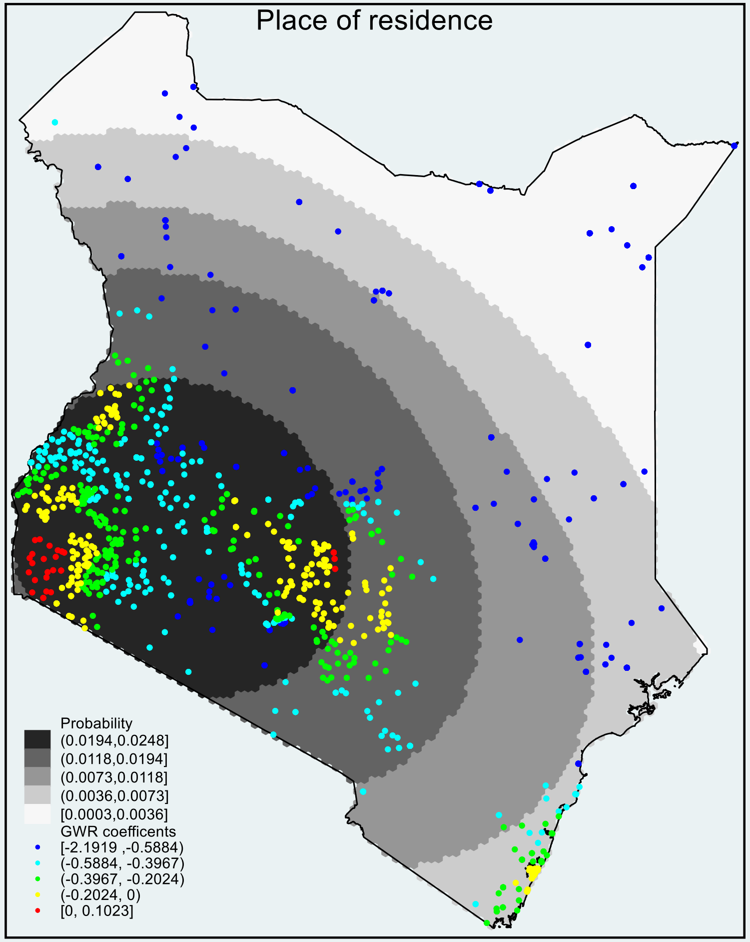
Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.4: Spatial distribution of the effects of education and household asset wealth on utilisation of deliveries assisted by a skilled provider



Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.5: Spatial distribution of the effects of place of residence on utilisation of deliveries assisted by a skilled provider



Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.6: Spatial distribution of the effects of the number of children and mother's age at child's birth on utilisation of deliveries by a skilled provider

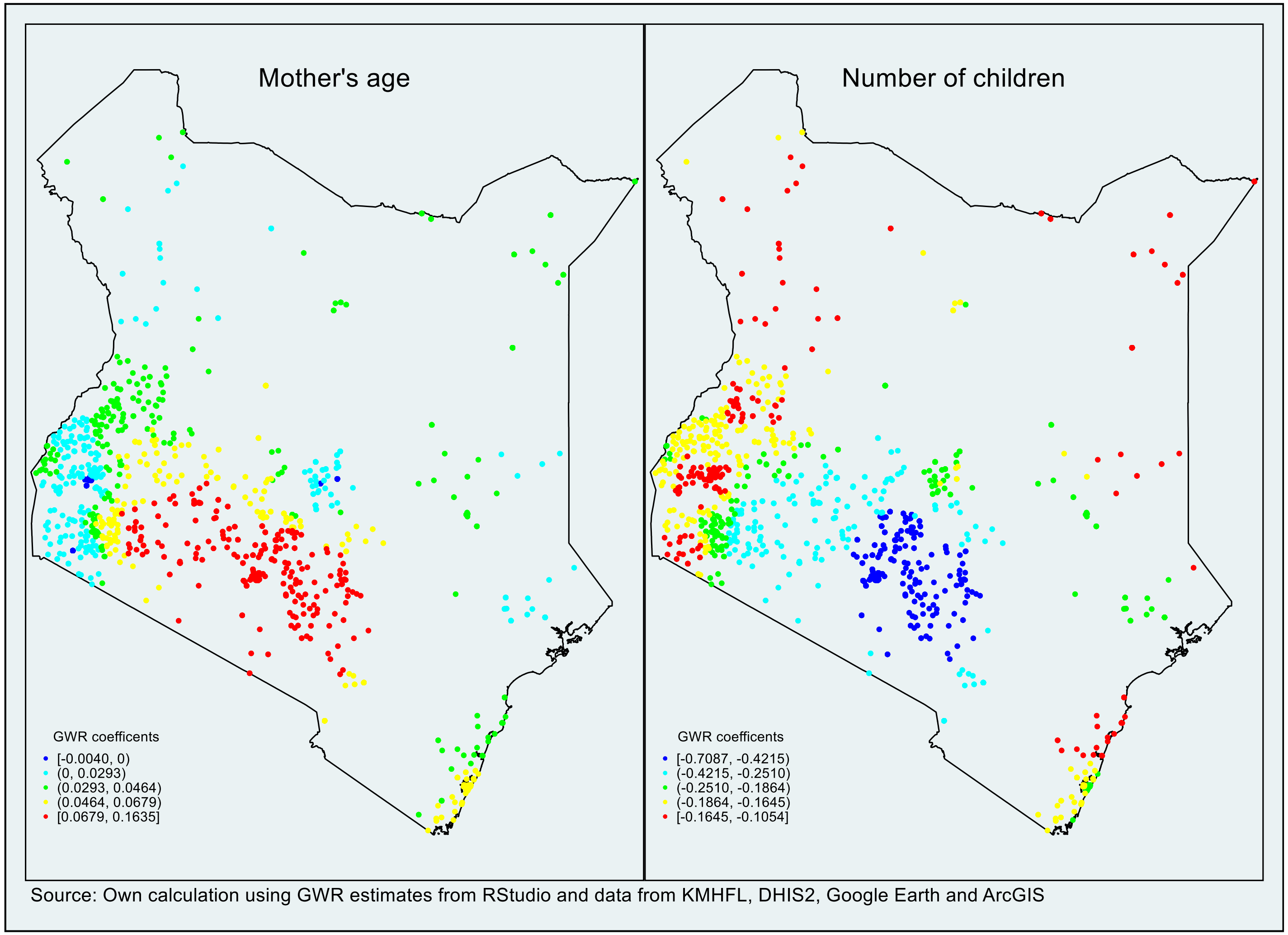
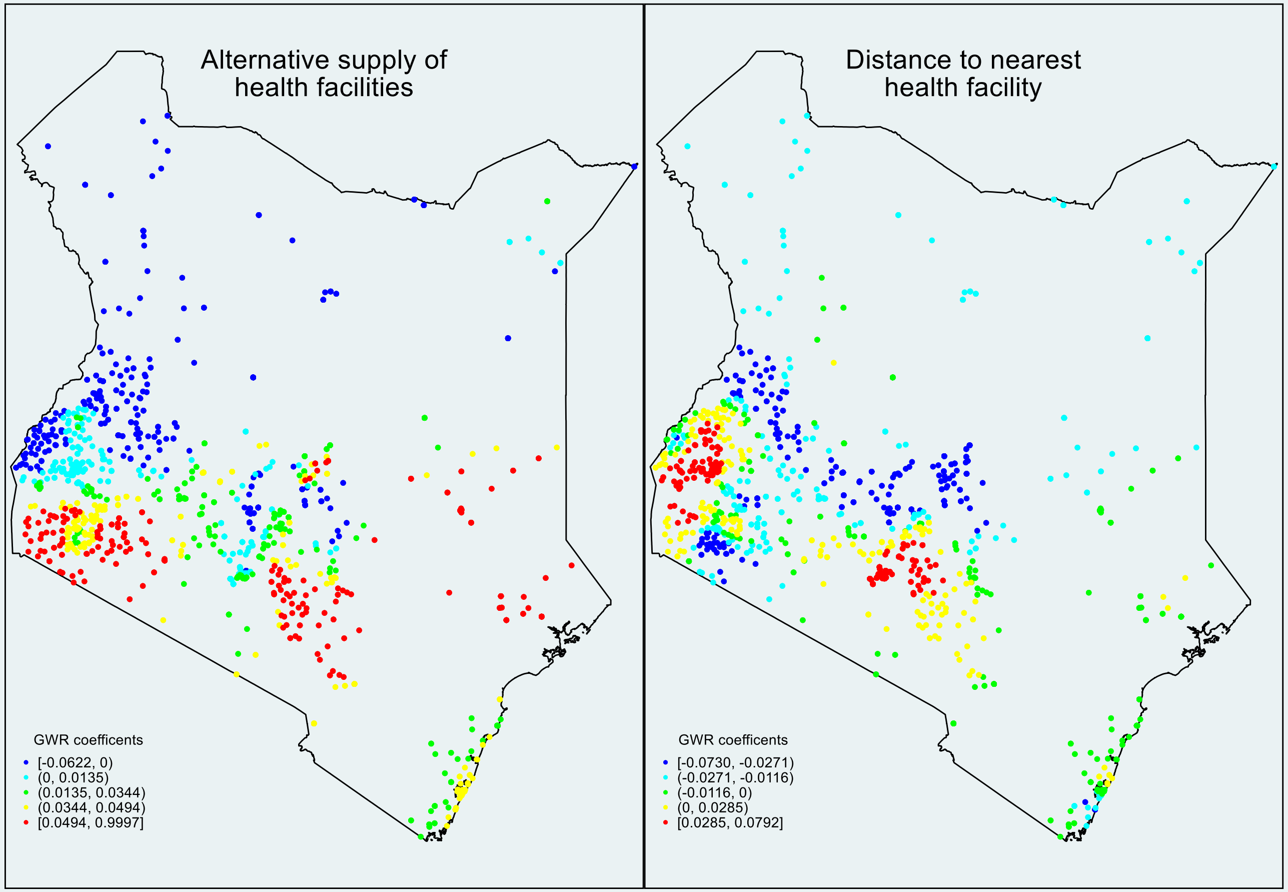
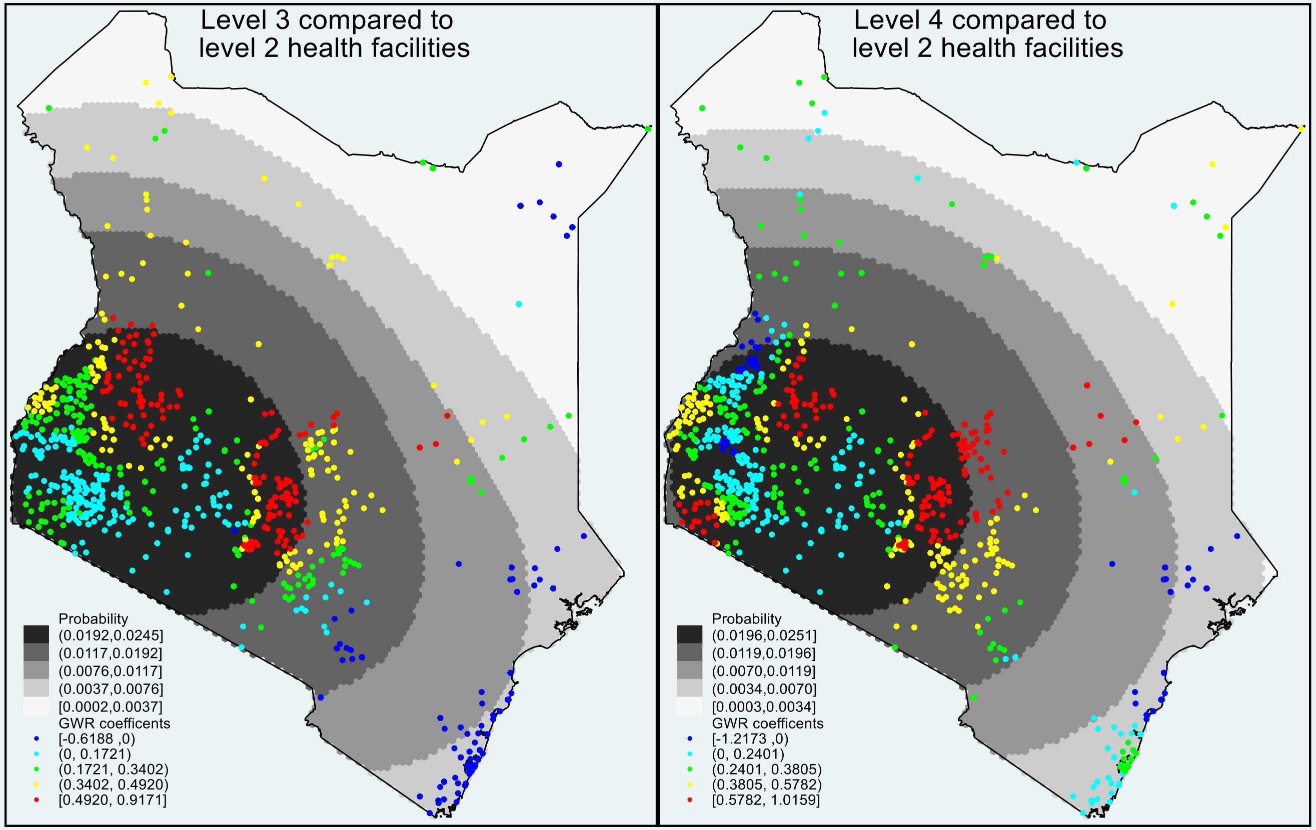


Figure B5.7: Spatial distribution of the effects of alternative supply of health facilities and distance to the nearest health facility on utilisation of deliveries by a skilled provider



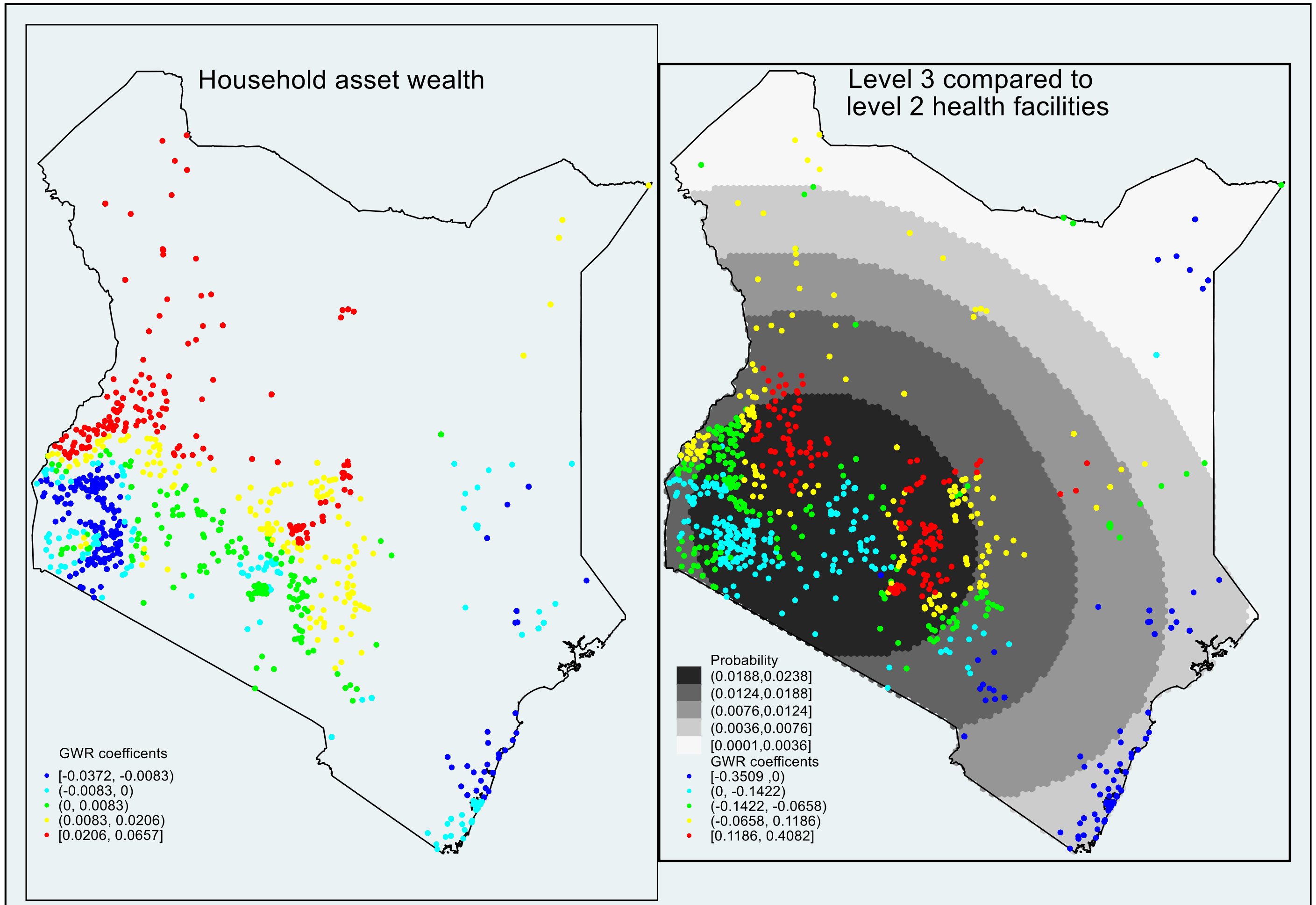
Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.8: Spatial distribution of the effects of proximity to level 3 and level 4 compared to level 2 health facilities on utilisation of deliveries by a skilled provider



Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B5.9: Spatial distribution of the effects of household asset wealth and level 3 compared to level 2 health facilities on utilisation of First PNC check from a skilled provider



Source: Own calculation using GWR estimates from RStudio and data from KMHFL, DHIS2, Google Earth and ArcGIS

Figure B6.1: Correlation coefficients for covariates explaining receipt of at least one ANC visit from a skilled provider and the underlying covariate characteristics

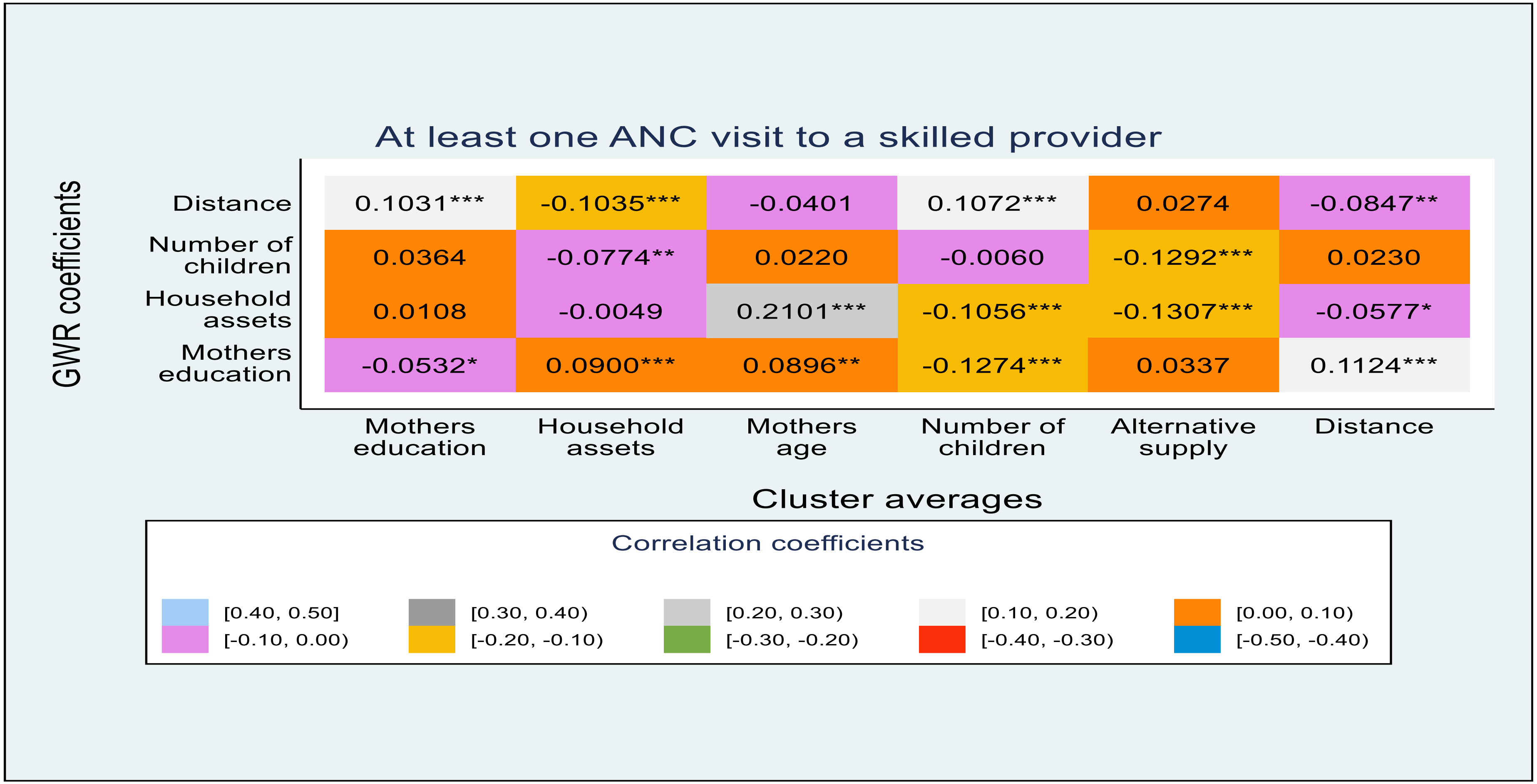


Figure B6.2: Correlation coefficients for covariates explaining deliveries assisted by a skilled provider and the underlying covariate characteristics

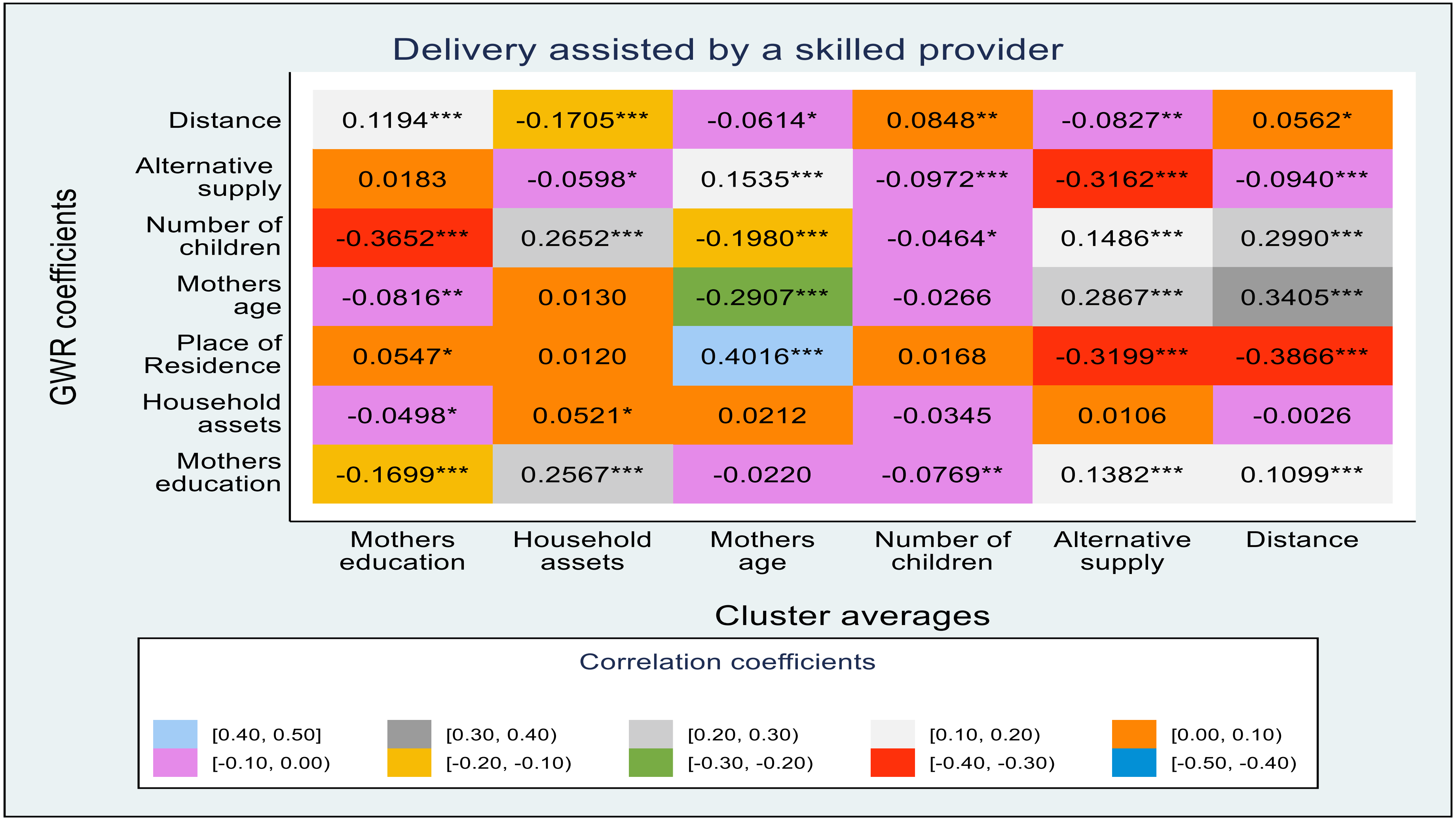
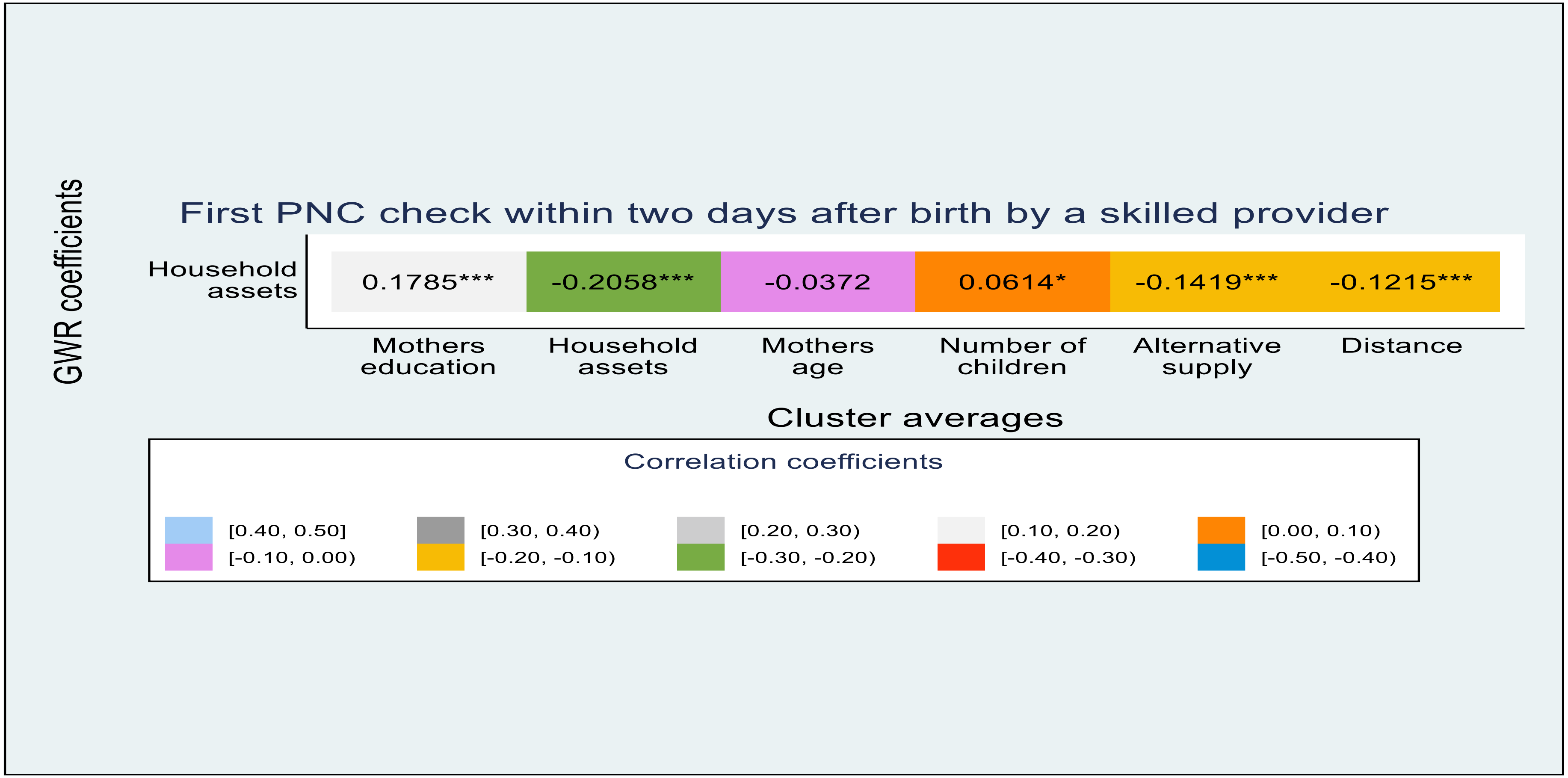


Figure B6.3: Correlation coefficients for covariates explaining receipt of at least one ANC visit from a skilled provider and the underlying covariate characteristics



Appendix C: Chapter Four

Figure C1: Cumulative distribution function for women who had the first PNC check within two days of delivery by a skilled provider in the 2003 DHS survey

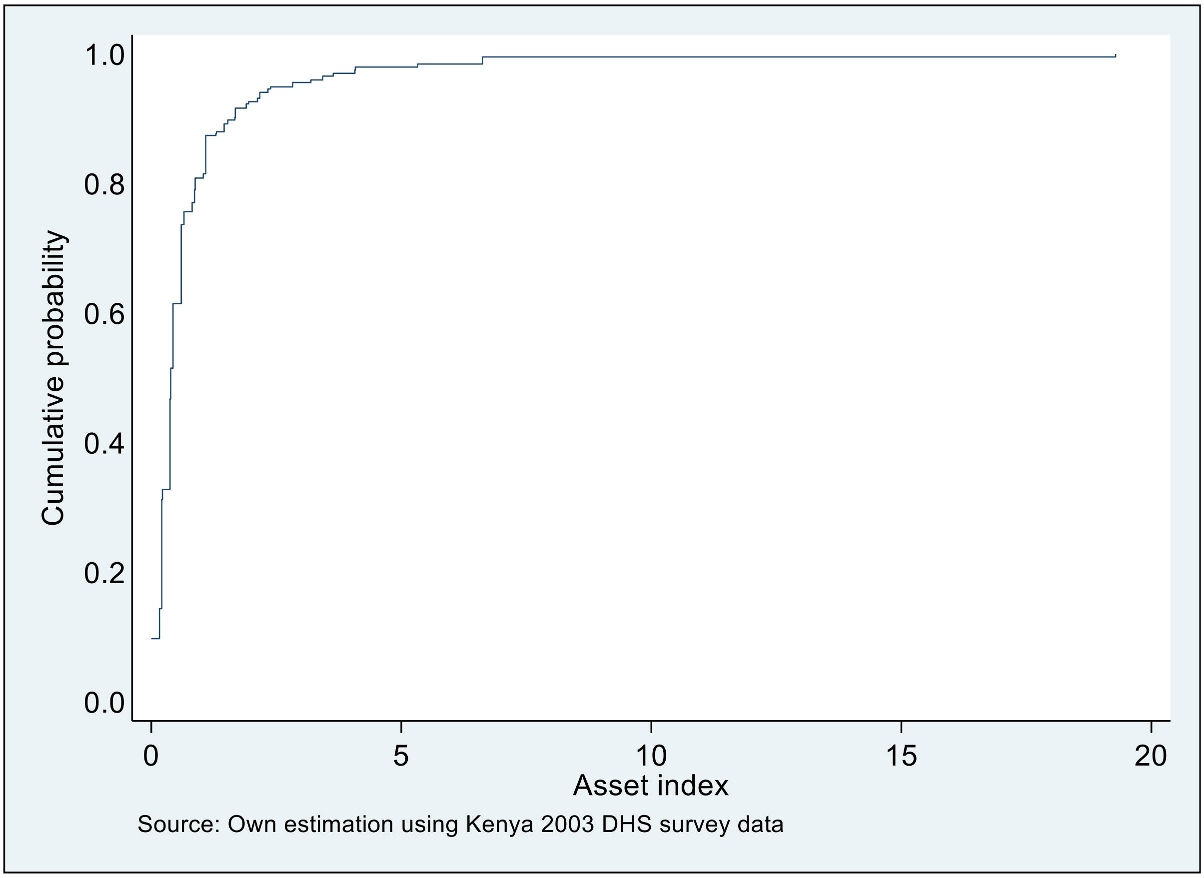


Figure C2.1: Utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider by the asset poor and non-poor across surveys using the 20th percentile asset index cut-off across surveys

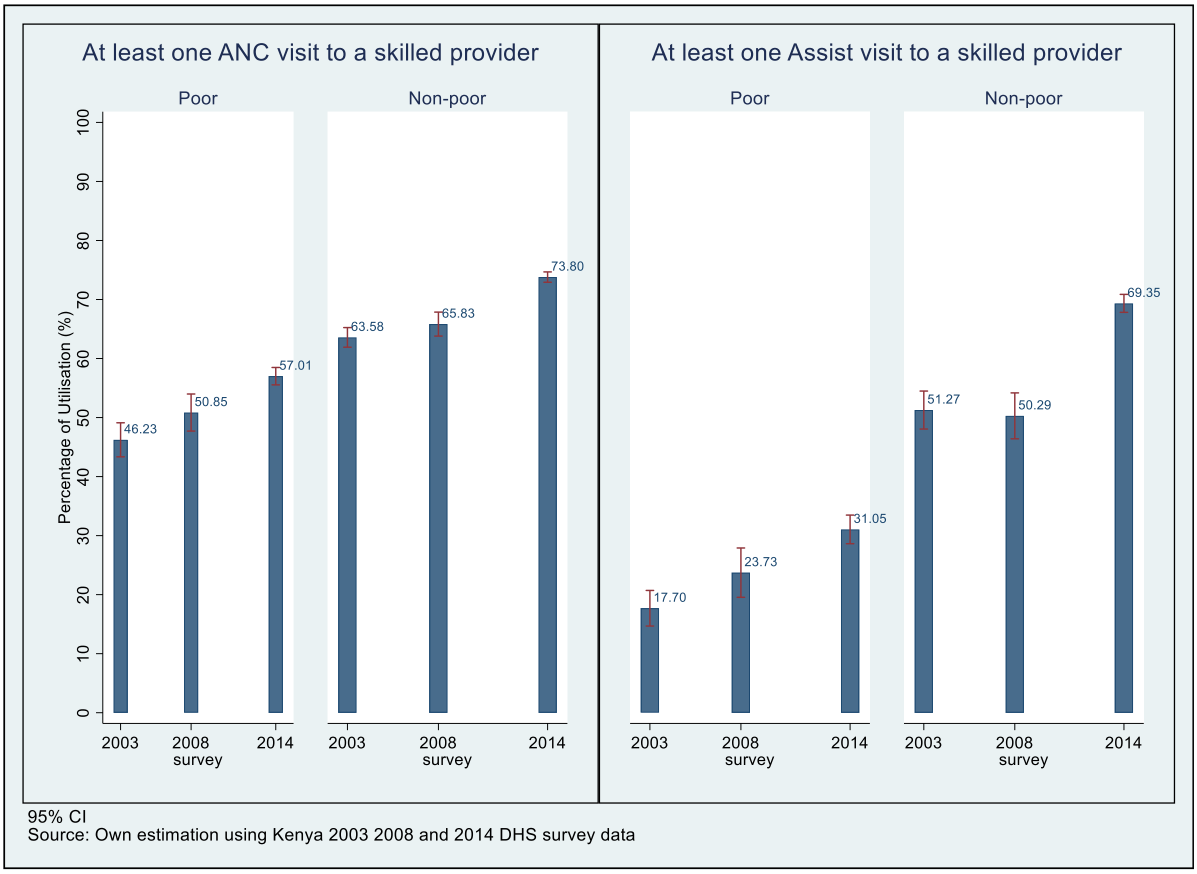


Figure C2.2: Utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider by the asset poor and non-poor across surveys using the 40th percentile asset index cut-off across surveys

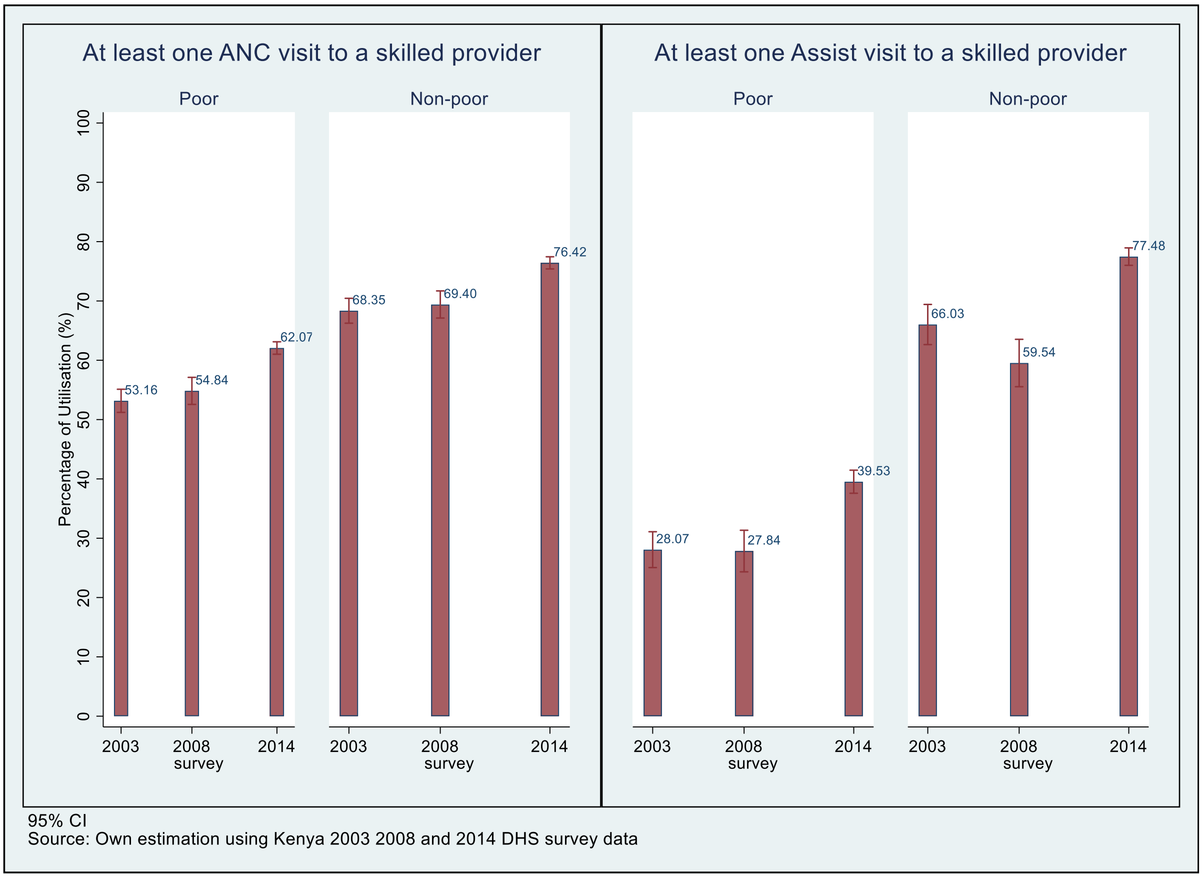


Figure C2.3: Utilisation of at least one ANC visit to a skilled provider and deliveries assisted by a skilled provider by the asset poor and non-poor across surveys using the 60th percentile asset index cut-off across surveys

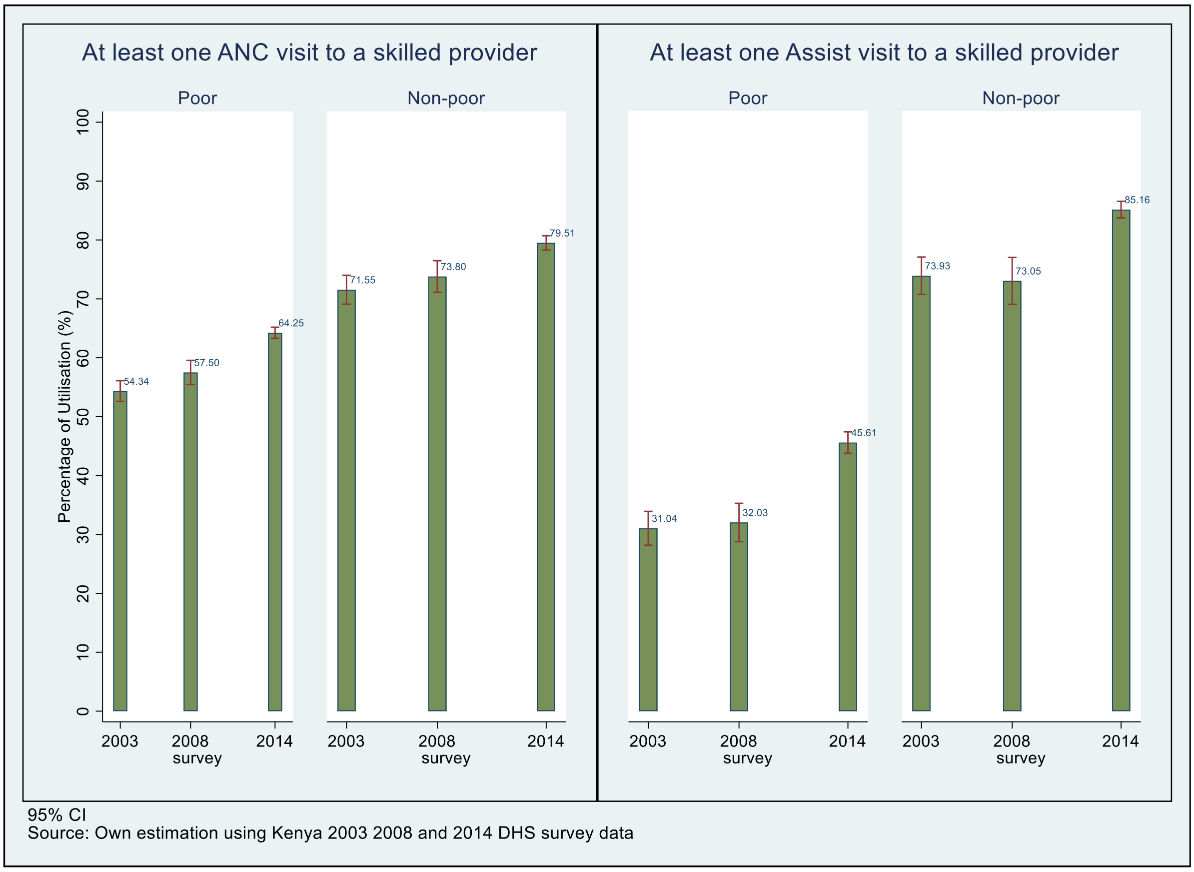


Table C1: Wagstaff concentration indices over the 20th, 40th and 60th percentile asset index cut-off points across surveys

Variable	***Survey***	***20th percentile***			***40th percentile***			***60th percentile***		
		Index value	*Std. error*	*p-value*	*Index value*	*Std. error*	*p-value*	*Index value*	*Std. error*	*p-value*
At least one ANC visit to a skilled provider	***2003***	0.1472	0.0135	0.0000	0.1433	0.0131	0.0000	0.1311	0.0111	0.0000
	2008	0.1174	0.0142	0.0000	0.1548	0.0167	0.0000	0.1420	0.0143	0.0000
	2014	0.1272	0.0066	0.0000	0.1672	0.0086	0.0000	0.1776	0.0091	0.0000
	Difference	-0.0200	0.0150	0.1810	0.0239	0.0157	0.1270	0.0465	0.0144	0.0012
Delivery assisted by a skilled provider	***2003***	0.2846	0.0166	0.0000	0.3579	0.0200	0.0000	0.3265	0.0157	0.0000
	2008	0.1987	0.0193	0.0000	0.3219	0.0243	0.0000	0.3413	0.0201	0.0000
	2014	0.2556	0.0093	0.0000	0.3896	0.0119	0.0000	0.4056	0.0118	0.0000
	Difference	-0.0290	0.0190	0.1278	0.0317	0.0233	0.1732	0.0791	0.0196	0.0001

Figure C3: Robustness check for Wagstaff concentration indices for utilisation of maternal health care across surveys

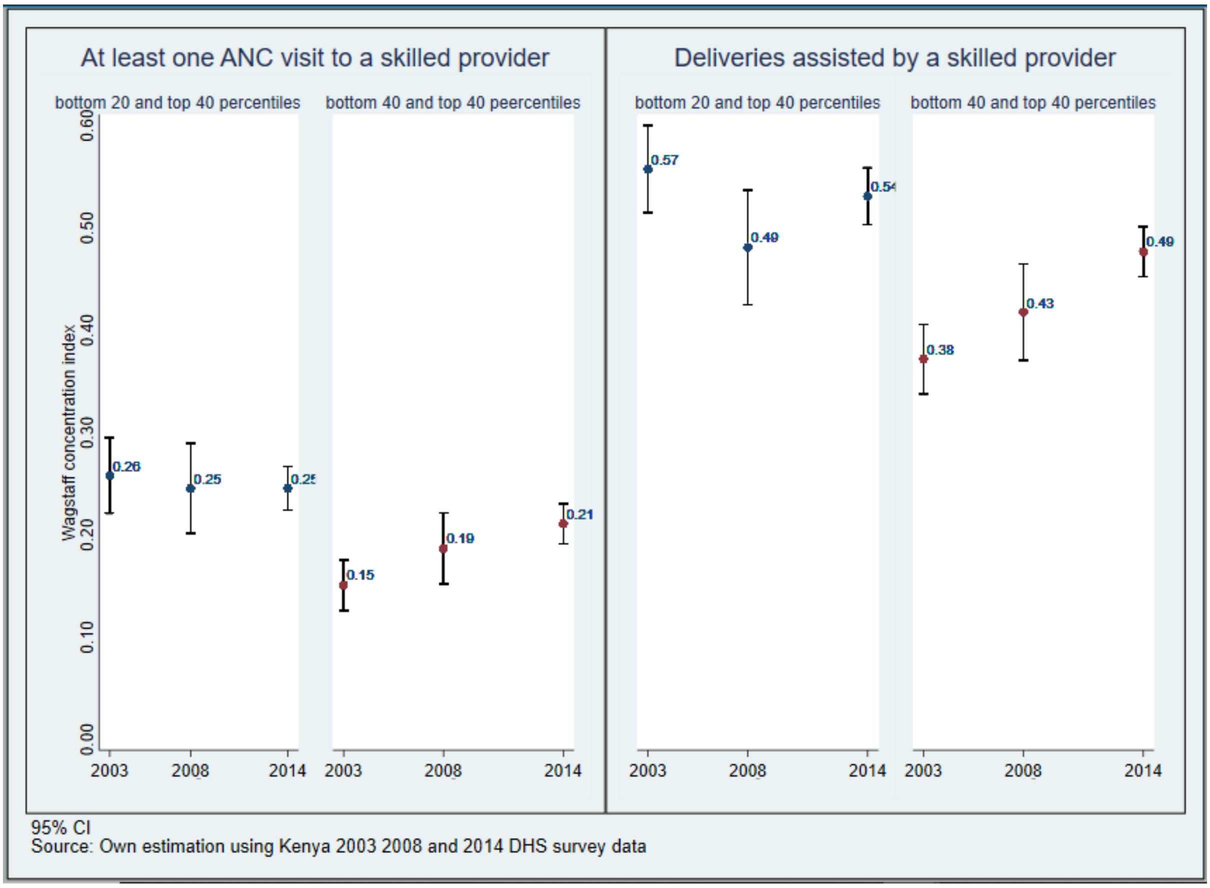


Table C2: Robustness check for Wagstaff concentration indices across surveys

Variable	***Survey***	***Top 40 and Bottom 20 percentiles***			***Top 40 and Bottom 40 percentiles***		
		Index value	*Std. error*	*p-value*	*Index value*	*Std. error*	*p-value*
At least one ANC visit to a skilled provider	***2003***	0.2578	0.0188	0.0000	0.1508	0.1226	0.0000
	2008	0.2452	0.0225	0.0000	0.1865	0.0177	0.0000
	2014	0.2453	0.0108	0.0000	0.2107	0.0100	0.0000
	Difference (2014 CI-2003 CI)	-0.0125	0.0217	0.5688	0.0600	0.0161	0.0002
Delivery assisted by a skilled provider	***2003***	0.5681	0.0223	0.0000	0.3789	0.0176	0.0000
	2008	0.4899	0.0291	0.0000	0.4254	0.0245	0.0000
	2014	0.5409	0.0144	0.0000	0.4857	0.0128	0.0000
	Difference (2014 CI-2003 CI)	-0.0272	0.0265	0.3046	0.1068	0.0217	0.0000

Figure C4: Utilisation of deliveries assisted by a skilled provider before and after the start of the FMC program by the poor and non-poor

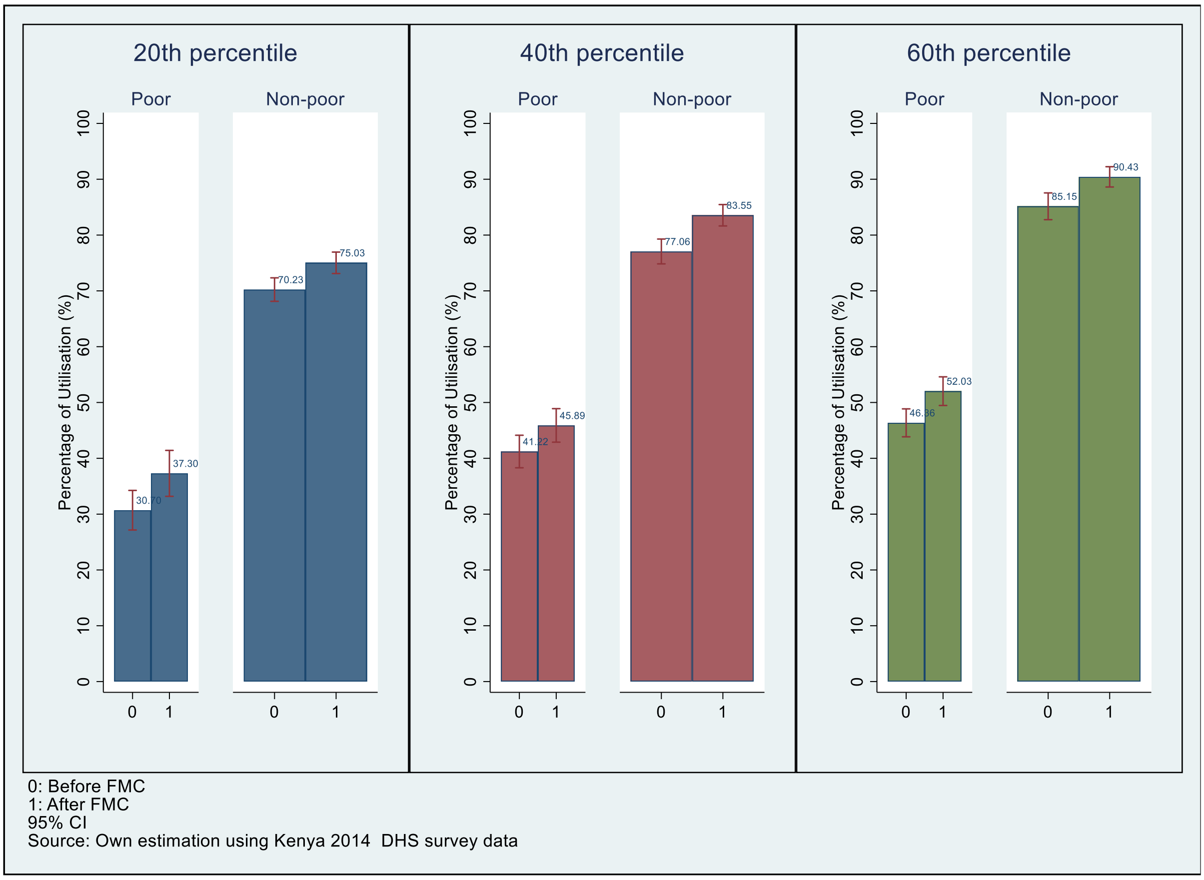


Table C3: Wagstaff concentration indices for utilisation of deliveries assisted by a skilled provider over the 20th, 40th and 60th asset index poverty lines before and after the start of the FMC program

		20th percentile			**40th percentile**			**60th percentiles**		
		Index	*Std. error*	*p-value*	*Index*	*Std. error*	*p-value*	*Index*	*Std. error*	*p-value*
Delivery assisted by a skilled provider	**Before FMC**	0.2695	0.0139	0.0000	0.3696	0.0189	0.0000	0.4001	0.0178	0.0000
	After FMC	0.2787	0.0168	0.0000	0.4198	0.0201	0.0000	0.4183	0.0174	0.0000
	Difference	0.0092	0.0218	0.6713	0.0502	0.0276	0.0692	0.0182	0.0249	0.4649

Figure C5: Robustness check for Wagstaff concentration indices for utilisation of maternal health care before and after the start of the FMC program

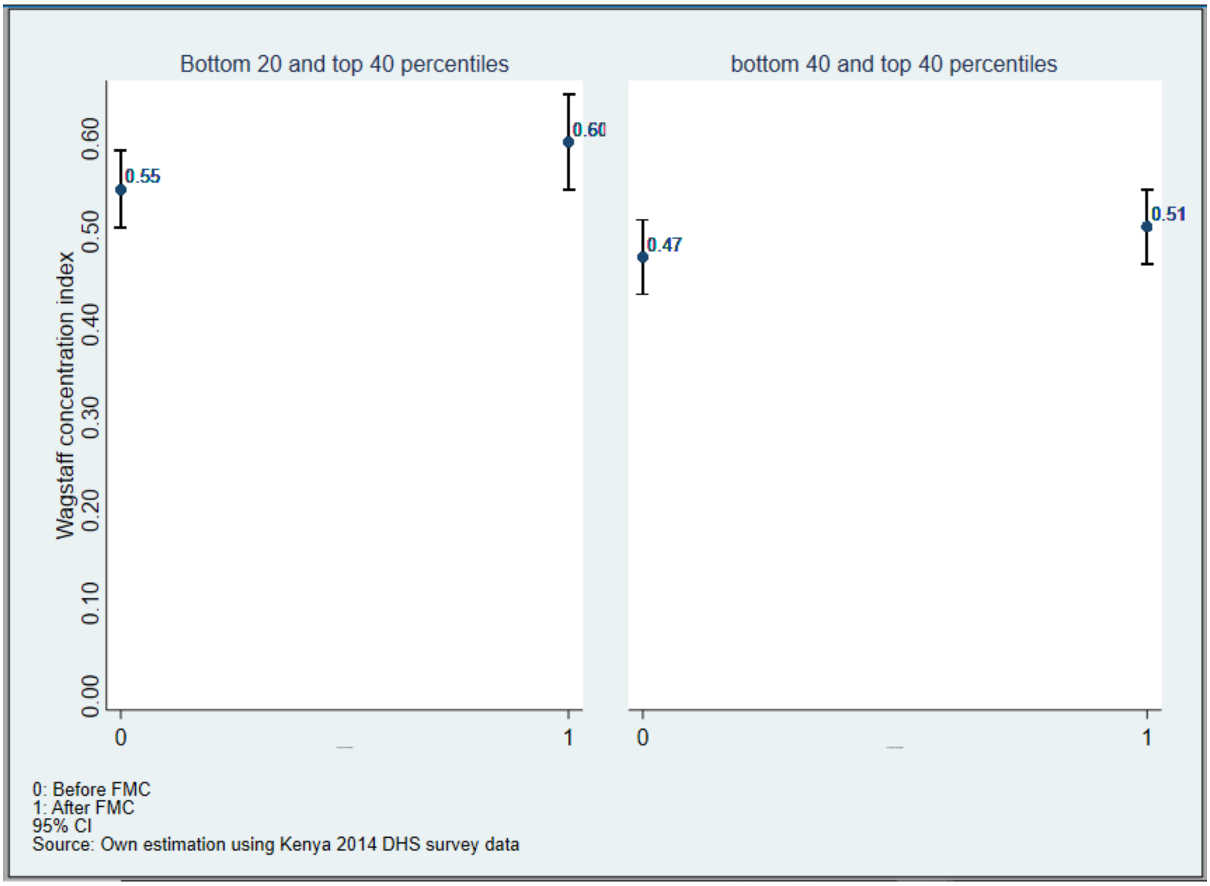


Table C4: Robustness check for Wagstaff concentration indices for utilisation of maternal health care before and after the start of the FMC program

Variable		***Top 40 and Bottom 20***			***Top 40 and Bottom 40***		
		Index	*Std.*	*p-value*	*Index*	*Std.*	*p-value*
Delivery assisted by a skilled provider	***Before***	0.5450	0.0212	0.0000	0.4722	0.0204	0.0000
	After	0.5960	0.0260	0.0000	0.5050	0.0205	0.0000
	Difference	0.0510	0.0335	0.1286	0.0328	0.0289	0.2565

Table C5: Robustness check for aggregate decomposition of the mean using Recentered Influence Functions (RIFs) when controlling for socioeconomic and demographic factors

	ANC by a skilled Provider		***Delivery by a skilled provider***	
	Top 40 and Bottom 20 percentiles	*Top 40 and Bottom 40 percentiles*	*Top 40 and Bottom 20 percentiles*	*Top 40 and Bottom 40 percentiles*
Non-poor	0.7949***	0.7949***	0.8516***	0.8516***
	(0.0063)	(0.0063)	(0.0072)	(0.0072)
Counterfactual	0.7449***	0.6676***	0.5454***	0.5010***
	(0.0228)	(0.0112)	(0.0381)	(0.0402)
Poor	0.5702***	0.6207***	0.3113***	0.3958***
	(0.0075)	(0.0053)	(0.0124)	(0.0097)
Difference	0.2247***	0.1742***	0.5404***	0.4558***
	(0.0100)	(0.0082)	(0.0143)	(0.0119)
Compositional	0.1747***	0.0469***	0.2342***	0.1052***
	(0.0235)	(0.0117)	(0.0387)	(0.0402)
Structural effect	0.0500**	0.1273***	0.3062***	0.3506***
	(0.0233)	(0.0118)	(0.0386)	(0.0414)
Observations	12,104	16,677	12,104	16,677

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table C6: Detailed decomposition of the contribution of the compositional effect to the total mean difference in utilisation of maternal health care between the poor and non-poor when controlling for socioeconomic and demographic factors

	ANC by a skilled provider					***Delivery by a skilled provider***				
	Top 80 and Bottom 20 percentiles	*Top 60 and Bottom 40 percentiles*	*Top 40 and Bottom 60 percentiles*	*Top 40 and Bottom 20 percentiles*	*Top 40 and Bottom 40 percentiles*	*Top 80 and Bottom 20 percentiles*	*Top 60 and Bottom 40 percentiles*	*Top 40 and Bottom 60 percentiles*	*Top 40 and Bottom 20 percentiles*	*Top 40 and Bottom 40 percentiles*
	Explained/compositional component									
Total Explained	0.1167***	0.0390***	0.0573	0.1747***	0.0469***	0.1745***	0.0942***	0.1791***	0.2342***	0.1052***
	(0.0127)	(0.0087)	(0.0519)	(0.0235)	(0.0117)	(0.0208)	(0.0254)	(0.0676)	(0.0387)	(0.0402)
Pure explained	0.1107***	0.0373***	0.0207	0.1661***	0.0442***	0.1895***	0.0880***	0.1522**	0.2760***	0.0922**
	(0.0124)	(0.0086)	(0.0508)	(0.0216)	(0.0126)	(0.0210)	(0.0245)	(0.0741)	(0.0342)	(0.0380)
Mother's education	0.0645***	0.0555***	0.0612***	0.0883***	0.0720***	0.1124***	0.0937***	0.1268***	0.1565***	0.1213***
	(0.0087)	(0.0092)	(0.0147)	(0.0138)	(0.0121)	(0.0148)	(0.0143)	(0.0251)	(0.0237)	(0.0187)
Province	0.0240***	-0.0318**	-0.0760	0.0282***	-0.0470***	0.0406***	-0.0580**	-0.0574	0.0452**	-0.0974**
	(0.0068)	(0.0127)	(0.0502)	(0.0097)	(0.0180)	(0.0129)	(0.0265)	(0.0607)	(0.0210)	(0.0378)
Place of residence	0.0198***	0.0165***	0.0241***	0.0417***	0.0219***	0.0210**	0.0393***	0.0559***	0.0440**	0.0522***
	(0.0058)	(0.0063)	(0.0063)	(0.0118)	(0.0083)	(0.0082)	(0.0102)	(0.0116)	(0.0176)	(0.0133)
Mother's age	-0.0002	-0.0026	0.0065	0.0017	-0.0017	0.0013	-0.0001	0.0010	0.0018	-0.0003
	(0.0033)	(0.0052)	(0.0069)	(0.0058)	(0.0069)	(0.0014)	(0.0011)	(0.0024)	(0.0025)	(0.0014)
Number of children	-0.0019	0.0004	0.0027	-0.0038	0.0005	0.0127***	0.0133*	0.0253***	0.0252***	0.0167
	(0.0024)	(0.0019)	(0.0026)	(0.0047)	(0.0025)	(0.0037)	(0.0078)	(0.0079)	(0.0065)	(0.0113)

Marital status	0.0044*	-0.0007	0.0022	0.0101**	-0.0013	0.0014	-0.0001	0.0006	0.0033	-0.0002
	(0.0024)	(0.0014)	(0.0046)	(0.0049)	(0.0020)	(0.0015)	(0.0004)	(0.0014)	(0.0034)	(0.0005)
Specification	0.0061	0.0017	0.0366	0.0086	0.0027	-0.0150	0.0062	0.0269	-0.0419	0.0130
Error	(0.0054)	(0.0057)	(0.0364)	(0.0156)	(0.0098)	(0.0102)	(0.0056)	(0.0363)	(0.0290)	(0.0102)
Mother's	-0.0031	0.0106	-0.0105	-0.0018	0.0060	0.0049	-0.0103	-0.0219*	-0.0010	-0.0106
education	(0.0057)	(0.0065)	(0.0093)	(0.0104)	(0.0084)	(0.0105)	(0.0075)	(0.0132)	(0.0176)	(0.0102)
Province	-0.0268	-0.0009	0.0091	0.0166	0.0029	-0.0269	-0.0059	0.0105	-0.0430	-0.0076
	(0.0290)	(0.0053)	(0.0153)	(0.0305)	(0.0093)	(0.0260)	(0.0051)	(0.0172)	(0.0314)	(0.0090)
Place of	-0.0036	-0.0003	-0.0014	0.0007	-0.0032	0.0127**	0.0006	-0.0042	-0.0064	0.0066**
residence	(0.0034)	(0.0007)	(0.0028)	(0.0026)	(0.0038)	(0.0063)	(0.0007)	(0.0033)	(0.0052)	(0.0033)
Mother's age	0.0123	0.0015	-0.0022	0.0323	0.0045	-0.0072	0.0012	0.0037	0.0077	0.0065
	(0.0138)	(0.0147)	(0.0194)	(0.0263)	(0.0184)	(0.0168)	(0.0090)	(0.0182)	(0.0317)	(0.0143)
Number of	-0.0013	0.0165***	0.0465***	-0.0097	0.0290***	0.0083*	0.0055	0.0240	0.0206	0.0073
children	(0.0026)	(0.0051)	(0.0150)	(0.0122)	(0.0102)	(0.0043)	(0.0040)	(0.0273)	(0.0164)	(0.0064)
Marital status	0.0101	-0.0083	0.0383	0.0112	-0.0126	0.0122	0.0142*	-0.0487**	0.0186	0.0224**
	(0.0078)	(0.0081)	(0.0239)	(0.0113)	(0.0118)	(0.0126)	(0.0076)	(0.0215)	(0.0177)	(0.0105)
Constant	0.0185	-0.0173	-0.0433	-0.0408	-0.0238	-0.0189	0.0009	0.0635**	-0.0384	-0.0116
	(0.0372)	(0.0188)	(0.0314)	(0.0468)	(0.0257)	(0.0397)	(0.0137)	(0.0316)	(0.0552)	(0.0192)

	Unexplained/Structural component									
Total unexplained	0.0510***	0.1046***	0.0952*	0.0500**	0.1273***	0.2082***	0.2854***	0.2160***	0.3062***	0.3506***
	(0.0134)	(0.0096)	(0.0518)	(0.0233)	(0.0118)	(0.0216)	(0.0257)	(0.0684)	(0.0386)	(0.0414)
Pure unexplained	0.0211	0.0914***	0.1110***	0.0945*	0.1081***	0.1593***	0.2623***	0.2096***	0.2158***	0.3255***
	(0.0248)	(0.0124)	(0.0357)	(0.0486)	(0.0201)	(0.0277)	(0.0142)	(0.0469)	(0.0422)	(0.0174)
Mother's education	0.0304***	0.0007	0.0144	0.0176	-0.0007	-0.0046	-0.0026	-0.0197	-0.0475***	-0.0391***
	(0.0110)	(0.0086)	(0.0115)	(0.0122)	(0.0101)	(0.0208)	(0.0093)	(0.0165)	(0.0166)	(0.0114)
Province	-0.0065	0.0086	0.0261	0.0245	0.0181*	-0.0000	0.0382***	0.0365	-0.0045	0.0807***
	(0.0053)	(0.0058)	(0.0188)	(0.0218)	(0.0107)	(0.0075)	(0.0102)	(0.0249)	(0.0133)	(0.0136)
Place of residence	0.0038**	0.0004	-0.0051	-0.0148**	-0.0019	-0.0083**	0.0000	-0.0001	0.0135	-0.0091*
	(0.0018)	(0.0011)	(0.0039)	(0.0061)	(0.0049)	(0.0034)	(0.0014)	(0.0043)	(0.0107)	(0.0051)
Mother's age	-0.0166	-0.0004	0.0408	-0.0342	0.0122	0.0105	-0.0066	-0.0093	-0.0157	-0.0149
	(0.0172)	(0.0278)	(0.0258)	(0.0329)	(0.0398)	(0.0212)	(0.0138)	(0.0249)	(0.0388)	(0.0171)
Number of children	0.0104*	-0.0277**	-0.0663***	0.0174	-0.0592***	-0.0056	-0.0042	-0.0350	-0.0252	-0.0146
	(0.0058)	(0.0118)	(0.0183)	(0.0178)	(0.0209)	(0.0088)	(0.0063)	(0.0347)	(0.0242)	(0.0096)
Marital status	-0.0123	0.0088	-0.0430	-0.0185	0.0096	-0.0017	-0.0039	0.0687***	-0.0051	-0.0053
	(0.0100)	(0.0093)	(0.0289)	(0.0155)	(0.0126)	(0.0159)	(0.0095)	(0.0261)	(0.0246)	(0.0115)
Constant	0.0118	0.1010***	0.1442***	0.1026**	0.1298***	0.1690***	0.2414***	0.1686***	0.3003***	0.3278***
	(0.0369)	(0.0238)	(0.0405)	(0.0469)	(0.0304)	(0.0482)	(0.0209)	(0.0441)	(0.0582)	(0.0255)

Reweighting error	0.0299	0.0132	-0.0158	-0.0445	0.0193	0.0489**	0.0232	0.0064	0.0904**	0.0251
	(0.0231)	(0.0106)	(0.0293)	(0.0458)	(0.0180)	(0.0212)	(0.0197)	(0.0341)	(0.0371)	(0.0340)
Mother's education	0.0183***	-0.0006	-0.0047	0.0271**	-0.0033	0.0186**	0.0081	-0.0122	0.0235	0.0054
	(0.0063)	(0.0067)	(0.0140)	(0.0132)	(0.0088)	(0.0089)	(0.0104)	(0.0307)	(0.0180)	(0.0139)
Province	0.0034	-0.0020	0.0085	-0.0756*	-0.0004	0.0132	-0.0056	0.0120	0.0445	-0.0045
	(0.0215)	(0.0050)	(0.0182)	(0.0422)	(0.0060)	(0.0166)	(0.0220)	(0.0180)	(0.0303)	(0.0337)
Place of residence	0.0125***	0.0006	-0.0001	0.0092*	0.0002	0.0024	0.0029	-0.0001	0.0005	0.0016
	(0.0040)	(0.0009)	(0.0016)	(0.0049)	(0.0009)	(0.0058)	(0.0025)	(0.0033)	(0.0060)	(0.0034)
Mother's age	-0.0001	-0.0033	-0.0350	0.0044	-0.0096	-0.0018	-0.0010	-0.0078	0.0006	-0.0015
	(0.0027)	(0.0182)	(0.0247)	(0.0073)	(0.0310)	(0.0028)	(0.0016)	(0.0120)	(0.0087)	(0.0025)
Number of children	-0.0025	0.0154	0.0151	-0.0053	0.0284	0.0162***	0.0193**	0.0168	0.0177*	0.0254*
	(0.0026)	(0.0113)	(0.0100)	(0.0060)	(0.0199)	(0.0052)	(0.0096)	(0.0135)	(0.0107)	(0.0149)
Marital status	-0.0017	0.0031**	0.0003	-0.0043	0.0039*	0.0002	-0.0005	-0.0023	0.0036	-0.0012
	(0.0013)	(0.0014)	(0.0034)	(0.0043)	(0.0024)	(0.0015)	(0.0007)	(0.0067)	(0.0072)	(0.0011)
Observations	20,783	20,783	20,783	12,104	16,677	20,783	20,783	20,783	12,104	16,677

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table C7: Robustness check for aggregate decomposition of the mean using Recentered Influence Functions (RIFs) when controlling for socioeconomic, demographic and supply-side factors

	ANC by a skilled Provider		***Delivery by a skilled provider***	
	Top 40 and Bottom 20 percentiles	*Top 40 and Bottom 40 percentiles*	*Top 40 and Bottom 20 percentiles*	*Top 40 and Bottom 40*
Non-poor	0.7949***	0.7949***	0.8516***	0.8516***
	(0.0062)	(0.0063)	(0.0070)	(0.0070)
Counterfactual	0.7399***	0.6335***	0.5678***	0.4642***
	(0.0232)	(0.0298)	(0.0454)	(0.0355)
Poor	0.5702***	0.6207***	0.3113***	0.3958***
	(0.0076)	(0.0052)	(0.0128)	(0.0097)
Difference	0.2247***	0.1742***	0.5404***	0.4558***
	(0.0099)	(0.0082)	(0.0148)	(0.0119)
Compositional	0.1697***	0.0129	0.2565***	0.0684*
	(0.0238)	(0.0302)	(0.0457)	(0.0360)
Structural	0.0550**	0.1614***	0.2839***	0.3874***
	(0.0237)	(0.0299)	(0.0457)	(0.0363)
Observations	12,104	16,677	12,104	16,677

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table C8: Detailed decomposition of the contribution of the compositional effect to the total mean difference in utilisation of maternal health care between the poor and non-poor when controlling for socioeconomic, demographic and supply-side factors

	ANC by a skilled provider					***Delivery by a skilled provider***				
	Top 80 and Bottom 20 percentiles	*Top 60 and Bottom 40*	*Top 40 and Bottom 60*	*Top 40 and Bottom 20*	*Top 40 and Bottom 40*	*Top 80 and Bottom 20*	*Top 60 and Bottom 40*	*Top 40 and Bottom 60*	*Top 40 and Bottom 20*	*Top 40 and Bottom 40*
	Explained/compositional component									
Total	0.1176***	0.0207	0.0529	0.1697***	0.0129	0.1829***	0.0859***	0.1368**	0.2565***	0.0684*
Explained	(0.0121)	(0.0194)	(0.0389)	(0.0238)	(0.0302)	(0.0215)	(0.0243)	(0.0614)	(0.0457)	(0.0360)
Pure	0.1122***	0.0129	0.0157	0.1639***	-0.0062	0.1860***	0.0796***	0.1412**	0.2687***	0.0575*
explained	(0.0122)	(0.0186)	(0.0437)	(0.0214)	(0.0316)	(0.0212)	(0.0236)	(0.0658)	(0.0360)	(0.0344)
Mother's	0.0577***	0.0496***	0.0492***	0.0800***	0.0610***	0.1043***	0.0885***	0.1085***	0.1483***	0.1111***
education	(0.0089)	(0.0109)	(0.0090)	(0.0139)	(0.0162)	(0.0145)	(0.0145)	(0.0191)	(0.0232)	(0.0206)
Province	0.0194***	-0.0734***	-0.0907**	0.0238**	-0.1165***	0.0387***	-0.0714***	-0.0605	0.0435**	-0.1340***
	(0.0069)	(0.0226)	(0.0424)	(0.0102)	(0.0352)	(0.0131)	(0.0254)	(0.0578)	(0.0220)	(0.0349)
Place of	0.0108	0.0049	0.0079	0.0239*	0.0066	0.0010	0.0178	0.0314**	0.0023	0.0240
residence	(0.0067)	(0.0086)	(0.0073)	(0.0143)	(0.0114)	(0.0096)	(0.0120)	(0.0126)	(0.0207)	(0.0157)
Mother's age	0.0005	-0.0079	0.0021	0.0016	-0.0112	0.0009	-0.0001	0.0005	0.0004	-0.0001
	(0.0030)	(0.0086)	(0.0066)	(0.0056)	(0.0132)	(0.0013)	(0.0013)	(0.0017)	(0.0026)	(0.0019)
Number of	-0.0016	0.0003	0.0023	-0.0035	0.0004	0.0115***	0.0137*	0.0237***	0.0237***	0.0172
children	(0.0021)	(0.0021)	(0.0025)	(0.0044)	(0.0030)	(0.0035)	(0.0082)	(0.0077)	(0.0066)	(0.0127)

Marital	0.0035	-0.0016	0.0014	0.0083*	-0.0030	0.0013	0.0000	0.0003	0.0027	-0.0002
	(0.0022)	(0.0015)	(0.0028)	(0.0045)	(0.0022)	(0.0013)	(0.0003)	(0.0009)	(0.0028)	(0.0005)
Distance	0.0022	0.0013	0.0007	0.0027	0.0017	-0.0171	-0.0097	-0.0047	-0.0205	-0.0121
	(0.0070)	(0.0041)	(0.0031)	(0.0084)	(0.0051)	(0.0114)	(0.0064)	(0.0043)	(0.0137)	(0.0077)
Facility size	0.0028	0.0047	0.0025	0.0031	0.0046	0.0124**	0.0132***	0.0109**	0.0266**	0.0174***
	(0.0022)	(0.0029)	(0.0016)	(0.0043)	(0.0039)	(0.0057)	(0.0043)	(0.0045)	(0.0108)	(0.0061)
Alternative supply	0.0067	0.0257	0.0319**	0.0104	0.0386	-0.0055	-0.0006	0.0069	-0.0090	-0.0009
	(0.0066)	(0.0170)	(0.0129)	(0.0107)	(0.0270)	(0.0094)	(0.0088)	(0.0084)	(0.0162)	(0.0138)
Distance & place of residence interaction	0.0101	0.0093*	0.0083*	0.0135	0.0117*	0.0385***	0.0281***	0.0242***	0.0507***	0.0352***
	(0.0081)	(0.0056)	(0.0045)	(0.0107)	(0.0068)	(0.0136)	(0.0093)	(0.0073)	(0.0176)	(0.0112)
Specification Error	0.0054	0.0078	0.0372**	0.0058	0.0191**	-0.0031	0.0063	-0.0044	-0.0122	0.0109
	(0.0054)	(0.0052)	(0.0182)	(0.0173)	(0.0091)	(0.0100)	(0.0047)	(0.0243)	(0.0344)	(0.0078)
Mother's education	-0.0008	0.0103	-0.0169*	-0.0027	0.0091	0.0018	-0.0100	-0.0102	-0.0052	-0.0125
	(0.0062)	(0.0085)	(0.0093)	(0.0113)	(0.0120)	(0.0119)	(0.0073)	(0.0110)	(0.0203)	(0.0106)
Province	-0.0313	0.0006	0.0146	-0.0158	-0.0157	-0.0223	0.0014	-0.0006	-0.0427	0.0047
	(0.0270)	(0.0136)	(0.0153)	(0.0305)	(0.0312)	(0.0245)	(0.0062)	(0.0156)	(0.0328)	(0.0136)

Place of residence	-0.0120**	-0.0005	-0.0072*	0.0027	-0.0068	0.0065	0.0008	0.0070	-0.0045	0.0097**
	(0.0053)	(0.0010)	(0.0044)	(0.0037)	(0.0058)	(0.0084)	(0.0010)	(0.0044)	(0.0060)	(0.0047)
Mother's age	0.0078	0.0017	0.0045	0.0281	-0.0015	-0.0056	-0.0024	0.0019	0.0074	0.0019
	(0.0103)	(0.0138)	(0.0176)	(0.0198)	(0.0228)	(0.0158)	(0.0088)	(0.0157)	(0.0262)	(0.0142)
Number of children	-0.0002	0.0227**	0.0407***	-0.0088	0.0407*	0.0045	0.0059	0.0161	0.0015	0.0075
	(0.0024)	(0.0093)	(0.0134)	(0.0131)	(0.0208)	(0.0039)	(0.0039)	(0.0246)	(0.0147)	(0.0066)
Marital	0.0115	-0.0120	0.0204	0.0117	-0.0207	0.0144	0.0125	-0.0421**	0.0214	0.0198*
	(0.0077)	(0.0098)	(0.0171)	(0.0107)	(0.0143)	(0.0118)	(0.0079)	(0.0172)	(0.0155)	(0.0104)
Distance	-0.0223*	-0.0141*	0.0116	-0.0240	-0.0156*	-0.0138	0.0033	-0.0121	-0.0105	-0.0017
	(0.0120)	(0.0073)	(0.0112)	(0.0155)	(0.0091)	(0.0179)	(0.0089)	(0.0114)	(0.0208)	(0.0098)
Facility size	0.0177*	0.0030	-0.0089	0.0281*	-0.0036	-0.0144	0.0044	0.0388**	-0.0254	-0.0005
	(0.0102)	(0.0142)	(0.0080)	(0.0156)	(0.0241)	(0.0267)	(0.0120)	(0.0170)	(0.0374)	(0.0157)
Alternative supply	-0.0091	0.0207	0.0304	-0.0149	0.0984	0.0105	-0.0109	-0.0802**	0.0178	-0.0165
	(0.0107)	(0.0323)	(0.0390)	(0.0184)	(0.0700)	(0.0189)	(0.0137)	(0.0325)	(0.0376)	(0.0243)
Distance & place of	0.0182*	0.0035	-0.0095	0.0171*	0.0006	0.0027	-0.0021	0.0034	-0.0005	0.0014
	(0.0096)	(0.0050)	(0.0064)	(0.0091)	(0.0056)	(0.0145)	(0.0055)	(0.0047)	(0.0107)	(0.0045)
Constant	0.0258	-0.0281	-0.0425	-0.0157	-0.0657	0.0126	0.0033	0.0737	0.0286	-0.0030
	(0.0345)	(0.0449)	(0.0409)	(0.0459)	(0.0701)	(0.0458)	(0.0209)	(0.0453)	(0.0669)	(0.0285)

	Unexplained/structural component									
Total unexplained	0.0501***	0.1229***	0.0996**	0.0550**	0.1614***	0.1997***	0.2937***	0.2583***	0.2839***	0.3874***
	(0.0127)	(0.0198)	(0.0387)	(0.0237)	(0.0299)	(0.0224)	(0.0248)	(0.0619)	(0.0457)	(0.0363)
Pure unexplained	0.0012	0.0655***	0.0853***	0.0090	0.0580**	0.1457***	0.2535***	0.2384***	0.1839***	0.3147***
	(0.0312)	(0.0133)	(0.0307)	(0.0602)	(0.0236)	(0.0323)	(0.0156)	(0.0470)	(0.0555)	(0.0196)
Mother's education	0.0317***	0.0057	0.0241**	0.0254**	0.0053	0.0020	0.0012	-0.0281**	-0.0417**	-0.0327***
	(0.0113)	(0.0081)	(0.0110)	(0.0122)	(0.0109)	(0.0206)	(0.0095)	(0.0136)	(0.0168)	(0.0119)
Province	-0.0042	0.0186**	0.0311	-0.0125	0.0507***	0.0044	0.0340***	0.0504**	-0.0039	0.0719***
	(0.0051)	(0.0080)	(0.0224)	(0.0221)	(0.0177)	(0.0078)	(0.0098)	(0.0237)	(0.0147)	(0.0155)
Place of residence	0.0050**	0.0012	0.0050	-0.0209***	0.0041	-0.0087**	-0.0002	-0.0072	0.0201	-0.0062
	(0.0025)	(0.0014)	(0.0061)	(0.0075)	(0.0062)	(0.0041)	(0.0018)	(0.0062)	(0.0123)	(0.0064)
Mother's age	-0.0108	-0.0149	0.0227	-0.0284	-0.0191	0.0093	-0.0030	-0.0086	-0.0143	-0.0100
	(0.0135)	(0.0390)	(0.0326)	(0.0252)	(0.0582)	(0.0205)	(0.0134)	(0.0224)	(0.0332)	(0.0172)
Number of children	0.0078	-0.0359**	-0.0635***	0.0163	-0.0751***	-0.0007	-0.0059	-0.0270	-0.0003	-0.0155
	(0.0062)	(0.0142)	(0.0185)	(0.0211)	(0.0262)	(0.0093)	(0.0066)	(0.0324)	(0.0228)	(0.0103)
Marital	-0.0135	0.0113	-0.0247	-0.0183	0.0155	-0.0032	-0.0029	0.0606***	-0.0061	-0.0031
	(0.0098)	(0.0106)	(0.0203)	(0.0136)	(0.0138)	(0.0152)	(0.0099)	(0.0210)	(0.0203)	(0.0114)
Distance	0.0190	0.0130	-0.0133	0.0208	0.0153	0.0014	-0.0120	0.0087	0.0001	-0.0073
	(0.0142)	(0.0105)	(0.0126)	(0.0154)	(0.0120)	(0.0239)	(0.0138)	(0.0122)	(0.0257)	(0.0133)

Facility size	0.0526***	0.0607***	0.0222*	0.0392*	0.0620**	0.0919*	0.0618**	-0.0563**	0.0994**	0.0614**
	(0.0199)	(0.0211)	(0.0127)	(0.0229)	(0.0284)	(0.0500)	(0.0271)	(0.0234)	(0.0423)	(0.0260)
Alternative	0.0010	-0.0364	-0.0696	0.0014	-0.1093**	0.0174	0.0402***	0.1076***	0.0249	0.0483**
supply	(0.0285)	(0.0274)	(0.0429)	(0.0495)	(0.0481)	(0.0319)	(0.0154)	(0.0388)	(0.0605)	(0.0221)
Distance &	-0.0101	0.0021	0.0110	-0.0100	0.0023	0.0104	0.0124	0.0076	0.0144	0.0118*
place of	(0.0102)	(0.0072)	(0.0067)	(0.0078)	(0.0070)	(0.0174)	(0.0088)	(0.0060)	(0.0121)	(0.0068)
Constant	-0.0773*	0.0402	0.1402***	-0.0039	0.1063	0.0214	0.1278***	0.1308**	0.0914	0.1960***
	(0.0397)	(0.0518)	(0.0525)	(0.0486)	(0.0760)	(0.0694)	(0.0389)	(0.0554)	(0.0754)	(0.0423)
Reweighting	0.0489*	0.0574**	0.0143	0.0460	0.1034**	0.0541**	0.0402**	0.0200	0.0999**	0.0728**
error	(0.0284)	(0.0256)	(0.0217)	(0.0570)	(0.0445)	(0.0254)	(0.0179)	(0.0294)	(0.0501)	(0.0293)
Mother's	0.0177***	0.0013	0.0057	0.0264**	0.0001	0.0189**	0.0095	0.0053	0.0277	0.0125
education	(0.0059)	(0.0084)	(0.0067)	(0.0120)	(0.0135)	(0.0091)	(0.0110)	(0.0191)	(0.0186)	(0.0158)
Province	0.0134	0.0199	0.0051	0.0017	0.0473	0.0113	0.0058	0.0087	0.0484	0.0287
	(0.0208)	(0.0144)	(0.0108)	(0.0436)	(0.0289)	(0.0182)	(0.0200)	(0.0127)	(0.0362)	(0.0289)
Place of	0.0162***	-0.0000	-0.0003	0.0162**	0.0005	-0.0038	0.0020	0.0015	-0.0048	0.0004
residence	(0.0058)	(0.0007)	(0.0007)	(0.0070)	(0.0013)	(0.0080)	(0.0018)	(0.0024)	(0.0068)	(0.0022)
Mother's age	-0.0013	0.0165	-0.0193	0.0033	0.0373	-0.0008	-0.0007	-0.0048	0.0025	-0.0012
	(0.0028)	(0.0378)	(0.0242)	(0.0081)	(0.0764)	(0.0029)	(0.0016)	(0.0082)	(0.0087)	(0.0026)

Number of children	-0.0019	0.0166	0.0179*	-0.0061	0.0320	0.0154***	0.0184*	0.0168	0.0118	0.0240
	(0.0033)	(0.0168)	(0.0107)	(0.0082)	(0.0323)	(0.0055)	(0.0103)	(0.0139)	(0.0094)	(0.0159)
Marital	-0.0011	0.0045**	-0.0002	-0.0034	0.0071**	0.0003	-0.0003	-0.0007	0.0030	-0.0010
	(0.0011)	(0.0019)	(0.0020)	(0.0033)	(0.0034)	(0.0013)	(0.0006)	(0.0041)	(0.0051)	(0.0011)
Distance	0.0018	0.0000	-0.0001	0.0026	-0.0008	-0.0002	0.0000	0.0003	-0.0001	0.0005
	(0.0014)	(0.0010)	(0.0009)	(0.0025)	(0.0018)	(0.0012)	(0.0008)	(0.0010)	(0.0018)	(0.0010)
Facility size	0.0021	0.0054	0.0026	0.0079	0.0103	0.0087	0.0042	-0.0022	0.0060	0.0066
	(0.0017)	(0.0033)	(0.0024)	(0.0078)	(0.0076)	(0.0068)	(0.0036)	(0.0062)	(0.0194)	(0.0067)
Alternative supply	0.0037	-0.0070	0.0020	0.0009	-0.0307	0.0006	0.0005	-0.0051	0.0028	0.0024
	(0.0171)	(0.0149)	(0.0125)	(0.0329)	(0.0414)	(0.0104)	(0.0017)	(0.0082)	(0.0219)	(0.0045)
	-0.0018	0.0001	0.0010	-0.0033	0.0000	0.0036	0.0008	0.0002	0.0024	-0.0002
	(0.0021)	(0.0007)	(0.0013)	(0.0028)	(0.0009)	(0.0030)	(0.0011)	(0.0006)	(0.0028)	(0.0010)
Observations	20,783	20,783	20,783	12,104	16,677	20,783	20,783	20,783	12,104	16,677

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table C9: Quantile decomposition of the total mean difference in utilisation of delivery by a skilled provider before and after the start of the FMC program across the asset wealth quantiles

VARIABLES	Quantile 5	Quantile 10	Quantile 15	Quantile 20	Quantile 25	Quantile 30	Quantile 35	Quantile 40	Quantile 45	Quantile 50
After FMC	0.2290***	0.3073***	0.4284***	0.5018***	0.5289***	0.5341***	0.5670***	0.5750***	0.6104***	0.5956***
	(0.0137)	(0.0248)	(0.0082)	(0.0291)	(0.0055)	(0.0066)	(0.0048)	(0.0099)	(0.0070)	(0.0365)
Counterfactual	0.2065***	0.3123***	0.3198***	0.4094***	0.4713***	0.5055***	0.5552***	0.5600***	0.5867***	0.6129***
	(0.0085)	(0.0157)	(0.0081)	(0.0149)	(0.0099)	(0.0102)	(0.0062)	(0.0065)	(0.0064)	(0.0112)
Before FMC	0.2086***	0.3146***	0.3218***	0.4125***	0.4735***	0.5073***	0.5560***	0.5610***	0.5873***	0.6132***
	(0.0087)	(0.0117)	(0.0086)	(0.0143)	(0.0095)	(0.0098)	(0.0054)	(0.0064)	(0.0060)	(0.0116)
Difference	0.0204	-0.0073	0.1066***	0.0893***	0.0554***	0.0268***	0.0110*	0.0140	0.0231***	-0.0176
	(0.0174)	(0.0252)	(0.0112)	(0.0263)	(0.0086)	(0.0098)	(0.0066)	(0.0102)	(0.0070)	(0.0390)
Compositional	-0.0021	-0.0023	-0.0020	-0.0031	-0.0022	-0.0018	-0.0008	-0.0011	-0.0006	-0.0003
	(0.0092)	(0.0118)	(0.0066)	(0.0095)	(0.0066)	(0.0073)	(0.0042)	(0.0065)	(0.0046)	(0.0148)
Structural	0.0224	-0.0050	0.1086***	0.0924***	0.0576***	0.0286***	0.0118*	0.0150	0.0237***	-0.0173
	(0.0170)	(0.0259)	(0.0111)	(0.0248)	(0.0080)	(0.0088)	(0.0069)	(0.0097)	(0.0053)	(0.0400)
Observations	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449

*Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

VARIABLES	***Quantile 55***	***Quantile 60***	***Quantile 65***	***Quantile 70***	***Quantile 75***	***Quantile 80***	***Quantile 85***	***Quantile 90***	***Quantile 95***
After FMC	0.7027***	0.7694***	0.8282***	0.8572***	0.8941***	0.9441***	0.9549***	0.9805***	0.9740***
	(0.0080)	(0.0251)	(0.0106)	(0.0039)	(0.0097)	(0.0123)	(0.0048)	(0.0043)	(0.0023)
Counterfactua	0.6345***	0.7218***	0.7492***	0.7872***	0.8440***	0.9126***	0.9371***	0.9540***	0.9826***
	(0.0163)	(0.0136)	(0.0069)	(0.0178)	(0.0122)	(0.0084)	(0.0054)	(0.0077)	(0.0047)
Before FMC	0.6341***	0.7212***	0.7493***	0.7870***	0.8431***	0.9119***	0.9366***	0.9536***	0.9822***
	(0.0163)	(0.0128)	(0.0068)	(0.0182)	(0.0132)	(0.0084)	(0.0056)	(0.0084)	(0.0050)
Difference	0.0686***	0.0482*	0.0789***	0.0702***	0.0510***	0.0323**	0.0182**	0.0269***	-0.0083
	(0.0159)	(0.0250)	(0.0113)	(0.0180)	(0.0151)	(0.0133)	(0.0075)	(0.0085)	(0.0057)
Compositional	0.0004	0.0006	-0.0001	0.0003	0.0008	0.0007	0.0004	0.0004	0.0003
	(0.0153)	(0.0136)	(0.0084)	(0.0177)	(0.0115)	(0.0073)	(0.0056)	(0.0063)	(0.0028)
Structural	0.0682***	0.0476**	0.0790***	0.0700***	0.0502***	0.0316***	0.0178**	0.0265***	-0.0086
	(0.0136)	(0.0198)	(0.0100)	(0.0165)	(0.0112)	(0.0110)	(0.0077)	(0.0066)	(0.0052)
Observations	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449	10,449

*Bootstrapped standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table C10: Means for the poor and non-poor at the 20th, 40th and 60th asset index percentiles

	Overall	***20th percentile***		***40th percentile***		***40th percentile***	
Variable		*poor*	*non-poor*	*poor*	*non-poor*	*poor*	*non-poor*
Individual-level (Mother's) characteristics							
Observations	**14820**	**3518**	**11302**	**6726**	**8094**	**9664**	**5156**
Mother's Education							
No education	0.0974	0.3226	0.0513	0.1884	0.0426	0.1573	0.0241
Primary	0.5441	0.6041	0.5318	0.6600	0.4743	0.6531	0.4109
Secondary	0.2615	0.0676	0.3012	0.1377	0.3361	0.1687	0.3751
Higher	0.0969	0.0057	0.1156	0.0138	0.1470	0.0209	0.1899
Region of residence							
Nairobi	0.1154	-	0.1390	0.0017	0.1839	0.0040	0.2515
Central	0.1051	0.0149	0.1236	0.0541	0.1358	0.0618	0.1580
Coast	0.1014	0.1475	0.0919	0.1028	0.1005	0.1052	0.0967
Eastern	0.1271	0.1420	0.1241	0.1436	0.1172	0.1569	0.0907
Nyanza	0.1377	0.1146	0.1425	0.1501	0.1303	0.1723	0.0955
Rift Valley	0.2767	0.3786	0.2558	0.3305	0.2443	0.3142	0.2308
Western	0.1108	0.1293	0.1070	0.1775	0.0705	0.1467	0.0668
North Eastern	0.0258	0.0731	0.0161	0.0396	0.0175	0.0389	0.0098
Mother's age at child's birth							
15-19 years	0.1075	0.1045	0.1082	0.1156	0.1027	0.1186	0.0940
20-29 years	0.5740	0.5300	0.5829	0.5326	0.5988	0.5340	0.6228
30-39 years	0.2787	0.3090	0.2725	0.2974	0.2674	0.2975	0.2557
40-49 years	0.0398	0.0566	0.0364	0.0543	0.0311	0.0498	0.0276
Parity							
Low Parity	0.6524	0.4579	0.6922	0.4970	0.7460	0.5283	0.8040
High Parity	0.3476	0.5421	0.3078	0.5030	0.2540	0.4717	0.1960
Marital Status							
Not Married/Not living together	0.1849	0.1736	0.1872	0.1765	0.1899	0.1833	0.1868
Married or living together	0.8151	0.8264	0.8128	0.8235	0.8101	0.8167	0.8132

Cluster level characteristics							
Observations	**1581**	**309**	**1272**	**647**	**934**	**940**	**641**
Place of residence							
Urban	0.4381	0.0618	0.5012	0.0942	0.6152	0.1693	0.6953
Rural	0.5619	0.9382	0.4988	0.9058	0.3848	0.8307	0.3047
Health facilities offering antenatal care							
Distance	4.3552	6.9339	3.9233	6.1505	3.4307	5.6127	3.1524
Size							
Level 2	0.5920	0.6711	0.5788	0.6597	0.5572	0.6496	0.5370
Level 3	0.2560	0.2553	0.2561	0.2266	0.2712	0.2207	0.2898
Level 4	0.1310	0.0736	0.1407	0.1127	0.1405	0.1224	0.1393
Level 5	0.0209	-	0.0244	0.0010	0.0312	0.0074	0.0339
Alternative supply	7.8289	1.8743	8.8261	2.2261	10.7138	2.8726	12.5695
Health facilities offering maternity services							
Distance	5.6119	8.6837	5.0974	7.3854	4.6987	6.8437	4.4336
Size							
Level 2	0.3805	0.5450	0.3529	0.5177	0.3098	0.5029	0.2634
Level 3	0.3637	0.3401	0.3676	0.3200	0.3862	0.3138	0.4114
Level 4	0.2114	0.1149	0.2275	0.1596	0.2380	0.1675	0.2533
Level 5	0.0335	-	0.0392	0.0027	0.0494	0.0129	0.0533
Level 6	0.0109	-	0.0128	-	0.0166	0.0029	0.0186
Alternative supply	3.2244	1.0946	3.5811	1.3977	4.1650	1.6052	4.7731

Appendix D: Chapter Five

Table D1: Two-sample t-test for pre-treatment characteristics of children not delivered in health facilities and those delivered at private health facilities

Variable	***Home***	***Private***	***Diff.***	***t-stat***	***P>t***
	Individual-level (Child) characteristics				
Pre-birth interval					
First-born children	0.123	0.322	0.199	10.45	0.0000***
Less than 33 months	0.452	0.209	-0.242	12.54	0.0000***
33 months or more	0.425	0.469	0.044	2.03	0.0421**
	Individual-level (Mother's) characteristics				
Mother's Education					
No education	0.359	0.048	-0.311	14.83	0.0000***
Primary	0.545	0.395	-0.149	5.82	0.0000***
Secondary	0.088	0.316	0.228	11.92	0.0000***
Higher	0.009	0.241	0.232	12.13	0.0000***
Region of residence					
Nairobi	0.006	0.071	0.065	4.74	0.0000***
Central	0.016	0.147	0.132	7.14	0.0000***
Coast	0.142	0.075	-0.067	3.71	0.0002***
Eastern	0.135	0.206	0.071	2.91	0.0037***
Nyanza	0.105	0.138	0.033	1.82	0.0688*
Rift Valley	0.389	0.26	-0.128	4.69	0.0000***
Western	0.102	0.068	-0.034	2.35	0.0187**
North Eastern	0.106	0.035	-0.071	3.93	0.0001***
Mother's age at child's birth					
15-19 years	0.095	0.077	-0.019	1.45	0.1483
20-29 years	0.55	0.612	0.062	2.9	0.0038***
30-39 years	0.294	0.286	-0.008	0.41	0.682
40-49 years	0.061	0.026	-0.036	4.38	0.0000***
Parity					
Low Parity	0.448	0.792	0.344	17.14	0.0000***
High Parity	0.552	0.208	-0.344	17.14	0.0000***

Marital Status					
Not Married/Not living together	0.145	0.155	0.01	0.63	0.5262
Married or living together	0.855	0.845	-0.01	0.63	0.5262
	Household-level characteristics				
Asset wealth					
1st asset quintile	0.449	0.059	-0.39	20.67	0.0000***
2nd asset quintile	0.267	0.124	-0.143	7.54	0.0000***
3rd asset quintile	0.198	0.209	0.01	0.51	0.6131
4th asset quintile	0.07	0.31	0.24	11.69	0.0000***
5th asset quintile	0.016	0.298	0.283	12.8	0.0000***
	Cluster-level characteristics				
Place of residence					
Urban	0.199	0.629	0.43	6.66	0.0000***
Rural	0.801	0.371	-0.43	6.66	0.0000***
Distance to the nearest health facility	16.179	6.209	-9.969	5.38	0.0000***
Size of the nearest health facility					
Level 2	0.622	0.257	-0.365	5.820	0.0000***
Level 3	0.219	0.357	0.138	2.140	0.0330**
Level 4	0.149	0.271	0.122	2.070	0.0394**
Level 5	0.000	0.100	0.100	2.780	0.0058***
Level 6	0.010	0.014	0.004	0.270	0.785
Alternative supply of health facilities	0.587	0.786	0.199	1.060	0.2881

Table D2: Two-sample t-test for pre-treatment characteristics of children delivered at public health facilities compared to those not delivered in health facilities and those delivered in private health facilities before propensity score matching

	Home/others vs Public					**Private vs Public**				
Variable	***Home***	***Public***	***Diff.***	***t-stat***	***P>t***	***Private***	***Public***	***Diff.***	***t-stat***	***P>t***
	Individual-level (Child) characteristics									
Pre-birth interval										
First-born children	0.123	0.306	0.183	15.57	0.0000***	0.322	0.306	-0.015	0.74	0.4611
Less than 33 months	0.452	0.265	-0.187	13.00	0.0000***	0.209	0.265	0.056	2.91	0.0037***
33 months or more	0.425	0.428	0.004	0.24	0.8099	0.469	0.428	-0.04	1.83	0.0677*
	Individual-level (Mother's) characteristics									
Mother's Education										
No education	0.359	0.099	-0.259	14.38	0.0000***	0.048	0.099	0.051	3.71	0.0002***
Primary	0.545	0.528	-0.017	0.88	0.3802	0.395	0.528	0.132	5.71	0.0000***
Secondary	0.088	0.294	0.206	16.29	0.0000***	0.316	0.294	-0.022	1.05	0.2926
Higher	0.009	0.079	0.070	10.67	0.0000***	0.241	0.079	-0.162	8.34	0.0000***
Mother's age at child's birth										
15-19 years	0.095	0.130	0.035	3.46	0.0006***	0.077	0.130	0.053	3.92	0.0001***
20-29 years	0.550	0.589	0.039	2.60	0.0094***	0.612	0.589	-0.023	1.05	0.2922
30-39 years	0.294	0.249	-0.045	3.24	0.0012***	0.286	0.249	-0.037	1.85	0.0639*
40-49 years	0.061	0.032	-0.029	4.33	0.0000***	0.026	0.032	0.006	0.90	0.3696

Region of residence										
Nairobi	0.006	0.027	0.021	4.67	0.0000***	0.071	0.027	-0.044	3.32	0.0009***
Central	0.016	0.109	0.094	9.25	0.0000***	0.147	0.109	-0.038	2.08	0.0378**
Coast	0.142	0.120	-0.021	1.52	0.1275	0.075	0.120	0.045	3.11	0.0019***
Eastern	0.135	0.128	-0.007	0.51	0.6114	0.206	0.128	-0.078	3.64	0.0003***
Nyanza	0.105	0.191	0.085	6.15	0.0000***	0.138	0.191	0.052	2.71	0.0068***
Rift Valley	0.389	0.273	-0.115	5.70	0.0000***	0.260	0.273	0.013	0.57	0.5667
Western	0.102	0.097	-0.005	0.47	0.6386	0.068	0.097	0.029	2.04	0.0420**
North Eastern	0.106	0.055	-0.050	3.64	0.0003***	0.035	0.055	0.021	1.46	0.1441
	Household-level characteristics									
Asset Wealth										
1st asset quintile	0.457	0.135	-0.322	17.82	0.0000***	0.057	0.135	0.077	6.00	0.0000***
2nd asset quintile	0.263	0.234	-0.029	1.71	0.0875*	0.121	0.234	0.113	6.20	0.0000***
3rd asset quintile	0.198	0.257	0.059	3.81	0.0001***	0.211	0.257	0.046	2.24	0.0255**
4th asset quintile	0.065	0.262	0.197	14.95	0.0000***	0.320	0.262	-0.058	2.63	0.0086***
5th asset quintile	0.017	0.112	0.095	9.93	0.0000***	0.290	0.112	-0.178	8.13	0.0000***
	Cluster-level characteristics									
Place of residence										
Urban	0.199	0.430	0.231	5.31	0.0000***	0.629	0.430	-0.198	2.96	0.0033***
Rural	0.801	0.570	-0.231	5.31	0.0000***	0.371	0.570	0.198	2.96	0.0033***

Distance to the nearest health facility	16.224	10.093	-6.132	3.22	0.0014***	6.198	10.093	3.895	2.25	0.0252**
Size of the nearest health facility										
Level 2	0.622	0.386	-0.236	4.99	0.0000***	0.257	0.386	0.129	2.08	0.0384**
Level 3	0.224	0.332	0.108	2.50	0.0129**	0.357	0.332	-0.025	0.39	0.700
Level 4	0.144	0.233	0.089	2.36	0.0189**	0.271	0.233	-0.038	0.63	0.527
Level 5	0.000	0.036	0.036	2.87	0.0043***	0.100	0.036	-0.064	1.68	0.0933*
Level 6	0.010	0.013	0.004	0.34	0.7375	0.014	0.013	-0.001	0.05	0.959
Alternative supply of health facilities	0.587	1.000	0.413	2.57	0.0106**	0.786	1.000	0.214	1.06	0.292

Table D3: Likelihood Ratio statistics for covariate selection for propensity score matching for children delivered in public health facilities to those not delivered in health facilities[26]

Variables	***Steps***							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Mother's education	795.64***	296.46***	-	-	-	-	-	-
Household asset wealth	925.20***	-	-	-	-	-	-	-
Region of residence	359.87***	183.30***	148.06***	-	-	-	-	-
Place of residence	334.72***	30.84***	37.11***	34.67***	28.55***	-	-	-
Mother's age at child's birth	38.28***	26.22***	17.52***	20.24***	7.32*	7.47*	7.25*	7.17*
Mother's parity	264.63***	126.64***	61.55***	63.34***	-	-	-	-
Mother's marital status	12.12***	4.10**	0.01#	-	-	-	-	-
Distance to the nearest health facility	170.27***	63.00***	8.98***	24.46***	20.97***	19.61***	-	-
Size of nearest health facility	136.59***	28.34***	23.35***	21.38***	21.00***	15.69***	11.49**	-
Alternative supply of health facilities	101.87***	33.15***	8.87***	4.30**	4.62**	2.12#	-	-

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

26 The variables being added to the baseline model at each step have their likelihood statistics are circled black while variables being dropped due to the likelihood statistic being statistically non-significant are indicated by #.

Table D4: Likelihood Ratio statistics for covariate selection for propensity score matching for children delivered in public health facilities to those delivered in private health facilities[27]

Variables	***Steps***				
	1	2	3	4	5
Mother's education	138.50***	52.95***	43. 85***	-	-
Household asset wealth	176.75***	-	-	-	-
Region of Residence	94.01***	59.82***	-	-	-
Place of residence	64.40***	2.79*	5.56**	5.19**	4.42**
Mother's age at child's birth	14.00***	5.76#	-	-	-
Mother's parity	27.58***	9.20***	3.58*	0.77#	0.49#
Mother's marital status	1.59#	-	-	-	-
Distance to the nearest health facility	27.28***	20.49***	10.44***	11. 34***	-
Size of nearest health facility	34.59***	9.79**	6.46#	-	-
Alternative supply of health facilities	0.55#	-	-	-	-

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

27 The variables being added to the baseline model at each step have their likelihood statistics are circled black while variables being dropped due to the likelihood statistic being statistically non-significant are indicated by #.

Table D5: Two-sample t-test for pre-treatment characteristics of children delivered at public health facilities compared to those not delivered in health facilities and those delivered in private health facilities after propensity score matching

	Home/others vs Public					**Private vs Public**				
Variable	***Home***	***Public***	***Diff.***	***t-stat***	***P>t***	***Private***	***Public***	***Diff.***	***t-stat***	***P>t***
	Individual-level (Child) characteristics									
Pre-birth interval										
First-born children	0.233	0.305	0.072	3.43	0.0006***	0.274	0.308	0.034	1.56	0.1182
Less than 33 months	0.355	0.266	-0.089	4.6	0.0000***	0.254	0.26	0.006	0.27	0.7894
33 months or more	0.413	0.429	0.016	0.78	0.4353	0.472	0.432	-0.04	1.62	0.1055
	Individual-level (Mother's) characteristics									
Mother's Education										
No education	0.093	0.099	0.005	0.59	0.5574	0.075	0.091	0.015	1.03	0.3019
Primary	0.574	0.532	-0.042	1.74	0.0816*	0.539	0.534	-0.005	0.19	0.8486
Secondary	0.28	0.294	0.014	0.59	0.5542	0.306	0.298	-0.008	0.36	0.7194
Higher	0.052	0.075	0.023	1.47	0.1411	0.080	0.078	-0.002	0.22	0.8234
Mother's age at child's birth										
15-19 years	0.154	0.131	-0.023	1.24	0.2165	0.096	0.132	0.036	2.22	0.0264**
20-29 years	0.582	0.588	0.006	0.26	0.7911	0.609	0.589	-0.019	0.77	0.4423
30-39 years	0.219	0.249	0.031	1.69	0.0902*	0.271	0.247	-0.024	1.07	0.2849
40-49 years	0.046	0.032	-0.014	1.58	0.1131	0.024	0.032	0.008	0.97	0.3308

Parity										
Low Parity	0.700	0.694	-0.006	0.31	0.7545	0.710	0.698	-0.012	0.5	0.6162
High Parity	0.300	0.306	0.006	0.31	0.7545	0.29	0.302	0.012	0.5	0.6162
Marital Status										
Not Married/Not living together	0.228	0.179	-0.049	2.25	0.0248**	0.16	0.181	0.021	1.09	0.2743
Married or living together	0.772	0.821	0.049	2.25	0.0248**	0.84	0.819	-0.021	1.09	0.2743
Region of residence										
Nairobi	0.022	0.028	0.005	0.67	0.506	0.030	0.027	-0.003	0.40	0.6875
Central	0.098	0.102	0.004	0.19	0.8468	0.110	0.111	0.001	0.06	0.9491
Coast	0.141	0.122	-0.019	1.29	0.196	0.082	0.116	0.033	2.25	0.0247**
Eastern	0.126	0.129	0.002	0.16	0.8711	0.136	0.127	-0.009	0.61	0.539
Nyanza	0.222	0.192	-0.029	1.49	0.1371	0.186	0.198	0.012	0.57	0.5689
Rift Valley	0.245	0.275	0.03	1.62	0.1051	0.296	0.28	-0.016	0.67	0.5052
Western	0.103	0.098	-0.005	0.42	0.6751	0.111	0.1	-0.011	0.61	0.5426
North Eastern	0.043	0.055	0.012	1.64	0.1015	0.05	0.042	-0.008	0.67	0.5009

	Household-level characteristics									
Asset Wealth										
1st asset quintile	0.134	0.131	-0.003	0.26	0.7911	0.105	0.123	0.018	0.89	0.3741
2nd asset quintile	0.235	0.237	0.001	0.07	0.9449	0.233	0.24	0.007	0.27	0.7877
3rd asset quintile	0.281	0.259	-0.022	1.04	0.2986	0.267	0.262	-0.005	0.2	0.8386
4th asset quintile	0.253	0.264	0.011	0.4	0.6903	0.283	0.263	-0.019	0.83	0.4044
5th asset quintile	0.096	0.109	0.013	0.6	0.5499	0.112	0.112	0.000	0.03	0.9796
	Cluster-level characteristics									
Place of residence										
Urban	0.365	0.427	0.063	0.91	0.364	0.378	0.422	0.044	0.57	0.5673
Rural	0.635	0.573	-0.063	0.91	0.364	0.622	0.578	-0.044	0.57	0.5673
Distance to the nearest health facility	9.126	9.969	0.843	0.52	0.6042	6.451	8.024	1.573	0.92	0.3584
Size of the nearest health facility										
Level 2	0.495	0.388	-0.107	1.51	0.1323	0.305	0.378	0.073	0.91	0.3641
Level 3	0.328	0.332	0.004	0.06	0.9513	0.353	0.338	-0.015	0.19	0.8508
Level 4	0.160	0.235	0.075	1.50	0.1336	0.265	0.235	-0.030	0.41	0.6791
Level 5	0.000	0.031	0.031	2.67	0.0078***	0.073	0.036	-0.037	0.96	0.3391
Level 6	0.017	0.014	-0.004	0.25	0.8054	0.004	0.013	0.009	1.13	0.2596
Alternative supply of health facilities	0.810	1.015	0.205	1.07	0.2834	0.875	1.023	0.148	0.62	0.5357