### UNIVERSITY OF KWAZULU-NATAL

# The determinants of access to health care services: Empirical evidence from African countries

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#### **DECLARATION**

#### I, Wa Ntita Serge Kabongo, declare that:

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I thank you!

#### **ABSTRACT**

It has been acknowledged that access to health care is instrumental in improving health status; and better health status has been considered crucial to socio-economic development. However, there is insufficient evidence on the factors that determine access to health care to inform policy makers. To this end, this study aimed to identify the key determinants of access to health care in Africa, distinguishing between the short and long-run determinants of such access. Panel data from 37 African countries were collected from the World Bank and World Health Organisation for the period 1995-2012 and analysed using a dynamic panel autoregressive distributed lags (ARDL) model. With the preliminary test suggesting common long-run coefficients and individual short-run coefficients, the model was estimated using the pooled mean group (PMG) estimators. The study found that a long-run and short-run stable relationship exists between access to health care and the variables included in the model, with income being the strongest determinant. The income elasticity of access to health care was 0.1149, suggesting that access to health care is a non-luxury good. These findings imply that income is an important determinant of access to health care and should therefore be the focus of policy making to improve such access in African countries.

## TABLE OF CONTENTS

DECLARATION	ii
ACKNOWLEDGEMENTS	iii
ABSTRACT	iv
TABLE OF CONTENTS	v
LIST OF TABLES	
LIST OF FIGURES	
LIST OF ACRONYMS	1X
Chapter One: Introduction	1
1.1 Background	1
1.2 Research problem and the significance of this study	3
1.3 Research objectives	3
1.4 Methodology	4
1.5 Delimitation of the study	4
1.6 Structure of the dissertation	4
Chapter Two: Literature review	6
2.1 Background to the interest in access to health care.	6
2.2 Access to healthcare: Process, Definition and Dimensions and Measurement	6
2.2.1 The process of access to healthcare	7
2.2.2 Definition and dimensions of access to healthcare	8
2.2.3 Measurement of access to healthcare	9
2.3 State of access to health care in Africa	10
2.4 Theoretical framework for access to health care	13
2.4.1 Aday and Andersen framework	13
2.4.2 Penchansky & Thomas framework	14
2.4.3 Peters-Garg-Bloom-Walker-Brieger-Rahman framework	15
2.5 Empirical evidence	17
2.6 Chapter summary	20
Chapter Three: Methodology	21
3.1 Access to healthcare: Dimensions used and Measurement	21
3.1.1 Dimensions used	21
3.1.2 Measuring access to health care	21

3.2 Determinants of access contemplated in the estimation	22
3.3.1 Variables of interest	22
3.3.2 Control variables	24
3.3 Data collection	25
3.3.1 Sources, period of analysis and variables definition	25
3.3.2 Variables summary	26
3.4 Modelling approach	27
3.4.1 Panel data modelling	27
3.4.2 Modelling in this study	28
3.4.3 Specifications adopted and estimation techniques	29
3.4.4 Estimation techniques	31
3.4.5 Data analysis	33
3.5 Chapter summary	35
Chapter Four: Empirical evidence and	36
discussion of the results	36
4.1 Descriptive analysis and Preliminary tests	36
4.1.1 Descriptive statistics	36
4.1.2 Preliminary tests	38
4.2 Determinants of access to health care	40
4.2.1 Main regression estimation	40
4.2.2 Regression estimations by income class	42
4.2.3 Regression at country level	43
4.3 Discussion of the results	44
Chapter Five: Conclusion, recommendations and limitations of the study	48
5.1 Conclusion	48
5.2 Recommendations	49
5.3 Limitations of the study	50
References	51
Appendix I. INDIVIDUAL COUNTRY REGRESSION RESULTS	64
Appendix II. REGRESSION AND TEST OUTPUTS	66

## LIST OF TABLES

Table 2.1 Indicators of health systems per 10,000 people	11
Table 3.2 Summary of variables used in the study	26
Table 4.3 Descriptive statistics of main variables, 1995-2012	36
Table 4.4 Unit root test of level variables (In logarithm)	38
Table 4.5 Unit root test of first-differenced variables (In logarithm)	39
Table 4.6 Cointegration test	40
Table 4.7 Main regression estimation	41
Table 4.8 Regression Income class	43

## LIST OF FIGURES

Figure 2.1 Aspects of a population's health care needs	7
Figure 2.2: Aday and Andersen framework	14
Figure 2.3: Penchansky & Thomas framework	15
Figure 2.4: Peters et al. Framework	16
Figure 4.5 African countries' health indicators (in level), 1995-2013	37

#### LIST OF ACRONYMS

ADF Augmented Dickey-Fuller

ARDL Autoregressive distributed lags

CBHI Community-based health insurance

DF Dickey-Fuller

DFE Dynamic fixed-effects

DHS Demographic and Health Surveys

ECM Error correction model

EIA Energy Information Administration

FDI Foreign direct investment

HIV Human immunodeficiency virus

LI Low income

LMI Lower middle income

MDG Millennium Development Goals

MG Mean group

PHI Private health insurance

PMG Pooled mean group

SHI Social health insurance

TB Tuberculosis

TDHS Timor-Leste Demographic and Health Survey

UMI Upper middle income

UR Unit root

VHI Voluntary health insurance

WB World Bank

WHO World Health Organization

## **Chapter One: Introduction**

## 1.1 Background

Improved health status is one of the most important items on the international development agenda. For example, the Millennium Development Goals (MDG) include three health-related items such as reducing child mortality, improving maternal health and fighting HIV/AIDS, malaria and other diseases (WHO, 2005). Improved health is also an important consideration in the most recent sustainable development goals adopted by the United Nations General Assembly (Dora et al., 2015). Furthermore, at a meeting in Abuja, African heads of state committed themselves to increase spending on healthcare despite constrained budgets.

These developments have been driven by the economic and social benefits of improved health status. More than four decades ago, Grossman (1972) developed a theory that showed that health stock is a capital that produces healthy days which in turn are used in the production process. Aside from enhancing productivity, Grossman also showed that improved health status promotes well-being as it is a source of enjoyment and happiness of households and individuals.

These theoretical benefits of improved health status have been supported by empirical evidence that shows the relationship between better health status and enhanced productivity and well-being. Tompa's (2002) review of evidence from developed and developing countries over a period of more than 200 years showed that improved physical and mental capacities among workers increased productivity levels. Other studies found similar results (Boles et al., 2004; Mitchell et al., 2013; Boman & Isiaka, 2015). Besides the link at micro level, analysis at macro level showed that better health status was positively associated with economic growth (Bloom & Canning, 2005; Mehmood et al., 2014; Oni, 2014). Another string of the evidence linked better health status to poverty reduction (Carrin & Politi, 1996; Peters et al., 2008).

Despite the positive association between health status and productivity and well-being, health status has remained relatively poor in low-income countries. In Africa in particular, health status indicators have been alarming. For example, statistics from WHO (2014) show that life expectancy at birth is lowest in Africa where it is estimated at 56 years compared with the global average of 70 years; in 2012, 16.6 percent of the 55.86 million deaths worldwide occurred on the African

continent; approximately 60.7 percent of these deaths were due to communicable, maternal, perinatal and nutritional diseases; and finally 29.7 percent were the result of non-communicable diseases and 9.6 percent were caused by injuries (WHO, 2014). Thus, the preventable burden of diseases and deaths in African countries remains extremely high. Diseases that could be prevented or cured, like malaria, diarrhoea and pneumonia, have remained the top killers in these countries due to a number of factors, including malnutrition, lifestyles, and unsafe water and sanitation (Loef et al., 2012; Ezeh et al., 2014; Corburn et al., 2015).

This level of diseases and the resulting increasing death raise the issue of access to health care that refers to the action of receiving health care when disease occurs. The literature notes that access to health care has proven an effective channel for vulnerable individuals to improve or maintain their health status (Tanaka, 2010). However, underutilisation of effective interventions negatively impacts such access in low-income countries (O'Donnell, 2007). As a result, millions of individuals suffer and perish from conditions that could be treated because they cannot access the health care they require (O'Donnell, 2007; Theuring et al., 2015). For example, the Africa is the only WHO region where communicable, neonatal, maternal and nutritional illnesses still dominate, causing 61 percent of deaths in 2012 (WHO, 2014).

The importance of access, coupled with its limitations in Africa, could explain why policy makers have taken a keen interest in this facet of the health sector. Although this interest has been consistent across time and the factors determining access to health care in low-income countries have become important in policy making, these factors have not been sufficiently analysed. Previous studies highlighted that access to health is affected by a number of factors, such social, economic, behavioural, and environmental factors (Andersen & Newman, 1973; Gulliford et al., 2002; Lalloo et al., 2004; Zheng & Zimmer, 2008; Gulliford & Morgan, 2013). Drabo & Ebeke (2011) noted that a few studies have been conducted on access to health care at macroeconomic level where evidence are particularly limited; and pointed out that Berthelemy & Seban's (2009) study was one of the first study to use country data to investigate this issue in developing countries. Furthermore, while previous studies analysed access to health care by measuring it in terms of health outcomes, health care utilisation, out-of-pocket payments, health status, mortality, or government budget allocations (Castro-Leal F., Dayton J. et al., 2000; Makinen et al., 2000; Aakvik & Holmas, 2006; Delamater et al., 2012; Moreno-Serra & Smith, 2015), they did not investigate the long-run demand-side determinants of access to health care.

This study contributes to the existing literature in two respects. First, it adopts a dynamic approach by seeking to determine the short and long run impact of determinants of access to health care using the ARDL model. Other studies have either used normal panel data or cross-sectional analysis and have been limited in the types of evidence they presented due to estimation issues that these econometric analyses cannot address. Second, in contrast with previous studies that used a single indicator, the current study used an access index to measure access to health care. This is a multidimensional indicator that considers various aspects of access to health care.

#### 1.2 Research problem and the significance of this study

The lingering problem in this area of research is that access to health care remains a challenge for many African countries. Yet, access to health care is considered to be important to health status which in turn is crucial for development. Given this context, perpetuating limited access compounds poverty and other associated problems in Africa. It is problematic that people in these countries continue to suffer ill health and to be killed by diseases that are preventable and treatable simply because access to health care is limited.

This study sought to contribute to solving this problem. Policy makers have scant evidence on the factors that determine access to health care. Furthermore, the evidence that has been presented is far from complete given the elusive, multidimensional nature of the concept "access to health care". Most studies have analysed a limited dataset and restricted the analysis to the short run effects of the determinants, thus producing limited evidence. The significance of this study lies in the fact that it not only analyses the short and long run determinants of access to health care but also uses a more broad measure of access encompassing several indicators of access to health care and thus producing consistent estimates.

#### 1.3 Research objectives

The overall objective of this study was to identify the demand-side factors that determine access to healthcare in African countries.

The specific objectives were:

- To establish the state of the literature on access to healthcare;
- To identify key demand-side factors influencing access to health care services in African countries;

- To determine whether there exists a long-run relationship between access to health care and the identified factors;
- To suggest policy options in order to enhance access to health care in Africa.

#### 1.4 Methodology

The objectives of this study were achieved by reviewing the relevant literature and conducting a quantitative analysis. The literature review aimed to establish the state of the literature on access to health care in line with the focus of this research. In the quantitative analysis, the dynamic panel econometric technique was applied to identify long and short run determinants of access to health care. The data were sourced from the databases of the Word Bank (WB), the World Health Organisation (WHO) and the US Energy Information Administration (EIA). Further details on the methodology used are presented in chapter 3.

## 1.5 Delimitation of the study

This study analysed access to health care from a demand rather than a supply perspective. Still, it should be noted that access to health care is a function of both demand and supply factors and that analysing this function by omitting any of these factors could result in bias. With this caveat in mind, it is not always possible to obtain all the empirical data required and alternative analyses can thus be conducted. For example, the only variable that was available on the supply side to represent price was the Consumer Price Index (CPI) but this variable does not appropriately represent the price of health care. Therefore, the study focused on the demand-side factors of access to health care after the researcher realised that data were not available to represent the quality and price of health care as supply-side factors at macro-economic level. Furthermore, it would have been interesting to analyse the evidence for all low and middle income countries. The researcher decided to focus on the African continent due to time and space constraints.

#### 1.6 Structure of the dissertation

This study is structured as follows: Chapter one introduced the study. It provided the background to the study, and highlighted the research problem and research objective as well as the structure of the dissertation. Chapter two reviews the theoretical and empirical literature with respect to access to health care and the factors that are likely to influence access to health care in African countries. Chapter three discusses the methodology employed to conduct this study and how the results are

presented. It focuses on the model used, the justification for using this model, and the source of data, analytical methods and how the results are presented. Chapter four presents and discusses the study's results. It focuses on the important demand-side factors that influence access to health care in Africa. The dissertation ends with Chapter five which summarises the study, provides conclusions and recommendations.

## **Chapter Two: Literature review**

This chapter reviews the literature on access to health care with the aim of highlighting the gaps. It begins with the background to the interest in analysing access to health care. This is followed by the state of health care in Africa in Section 2. Concepts of access to health care are reviewed in Section 3, the theoretical framework for studying access to health care is discussed in Section 4, and the empirical evidence is analysed in Section 5. The chapter ends with a summary.

#### 2.1 Background to the interest in access to health care.

Interest in analysing access to health care stemmed from the benefits of health care for health status and the importance of health status in economic development. It is recognised that improved health status is indispensable for economic development and well-being (Sotiriadou et al., 2015). Evidence has shown that improved health status could affect economic performance through channels like labour supply and productivity (Novignon et al., 2015), foreign direct investment (Alsan et al., 2006), eduction (Awaworyi et al., 2015) and income (Ashraf et al., 2008).

Besides being a development factor, improved health status also contributes to the well-being of the population (Sun et al., 2015). Since health is positively related to labour force participation, earnings and household savings, individuals with better health status not only enjoy being healthy but also derive happiness from the fruits of their labour. When individuals are unhealthy they cannot work and their household will not be able to satisfy their basic needs, leading to unhappiness.

However, improved health status is dependent on the extent to which people access health care. The evidence in this regard suggests that access to health care, especially in countries with a high burden of diseases, has made a difference to people's health (Gu et al., 2009). This has prompted interest among policy makers and researchers in access to health care as demonstrated by studies by Gulliford et al. (2002); McIntyre et al. (2009); Rutherford et al. (2010); Morreale et al. (2014); and Ganesh (2015).

#### 2.2 Access to healthcare: Process, Definition and Dimensions and Measurement

It is worth noting the different aspects of access to health care as way of laying the foundation for the analysis of the determinants of access to health care. There are many definitions of access to health care in the literature. This section contextualises the process of access to health, followed by a discussion on various definitions, measurements and dimensions of such access.

#### 2.2.1 The process of access to healthcare

The population's health is the starting point in the process of access to health care (Figure 2.1). For example, the prevalence of diseases determines the population's needs or wants. When an individual is sick, he/she feels the need for health care even though he/she may not be able to pay for such care due to financial or other barriers. If these barriers are overcome, the person receives health care and thus has access to such care. In contrast, access is limited when the health care needed by the person is not provided due to constraints in the supply of health care (Wright et al., 1998).

Figure 2.1 Aspects of a population's health care needs

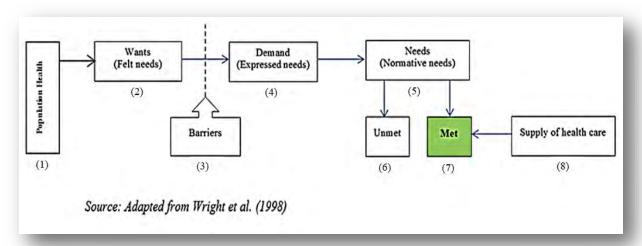


Figure 2.1 shows that the departing point of the population's health care needs is the population health status which depends on environmental factors (housing, education, socioeconomic status, and pollution), behavioural factors (diet, smoking, and exercise), genes (inherited health potential) and the provision of preventive health care (Jamison et al., 2006). Given their health status (1), population have some non-expressed desires in terms of health care based on what they are physically feeling (2). After evaluating the factors allowing them to get health care (like Income, distance to hospital or type and quality of care) and realising that they can have care, meaning they overcome barriers (3), they can then be seeking health care or express their needs (4). By willing to access health care (5), they can find (7) or not (6) the desired care in the health care facilities (8).

#### 2.2.2 Definition and dimensions of access to healthcare

Having outlined the process of access to health care, definitions and dimension of access to health care are discussed to contextualise the analysis of the factors determining access to health care in this study.

#### • Definition of access to health care

Since the 1970s the literature has provided different definitions of access to health care (Donabedian, 1972; Aday and Andersen, 1974; Penchansky, 1977; Gulliford et al., 2002; Oliver & Mossialos, 2004; Peters et al., 2008). The earliest definition was offered by Donabedian (1972) who defined access as the utilisation of services and distinguished between initiation, or first use, and continuation, that is, the subsequent use of health care. This definition ignored the supply side aspects of access to health care as the focus was on who receives care and for how long. A later study by Aday and Anderson (1974) identified two concepts relating to access to health care, namely, "gaining access", that is, actually using health care and 'having access", or the potential to use health care. This conceptualisation focused on the availability of health care services. However, the fact that health care facilities are available does not necessarily mean that people receive the care they need.

Based on these conceptualisations, subsequent studies referred to access to health care in many ways. One set of studies referred to access to health care in terms of the time and money available to use health care services (Le Grand, 1982; Mooney, 1983; Olsen & Rogers, 1991). Others defined access as the extent to which health care was of high quality with consumers well informed about the costs and other information (Goddard & Smith, 2001). Some studies simply referred to access as the use of health care services (Penchansky, 1977; Mooney, 1983; Oliver & Mossialos, 2004). While most of these studies defined access as the relationship between the individual and the health care system encompassing aspects of demand and supply (Donabedian, 1972; Penchansky, 1977; Gulliford et al., 2002; Oliver & Mossialos, 2004; Delamater et al., 2012) focused on access from only the demand perspective.

Delamater et al. (2012) argue that access to health care depends on the characteristics of demand. According to these authors, given the supply of health care, access to health care services is determined by whether or not individuals utilise existing infrastructure and resources. Due to its delimitation, this study followed a demand-side perspective as per Delamater et al. (2012).

#### • Dimensions of access to healthcare

Two main dimensions emerge from the definitions of access to health care: the demand dimension and supply dimensions with some variants. Variants in the demand and supply perspectives include, for example, an environment that is conducive for patients to use health care (Clark, 1983). The extent to which individuals want to use health care depends on their socioeconomic, cultural and geographical setting. These include structural factors and personal attitudes (Millman, 1993).

Other variants of access that can be related to the demand or supply perspective include availability, accessibility, affordability, accommodation, acceptability and adequacy (Penchansky & Thomas, 1981; Obrist et al., 2007, Peters et al., 2008). These variants relate to the geographic, financial, cultural and structural factors of access to health care. Studies on access to health care have mainly investigated financial variants of demand dimensions such as participation in health insurance (Morestin & Ridde, 2009; Carapinha et al., 2011; Addae-Korankye, 2013) or health care expenditure (Okunade, 2009; Angko, 2013; Muftaudeen & Bello, 2014; Odhiambo et al., 2015).

#### 2.2.3 Measurement of access to healthcare

The focus now turns to the literature on how access to health care has been measured. Access to health care has been measured by health system outcome indicators such as health care utilisation or availability indicators and health care access indices.

In terms of health system outcome indicators, mortality or life expectancy have been the most common tools used to measure access to health care. This perspective assumes that better access leads to low mortality rates and higher life expectancy (Aday and Andersen, 1974; Aakvik & Holmas, 2006). Other indicators of access to health care that have been used include health care utilisation, the number of physicians or number of hospital beds per a certain number of people, or the number of general practitioner (GP) contacts per capita per year (Donabedian, 1972). Other studies, from which this study's approach to measuring access is borrowed, measured access by building indices of access to health care from various indicators (Field, 2000; Iversen & Kopperud, 2005; Wang & Luo, 2005).

Measures of access to health care have, however, been used to a different extent. Akweongo's (2005) review of the literature on access to health care found that the utilisation of health care is often used as a proxy to measure access to health care. This view was supported by Jacobs et al.

(2012) who argued that the utilisation of health care offered various indicators that could be used to capture access to health care. However, this means of measuring access has been criticised because it excludes contact with health care providers that are outside the health system as well as preventive measures. Moreover, utilisation measures are silent on the quality or quantity of the health care delivered (Burstrom, 2002). Hence, it is probable that underutilisation of health services found using this measure might be a consequence of the use of alternative treatments provided outside the formal system (Goddard & Smith, 2001).

#### 2.3 State of access to health care in Africa

While access to health care appears to be important for countries' development, the context of Africa suggests a limited access to health care forcing Africa to be an unhealthy continent. All the health indicators show that Africa lags behind the rest of the world and this gap was merely amplified since the 1980s as a result of the HIV/AIDS epidemic which has stricken Africa harder than any region in the world, as well as the slow and ineffective responses to HIV/AIDS. Although on other factors can be responsible of this gap. For example, while many countries started to make health insurance schemes easier, African governments continued largely to be focussed on out-of-pocket payments. Considerable shares of health budgets have disappeared because of the prevalent and destructive corruption. Many people in more remote regions experience problem in accessing care facilities due to lack of adequate infrastructure. All these problems and other such as poverty and conflicts, as well as Africa's sheer size and its position on the globe – most of it is in the tropical regions where the worst parasites and germs proliferate – have made Africans unhealthier than the dwellers of any other continent (KPMG, 2012).

#### • Health workforce and Infrastructure

Widespread shortages of health care professionals and infrastructure in Africa are mainly due to the underfunded health system. This has led to a shortage of medical equipment, health personnel and health care facilities, limiting both the quality and quantity of health care on the continent (Kasilo et al., 2010; Cisse, 2011; Enyioko & Samuel, 2012; Decroo et al., 2013; Blaauw et al., 2013; Aluttis et al., 2014). As a result, indicators of access to health care have been worse than other regions as shown in Table 2.1.

Table 2.1 Indicators of health systems per 10,000 people

Health System Indicators	Africa	South-East Asia Region	World - Global
Density of health workforce (per 10, 000 people)			
Physicians	2.6	5.9	14.1
Nursing and midwifery personnel	12.0	15.3	29.2
Dentistry personnel	0.5	1.0	2.7
Pharmaceutical personnel	0.9	3.8	4.3
Psychiatrists	< 0.05	< 0.05	0.3
Infrastructure (per 10, 000 people)			
Hospitals	0.8	NA	NA
Hospital beds	NA	10	27
Psychiatric beds	0.6	0.3	2.5

Source: Adapted from World Health Statistics 2015

As Table 2.1 shows, Africa is lagging behind all other regions in terms of the availability of health personnel and infrastructure. The data in the table show that Africa has the lowest density of physicians at 2.6 physicians per 10,000 people, which is lower than the global average of 14.1 physicians per 10,000 people. The table also highlights the limited infrastructure in Africa. For instance, while Africa has 0.6 psychiatric beds per 10,000 people, the global average stands at 2.5. The World Health Statistics (WHS) (2015) also show that the African region has 0.1 radiotherapy units per 1 million people, while the global average is 1.8.

Furthermore, due to the limited number of health care facilities, people that require their services have to travel long distances to access them and spend a long time waiting in queues to be served. Poor transport and communication networks compounded by the lack of roads density and inappropriate means of transport compound the situation. Africa has the lowest national road density (137 kilometres of roads per 100 square kilometres) compared to the average of 211 kilometers per 100 square kilometres from other low-income-countries and access to infrastructure in rural areas represents merely a fraction of that in urban areas (Foster & Briceño-Garmendia, 2010).

Another factor that impacts access to health care in Africa is the fact that such access has been unequally distributed. Urban areas in Africa offer better access to health care than rural areas because of the lack of health care personnel and infrastructure in the latter areas. Furthermore, the unequal access to health care across countries in Africa causes people living in under-resourced areas to turn to unconventional and traditional health care services, causing huge inequity in access to modern health care (Cisse, 2011).

#### • Population

From the demand side, Africa's growing population in the context of limited growth of infrastructure is another factor that limits access to health care. In 2014 the African population was estimated at around 893 million and it is projected to grow to 1.2 billion by 2025 (WHO, 2015). Africa is urbanizing quickly. Its rate of urbanization flew from 15 percent in 1960 to 40 percent in 2010, and is projected to reach 60 percent in 2050 (UN Habitat, 2010). In 2014, 62.77 percent of people in Sub-Saharan Africa have been living in rural area, while in the Northern Africa around 36 percent were located in rural areas. This is a factor to account in predicting the demand for services given the prevalent burden of diseases on the continent. Indeed, Africa suffers a greater number of epidemics such as HIV/AIDS and malaria that can be expected to exacerbate the lack of access to health care within the context of a growing population. Despite significant improvements in the health sector over the past two decades in most African countries, the population's health is declining and remains well below the world average (Audibert et al., 2011). Indeed, while underfive mortality caused by acute respiratory infections decreased between 2000 and 2011 in lower income countries in Asia, during the same period, this mortality rose from 14 percent to 16 percent on the African continent (WHO, 2015).

Other barriers on the demand side include a population that is health illiterate and is unwilling to use available facilities due to the perceived poor quality of the health care system (Jaffré & De Sardan, 2003). In some instances, health illiteracy coupled with poor quality services has caused the population to believe that traditional medicine is superior which complicates the problem of access to health care as the use of traditional medicine can give rise to new health problems. Limited access to health care has also been due to a lack of financial means as most populations in Africa are poor (Drabo & Ebeke, 2011; Angko, 2013; Hilaire, 2014). This poverty is so deep that people cannot afford the bus fare to a health facility. With health care services being offered free of charge in some African countries, inability to access these health care services highlights the extent to which poverty prevents access to health care (Audibert & Mathonnat, 2013).

#### • Strategies to improve access to health care

Limited access to health care in the African context has given rise to a number of strategies to remedy the situation. Raising the utilization of operative health care in Africa means more financial resources should be invested in health care. It is important for spending to be canalised to the most effective programs and interventions in a way that the geographic dispersal of these programs match that of the population. It is also important to carry on reforms to management,

regulatory, and political mechanisms to foster providers to deliver quality health care (O'Donnell, 2007). While these basic conditions for solving the access problem will guarantee that effective health care is available, people should be willing to use effective those operative interventions and they should have the purchasing power to achieve this desire.

The Alma-Ata Declaration (1978) underlining the importance of primary health care is one of the strategies that African have adopted. The declaration called for a national and international support the commitment to primary health care, and to guide additional financial and technical support to it, principally in developing countries. While generally the Alma-Ata Declaration was criticised for not having clear targets, the study by Cueto (2004) proved that the declaration was unrealistic, idealistic and too broad. As a result of these criticisms the Health and Population Development Conference was held in Bellagio (1979) to identify the goals of primary health care vowed by the Alma-Ata Declaration (1978) and to accomplish more effective strategies.

Another strategy to improve access to health care by African countries was the Bamako Initiative (1987) aimed at increasing access to primary health care by raising the financial feasibility, efficiency, effectiveness, and equity of health facilities. It suggested the decentralisation of health decision making to local levels and the implementation of realistic national drug policies to increase the delivery of essential drugs for Sub-Saharan Africans. The Bamako Initiative was strongly criticised for the application of user-fees to poor households as it is known that majority of African household are poor (Fifield, 2015).

#### 2.4 Theoretical framework for access to health care

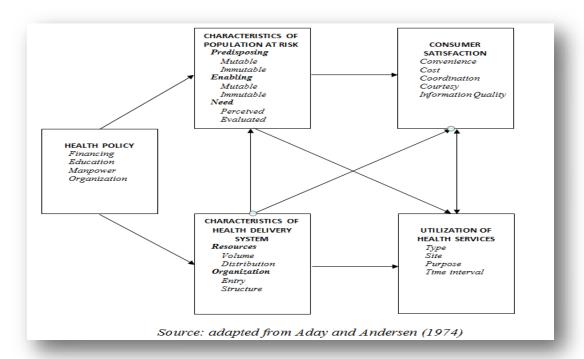
While measuring access to health care is important, one of this study's objectives was to establish the determinants of such access. As a starting point, the relevant theories were reviewed. The key frameworks formulated to analyse the factors that determine access to health care are those of Aday and Andersen (1974), Penchansky & Thomas (1981), and Peters-Garg-Bloom-Walker-Brieger-Rahman (2008).

#### 2.4.1 Aday and Andersen framework

Aday and Andersen (1974) developed the behavioural model of health services to explain access to health care. The model assumed that the predisposing characteristics of the population seeking health care and enabling resources in the environment are combined with perceived or professional

evaluation of the need to use health care. This is the most popular model in studying the utilisation of health care by different population groups (Andersen, 1995). It is built on the Donabedian assumption which suggests that the proof of access is the use of services (Ricketts & Goldsmith, 2005). The model analyses access throughout the use of health care services, the process of interaction between suppliers (the health care system) and clients (the population at risk), and the outcomes resulting from the utilisation of health care and satisfaction of clients (Figure 2.2).

Figure 2.2: Aday and Andersen framework



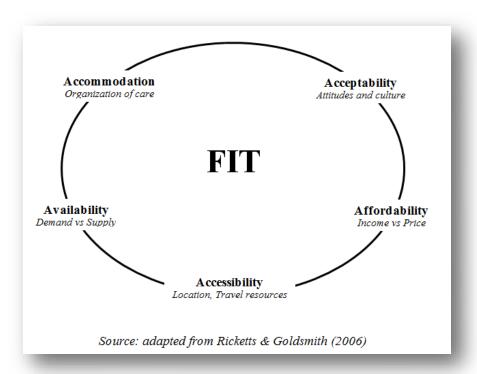
A critical analysis of the model proposed by Andersen & Newman (1973) shows that, while describing the factors that determine access to health care, it integrates more of the supply side factors, with income being the only factor on the demand side. It is also worth noting that all these models use facility utilisation as a proxy for access to health care, and can thus be considered as models that predict utilisation rather than access to health care.

#### 2.4.2 Penchansky & Thomas framework

While the Aday and Andersen framework suggests the use of service as proof of access, the model developed by Penchansky & Thomas (1981) proposes the utilisation of health care services on a local scale to measure access to health care. Penchansky & Thomas (1981) suggested the theory of "fit" between the needs of the consumer and the capability of the health system to accommodate

these needs. They built the Penchansky's "5 As", a model of health service access that disaggregates the wide and ambiguous concept of access to health care into five interacting dimensions that determine the use of health care services: availability, accessibility, accessibility, accommodation and affordability (Figure 2.3).

Figure 2.3: Penchansky & Thomas framework

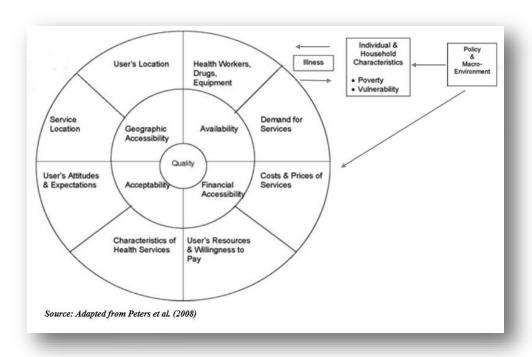


The advantage of Penchansky and Thomas's conceptualisation of access to health care is that it is not only related to entry or utilisation of services but also identifies different dimensions of the client-provider relationship. Ricketts & Goldsmith (2005) argue that Penchansky's concept suggests the existence of recursive and measurable interrelationships between needs, demands, and resources.

#### 2.4.3 Peters-Garg-Bloom-Walker-Brieger-Rahman framework

While Penchansky & Thomas's (1981) framework focuses on five aspects, Peters et al.'s (2008) model is based on the description of access by both Aday & Andersen (1974) and Penchansky & Thomas (1981). This framework differs from the other two in that it accounts for both demand and supply aspects and presents access to health care in four dimensions instead of five. This conceptual framework is built on long-lasting descriptions of access to health services that comprise actual use (Figure 2.4).

Figure 2.4: Peters et al. Framework



This framework shows four main dimensions of access surrounding quality. Each dimension has a supply and demand element. The dimensions presented are (Peters et al., 2008):

- Geographic accessibility the physical distance or travel time from service delivery location (supply side) to the user's location (demand side).
- Availability having the right type of care available or appropriate type of service providers and materials (supply side) to those who need it or to meet the demands of those who would use care (demand side).
- Financial accessibility the relationship between the cost and price of services (supply side),
   and the willingness and ability of users to pay for these services, as well as be protected
   from the economic consequences of health costs (demand side).
- Acceptability the match between how responsive health service providers are (supply side)
   and the social and cultural expectations of individual users and communities (demand side).

In Figure 2.4, healthcare quality stands in the middle of the circle of all four health care access dimensions, meaning that it is a significant component of each dimension. This is also related to the technical capacity of health care services to influence individuals' health. To the right of the circle stands a group of distal determinants of access to health care services, illustrated at policy or macro-environmental level and individual and household levels.

The above dimensions of access represent closely-related facts, showing why they have been seen as components of the concept of access. There are links between these dimensions such that, for example, geographic availability undeniably affects acceptability; in some settings accessibility may be closely related to availability; and various service areas with equivalent availability may have different accessibility. The question remains whether these dimensions are sufficiently differentiated in order to be measured and studied separately (Penchansky & Thomas, 1981). Further insight on access to health care can be gained by examining the empirical evidence.

#### 2.5 Empirical evidence

Studies analysing access to health care can be divided into those at micro level and those at macro level. At micro level, the first study in the public domain that analysed access to health care was one by Alderman and Gertler (1989). Using survey data and applying a nested multinomial logit model, this study analysed access to health care to determine how imposing user fees at public health care facilities affects access. It found that an increase in user fees leads to a decrease in access to public health care facilities followed by an increase in the use of private health care instead of an increase in self-care.

Subsequent studies measured access in terms of the probability of using health care facilities and used either dichotomous or multinomial variables as the dependent variables (Bryant, 1972; Dor & Van der Gaag, 1988; Alderman and Gertler, 1989; Gertler and Van der Gaag, 1990; Mwabu, 1991; Sauerborn et al., 1994; Kasirye et al., 2004). Typical of these studies is one by Gage (2007) which analysed barriers to the utilisation of maternal health amenities in a rural area in Mali. Access to health care was considered a dependent variable in a multilevel logit model and was measured as "receipt of prenatal care" at different periods in time. The study used data from the 2001 Mali Demographic and Health Survey and showed that a lack of health amenities and means of transport, distance, household poverty and individual problems remained the main barriers to accessing maternal medical care facilities. In brief, all these earlier studies showed that access to health care facilities was influenced either by geographical or non-geographical factors. In terms of non-

geographical factors a distinction was made between economic determinants of access to health care (Alderman & Gertler, 1989; Iversen & Kopperud, 2005) and social determinants (Gertler & Gaag, 1990; Garcia-Subirats et al., 2014).

In Africa, Smith & Sulzbach's (2008) study, conducted at micro level, measured access as the utilisation of health care services linked access to health care to insurance. Using data from household surveys in three western African countries, Senegal, Mali, and Ghana, the study applied a comparison group design to study the link between CBHI membership and access to modern maternal health care. The findings suggest that membership of a CBHI scheme was positively related to the utilisation of maternal health care facilities, mainly in locations where utilisation rates were very low and for more costly delivery-related care. More recently, Envioko & Samuel (2012) examined the utilisation of health care facilities in selected facilities in Rivers State, Nigeria. The respondents were asked to report on their utilisation of health care facilities. Using the data from a survey conducted in local areas and applying a descriptive analysis, the study found that poor health status in rural areas is the cause of underutilisation of modern health care services. It also found that the low-income population in rural areas had limited access to modern health care and resorted to traditional medicine. While access was either linked to health insurance or self-reported by users in the above-mentioned studies, Lalloo et al. (2004) analysed access using an index of many variables. Using socio-economic variables based on the basic services accessed by a household; the difficulty faced by a household in paying for an assortment of basic goods and services; an estimate of the number of consumer durables in the household; the highest educational level in the household; the reported monthly income of the household; and the number of people per room in the house, the study constructed an access indicator and used a binary logistical regression to analyse access to health care. It found that the race was the principal predictor of observed variations in access to health care.

At macro level, studies that have analysed access have been relatively more recent and are thin on the ground. Aakvik & Holmas's (2006) study was the first in the public domain. It measured access to health care as the number of GPs per capita using data from a municipality in Norway and analysed these data using dynamic panel data methods. The analysis sought to determine the effect of access to health care on mortality and found that there was no significant relationship between the number of GPs per capita and mortality. Berthelemy and Seban (2009) examined how health expenditure impacts the degree of concentration of access to maternal and child health care in 52 low-income countries. Measuring access by means of an index built on health indicators from data

from the Demographic and Health Surveys (DHS) and applying quintile regression in the analysis, this study found that an increase in public health expenditure benefited the poor more than the rich, and that access to health services mainly depended on the mother's education level. The study also found that improvements in many aspects of governance made access to health care facilities more equitable. Moreno-Serra & Smith (2015) measured access to health care using a group of variables (government health expenditure, voluntary health insurance, non-pooled out of pocket (OOP) payments and aggregate immunisation rate). This study sought to determine how health coverage or access affects health outcomes at the macro level. It used a wide panel data set of 153 countries with annual observations and applied both the generalised methods of moments and the two-stage least square approaches in a two-step procedure. The study found that an increase in health coverage, mainly via greater government outlay on health, led to a decrease in mortality. Jacobs et al. (2012) presented an outline of the dimensions of barriers to access to health care in low-income countries as well as interventions aimed at overcoming these barriers focusing on Cambodia. The study found that it is better to combine interventions to tackle specific access barriers even though contextual factors come into play. Moreover, the authors suggested that it is crucial to address supply-side and demand-side barriers simultaneously.

Studies at macro level in Africa are scarce. Soors et al. (2008) examined the role of CBHI in accessing maternal health care services in Uganda, Togo, Mauritania and Mali. The study used secondary data from the existing literature and primary data from authors' consultations in the health field. Through a comparative analysis, the study illustrates the potential contribution of community health insurance to increase access to emergency obstetric care in African countries. Rutherford et al. (2010) reviewed access to health care in relation to under-five mortality rates in sub-Saharan Africa. The study suggests that access includes factors beyond price or cost and distance to health care services and recommends that, in planning health care services, access should be analysed to account for both traditional and additional barriers to access. Cisse's (2011) study in Cote d'Ivoire analysed access by considering the determinants of individuals' choice of health care providers. A multinomial logit model was applied to the data from the National Institute of Statistics. The findings suggest that the level of education of the household head, the household's income, the cost of medication, and the distance to a health care facility are the key determinants of the choice of a particular health care provider.

The studies reviewed above did not all focus on macro level analysis. Moreover, those that did so did not apply the autoregressive distributed lag model (ARDL) or those which applied the ARDL

model did not do so in Africa. Furthermore, no study carried in African countries has used an index to measure access to health care. Therefore, this study contributes to the literature in that it used an index measure and an ARDL model to analyse access to health care at macro level in Africa.

#### 2.6 Chapter summary

This chapter reviewed the literature in relation to access to health care. It contextualised the current study by reviewing the conceptualisation of access to health care, the theoretical framework within which access to health care can be analysed and the empirical evidence on access to health care to date. The gaps in the literature were noted and the study's contribution was highlighted. This study contributes to the literature by analysing the demand-side determinants of access to health care using two dimensions of the Peters et al. (2008) framework, namely the financial and the geographic accessibility. The Peters et al. (2008) framework is the only that distinguishes clearly the demand-side from the supply side while studying access to healthcare. This study also models the demand-side of healthcare access as an ARDL measuring access by means of an index built from many indicators of access to health care. The following chapter describes the methodology used to conduct this analysis.

## **Chapter Three: Methodology**

This chapter describes the methodology used to identify the factors that determine access to health care in Africa. It begins by highlighting the dimensions of access used and how measurement was done in Section 1. Section 2 outlines the determinants of access that were analysed, Section 3 discusses data collection and the final section discusses the modelling approach used.

#### 3.1 Access to healthcare: Dimensions used and Measurement

#### 3.1.1 Dimensions used

The literature on health access reviewed in the previous chapter has noticed that the concept of access to health care is complex. As the first step in analysing the determinants of access, a discussion is presented on how these determinants were conceptualised and measured. This study follows the demand perspective of Peters et al.'s (2008) framework and focuses only on two dimensions of access, namely financial access (price of care, income) and geographical access (distance to facility). These two dimensions were selected because they are considered to include more objective factors that influence the demand side of access to health care that can be measured and are relevant to policy making.

#### 3.1.2 Measuring access to health care

The study used an index of access built on the indicators of access to health care formulated by Moreno-Serra & Smith (2015), namely: (i) government health expenditure per capita, (ii) voluntary health insurance (VHI) expenditure per capita, (iii) non-pooled OOP payments per capita, and (iv) the aggregate immunisation rate constructed from six immunisation rates (diphtheria tetanus toxoid and pertussis, polio, measles, haemophilus influenzae type b, BCG, and hepatitis B). The methodology used to build the index is from the Colorado Institute. Each series of the above variable indicators was normalised using its maximum value, meaning it was divided by the maximum of the series, assuming the maximum value represents the best score of access for the indicator considered. Thereafter, the four series of indicators normalised were merged using the average in order to obtain the index of access to health care.

It is noteworthy to notice that the index is computed on outcome indicators from both the inpatients and the outpatients care. The government expenditure and the OOP payments include the spending

on in- and out-hospital care. The VHI expenditure also cover the in- and out-hospital interventions. Finally, the immunisation rates also capture the immunisation of inpatients and outpatients.

It could be argued that the weakness of this methodology is taking an un-weighted average of all the indicators to build the index since the indicators do not have the same weight. However, in the absence of weighting criteria, this built indicator provides a proxy of access to health care that captures more dimensions of access than individual indicators would capture.

#### 3.2 Determinants of access contemplated in the estimation

Having defined access to health care (ha) in the empirical results of this study in Chapter four as a dependent variable, this section explains the determinants used in this study based on the literature. The determinants were divided into two groups: the group of variables of interest ( $VI_{it}$ ) and the group of control variables ( $C_{it}$ ).

#### 3.3.1 Variables of interest

Following Peters et al. (2008), and depending on the availability of data, the variables income and the distance to the health care facility were considered in this study.

#### • *Income (GDP)*

Household income has been the most commonly-used variable in demand-side investigations in microeconomic studies. Since this analysis was carried out at macro level, Gross Domestic Product (GDP) measured in constant (2005) US\$ was used as measure of income in line with Angko (2013). According to the demand theory, income (GDP) is expected to be positively related to access to health care.

#### • Distance to the healthcare facilities

Good roads are essential for people to get health facilities, for easy distribution of medicines and other items to health care services, for timely transfers in case of emergency, and for better supervision of health workers. Remote health centres mean that more time and money is spent on travel related expenditures, all of which acting as obstacles to gaining care, especially for the poor (Peters et al, 2008). While the study from Adesiji & Komolafe (2012) argues that long distances entail higher cost of transport, it specifies that costs include hiring a vehicle and driver, fuel expenses, and the opportunity costs of the person accompanying the patient. At micro level, surveys

provide indicators on distance to health care through information directly collected on what individuals spend on transport toward health facilities, or self-reported distance to the health facility (Franco et al., 2008). Another types of indicators are collected using new techniques that use the geographic information system (GIS) where the data on the location of the health care services and individuals are collected using the Global Positioning System (GPS) devices. The distance, time to travel as well as the related cost are computed and used in the distance to health care analyses (Okwaraji et al., 2012; Yao et al., 2012; Asuo-Mante et al., 2015). Still this technique is costly as it is complex and requires high skilled data capturers. It is also used only on small sample surveys. At macro level it appears difficult to get indicators that capture the distance to health care facilities as it is at micro level. Whether at the micro or macro level the distance to health care is proxied by indicators like the density of health care services (Hjortsberg, 2003), the level of public infrastructure (Vos & Sánchez, 2014) or the Euclidean distance between the population and health facilities (Larson et al., 2012). While the Euclidean distance appears to better capture the distance, the availability of the data at country level is an issue.

This study used consumption of fuel (cons\_fuel), the quantities of petrol and diesel used in all vehicles in the countries, as a proxy for the distance between the healthcare facilities and the patients' location. While Hjortsberg (2003) captures indirectly the distance to health care services by assuming that high density of health care services (a high number of hospitals settled in a region) ensures that people do not travel long distance to reach medical services and betters health access, this study captures indirectly the distance to health care services through the fuel consumption assuming that long distance covered by vehicles to reach medical services require more fuels (the very direct cost for travelling) given the vehicles are powered by fuels. More consumption of fuels induce high cost of travelling. Given this cost is related to the use of health care, high cost of travelling increases the cost of access or utilization of health care and then decreases the quantity of health care used. Therefore an increase in fuel consumption decreases access to health care services. The consumption of fuel is expected to have a negative sign, meaning that distance to health care facilities is negatively associated with access to health care.

This selected proxy for the distance to health care facilities, namely the fuel consumption, misses to capture for example the fact that some people walk to go to the health care services or some benefits from the outpatient care. Still it does better especially in the context of missing data issues at macro level in African countries.

While the geographic accessibility dimension of access to health care is essential and prima fasciae rural area concerns, access to health care discussions while informing the distance between patient and provider should also allude other factors such community settlements. (Mackinney et al. 2014). Still, the challenge, especially at macro level, is to get an indicator or a proxy that could capture all the aspect of the distance to health care services; this limitation opens the way to further researches.

#### 3.3.2 Control variables

The control variables used in this study were selected on the basis of their relevance as well as the literature review. These variables were selected to control for the health system, the structure of the population and the environment.

#### • The OOP payment share of total expenditure on health

This indicator is used to show the characteristics of a country's health system (Heijink et al., 2011). The OOP payment is expected to decrease access to health care since it involves the patient spending money.

#### • The elderly and the under-five population

These two variables are indicators of the structure of the population (Malmberg, 1994). Aged people have a high disease burden and are expected to increase their use of health care services. Children under five also have a high disease burden in African countries where they are exposed to chronic malnutrition, which has serious and long-lasting impacts on health (WHO, 2015). The under-five population is also expected to increase the use of health care.

#### • *Urban population share of total population*

This indicator shows how the population is distributed between urban and rural areas (Sanglimsuwan, 2011). It enables an understanding of access to health care since the life conditions that affect people's health are different in rural and urban areas. The urban population is expected to increase use of health care because urbanisation in Africa generally goes hand in hand with many issues relating to sanitation that affect people's health.

#### 3.3 Data collection

#### 3.3.1 Sources, period of analysis and variables definition

Data on the variables that determine access to health care were collected for the period 1995 to 2012 for 37 African countries (see appendix for countries included in the analysis) from different online databases. Data on petroleum consumption were obtained from the USEIA, while data on the health sector were obtained from the WHO and data relating to other sectors were sourced from WDI. The STATA 13 and EVIEWS 9 econometric software have been used to perform all the analyses of this study.

While Africa is made up of 54 countries, 17 countries were excluded from the analysis due to missing data in order to ensure balanced panel data. Since the remaining countries in the analysis are representative of all sub-regions in Africa, this would not have a negative effect on the estimates.

### 3.3.2 Variables summary

Table 3.2 Summary of variables used in the study

No	Variable	Proxy	Description / Source
1	Access to health care	Health care access index (ha)	Description: Index of healthcare access computed by author with indicators of health coverage from Moreno-Serra & Smith (2015) applying adapted CACI methodology. Source: Author computed from WHO Global Health Expenditure database (see http://apps.who.int/nha/database for the most recent updates).
2	Income	GDP per capita (gdp)	Description: GDP per capita is GDP divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included. Source: World Bank national accounts data, and OECD National Accounts data files.
3	Distance to health care services	Consumption of fuel (consf)	Description: Indicator computed by author using total petroleum consumption of motor gasoline and distilled fuel oil. Source: US EIA (2015) database. <a href="http://www.eia.gov">http://www.eia.gov</a>
4	OOP payment	OOP expenditure share of total expenditure on health (oop)	Description: Out of pocket expenditure is any direct outlay by households, including gratuities and in-kind payments, to health practitioners and suppliers of pharmaceuticals, therapeutic appliances, and other goods and services whose primary intention is to contribute to the restoration or enhancement of the health status of individuals or population groups. It is a part of private health expenditure.  Source: WHO Global Health Expenditure database (see http://apps.who.int/nha/database for the most recent updates).
5	Elderly population	Population aged 65 and above share of total population (pop65)	Description: Population aged 65 and above as a percentage of the total population. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship - except for refugees not permanently settled in the country of asylum that are generally considered part of the population of the country of origin. Source: The United Nations Population Division's World Population Prospects.
6	Under-five population	Under-five population share of total population (popu5)	Description: Population between the ages 0 to 4 as a percentage of the total population. Population is based on the de facto definition of population. Source: The United Nations Population Division's World Population Prospects.
7	Urbanisation	Urban population share of total population (urb)	Description: Urban population refers to people living in urban areas as defined by national statistical offices. It is calculated using World Bank population estimates and urban ratios from the United Nations World Urbanization Prospects.  Source: United Nations, World Urbanization Prospects.

Source: Author compiled from WDI (2015)

In Table 3.2, the variables' names are in column 1, while column 2 presents the proxies of the variables and their abbreviated versions (in brackets) used in the empirical results. Column 3 provides a description of the indicators used as proxies for the variables as well as their sources.

#### 3.4 Modelling approach

#### 3.4.1 Panel data modelling

As the data on which the analysis was based was panel data, the study adopted the panel data modelling approach. This approach has become more popular recently because of the increasing amount of panel data available and new panel data techniques that explore more issues than cross-sectional or time-series data (Kennedy, 2008: 282). Panel data are data observations on cross-sectional units (N) at different time periods (T). While this type of data set has attracted research interest, care must be exercised in handling panel data.

In particular, it has been recommended that cognisance should be taken of the fact that there are many modelling techniques in panel data and any technique chosen might depend on the size of T and N. T and N are small when they are less than ten (T<10 and N<10) (Breitung & Pesaran, 2005). When T is small, the static panels are applied and in this case the modelling can be done using fixed or random effect models with the choice depending either on diagnostic tests such as F-test for fixed effects or Breusch Pagan Lagrangian Multiplier test for random effects (Park, 2011).

Panel data with large T (T>10) raise issues of spurious regression due to non-stationary time series, that is, the phenomenon of finding a relationship between two or more trending variables simply because each is growing over time (Wooldridge, 2009); and cross-sectional dependence, meaning that the probability that the individual units are interdependent or are induced by common considerations (Sarafidis & Wandsbeek, 2010). In this case, the usual fixed and random effects might not work because they could yield biased estimates. Thus, these types of data have been modelled using methods in dynamic panel modelling to take account of the non-stationarity (Green, 2000) possible cross-sectional dependence and whether or not such panels have the same slope (Binder, 2008). Therefore, besides a different modelling approach, these techniques recommend that before estimation, preliminary tests of cross-sectional dependence, unit root (UR) and cointegration should be conducted.

While the cross-sectional dependence test is done on variables using the Pesaran CD test (Pesaran, 2004), the Friedman test (Friedman, 1937) or the Frees test (Frees; 1995, 2004), or on residuals using the Pesaran CD test (Pesaran, 2004), the UR tests are in turn applied depending on the presence of cross-sectional dependence. In cases of cross-sectional independence either with homogeneity of the UR process (Breitung, 1999; Hadri, 2000 and Levin et al., 2002) or with

heterogeneity of the UR process (Maddala & Wu, 1999; Choi, 2001 and Im et al., 2003) they are called first generation tests. In cases of the dependence of cross-sectional units (O' Connell, 1998; Pesaran, 2003; Moon & Perron, 2004; Bai & Ng, 2004; and Breitung & Das, 2005), they are referred to as second generation tests.

The UR tests usually allow one to obtain the order of integration of the variables which shows the extent to which the variables of a dynamic panel are cointegrated and can be modelled as ARDL which can be re-parameterised into an error correction model (ECM) to study the long and short run relationship between variables. For variables to be modelled as a panel cointegrating relationship such to avoid spurious results, the UR tests need to have suggested that all the variables are integrated of order one, I(1), or they are is a mixture of variables integrated of order zero, I(0) and variables I(1) (Mehmood et al., 2014). The following tests of cointegration can be residual-based tests like the Dickey-Fuller test (Kao, 1999), LM test (McCoskey & Kao, 1998) and Pedroni test (Pedroni; 1999, 2004), or error correction-based tests like the Westerlund test (Westerlund, 2007) and GUW test (Gengenbach et al., 2009).

Allowing for stationary variable series integrated in order one or zero and cointegrated, the dynamic panel models, meaning that the autoregressive distributed lag (ARDL) is re-parameterised into the error correction model (ECM) or vector ECM in order to analyse the long and short run relationship. Following the ECM, the panel cointegration has three competing estimators, the mean group (MG) estimator (Pesaran & Smith, 1995), the dynamic fixed effect (DFE) estimator and the pooled mean group (PMG) estimator (Pesaran et al., 1999) with the one chosen depending on how well it fits the data. These estimators differ in that while the MG estimator assumes all the long and short run coefficients to be heterogeneous and the DFE estimator assumes them to be homogeneous, the PMG appears to be the intermediary estimator that assumes that the long run coefficients are homogenous but in the short run they are heterogeneous (Mehmood et al., 2014).

# 3.4.2 Modelling in this study

Because the panel data in this study consisted of large N and large T, dynamic panel modelling was adopted. The study adopted the general model of health access function (Dor and Van der Gaag, 1988) presented in equation 1.

$$ha = f(Y, D, Z) \tag{1}$$

Where access to health care (ha) is the outcome variable and the independent variables are represented by income (Y), the distance to health care facilities (D), and other control variables (Z).

Following the developments from the previous section, the model in Equation 1 was re-written in an ARDL panel data model with country-specific fixed intercepts and time trends (Equation 2) as follows.

$$ha_{it} = \sum_{i=1}^{p} \lambda_{ij} ha_{i,t-j} + \sum_{i=0}^{q} \delta'_{ij} X_{i,t-j} + \omega_i + u_{it}$$
(2)

#### Where:

-  $ha_{it}$ : access to health care in country i at time t

-  $X_{i,t}$ : the independent variables of country i at time t

 $\delta_{ij}^{'}$ : coefficients of independent variables

-  $\lambda_{ii}$ : coefficients on lagged access to healthcare

-  $\omega_i$ : stands for the fixed effects

-  $u_{ii}$ : the error term

This equation shows that access to health care services in country i in current period t is linearly jointly related to past access to health care services, the current and past values of the covariates, the common unobserved country factors and the error term.

This modelling better suits African countries because firstly, the lagged variables in the model relate how the effects of variables last over time, and secondly, the model encompasses the common unobserved factors showing the extent to which African countries are similar to one another since they are responding to similar economic, political, or spatial incentives.

# 3.4.3 Specifications adopted and estimation techniques

Using the variables considered in the study, the ARDL model in Equation (2) is re-parameterised into an ECM as follows:

$$\Delta ha_{it} = \phi_{i}(y_{i,t-1} - \theta_{1i}gdp_{i,t-1} - \theta_{2i}consf_{i,t-1} - \theta_{3i}oop_{i,t-1} - \theta_{4i}pop65_{i,t-1}$$

$$-\theta_{5i}popu5_{i,t-1} - \theta_{6i}urb_{i,t-1}) + \sum_{j=1}^{p-1} \lambda_{ij}\Delta ha_{i,t-j} + \sum_{j=0}^{q-1} \delta_{1ij}\Delta gdp_{i,t-j}$$

$$+ \sum_{j=0}^{q-1} \delta_{2ij}\Delta consf_{i,t-j} + \sum_{j=0}^{q-1} \delta_{3ij}\Delta oop_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4ij}\Delta pop65_{i,t-j}$$

$$+ \sum_{j=0}^{q-1} \delta_{5ij}\Delta popu5_{i,t-j} + \sum_{j=0}^{q-1} \delta_{6ij}\Delta urb_{i,t-j} + \omega_{i} + u_{it}$$

$$i = 1, 2, ... 37 \quad t = 1, 2, ... 18$$

$$(3)$$

Where, for any country i at time t:

- $ha_{ii}$  is logarithm of access to health care,
- $gdp_{ii}$  is the logarithms of GDP per capita,
- consf<sub>it</sub> is fuel consumption,
- $oop_{ii}$  is OOP share of health expenditure,
- pop65<sub>ii</sub> is the elderly population,
- $popu5_{it}$  is the population under five, and
- $urb_{ii}$  is the urban population as a share of total population.

These variables in Equation 3 are either lagged or differenced. The  $\theta_{ki}$  and  $\delta_{k,i,t}$  are the long-run and the short-run independent variables coefficients (k = 1,...6). The  $\lambda_{ij}$  are the coefficients on lagged access to health care.  $\theta_i$  stands for the fixed effects and  $u_{it}$ , the idiosyncratic error terms.

This study used the Translog or Log-log model – the most popular flexible functional form – to guarantee the linearity of the model and to interpret the coefficient as elasticities. Like modern studies of demand and production, this enables the use of flexible functional forms that enable the modelling of second-order effects such as elasticities (Green, 2002). The parameters of interest are those that have direct structural interpretation, explicitly the long-run coefficients  $\theta_{ki}$  and the speed of adjustment parameter  $\phi_i$ . The coefficient  $\theta_{li}$  measures the long-run income elasticity for access to health care which is expected to be positive. The coefficient  $\theta_{2i}$  measures the long-run fuel

consumption elasticity for access to health care which is expected to be positive since mobility is thought to improve access. The coefficient  $\theta_{3i}$  measures the long-run price elasticity for access to health care which is expected to be negative and higher than one (more elastic).

The long run coefficients on the variables  $\theta_{ki}$  and the speed of adjustment  $\phi_i$  could be hypothesised to be either homogeneous or heterogeneous within the countries depending on the estimation technique applied. In the following sub-section, a debate on the estimator to use with regard to the hypotheses on the long and short run coefficients has been conducted.

# 3.4.4 Estimation techniques

This study tried the three types of estimators highlighted in section 3.4.1.

# • The mean group estimator

The MG estimator was suggested by Pesaran and Smith (1995) to obtain consistent estimators of the means of the slope coefficients and to resolve the bias due to heterogeneous slopes. This estimator provides the long-run parameters for the panel by averaging the long-run parameters from ARDL models for individual countries (equations 4 & 5).

$$\widehat{\theta} = \frac{1}{N} \sum_{i=1}^{N} \theta_i \tag{4}$$

and

$$\widehat{a} = \frac{1}{N} \sum_{i=1}^{N} a_i \tag{5}$$

Where  $\theta_i$  and  $a_i$  are individual countries' parameters. The coefficients are calculated as the unweighted mean of the estimated coefficients for the individual countries, without any restriction. Therefore, all coefficients could vary and be heterogeneous in the long-run and short-run. Common features are frequently expected to exist in long-run relationships while short-run dynamics beyond some common stocks are likely to be country specific. The MG estimator has the drawback of not allowing for the efficiency gains that are feasible when some economic features are common across countries. Nonetheless, the consistency and validity of this approach rely on the availability of a large time-series dimension in the data (Binder & Offermanns, 2007).

# • The dynamic fixed effect

The DFE estimator restricts not only the coefficient of the cointegrating vector to be identical across all panels in the long run, but also the speed of adjustment coefficient and the short-run coefficients. The DFE allows panel-specific intercepts and calculates the standard error, allowing for intragroup correlation. The DFE models are subject to a simultaneous equation bias from the endogeneity between the error term and the lagged dependent variable (Baltagi, Grin, and Xiong, 2000).

# • The pooled mean group estimator

Suggested by Pesaran, Shin, and Smith (1997, 1999), the PMG aims to detect the long and short run association between variables, and investigate the possibly heterogeneous dynamic issue across countries. It combines pooling and averaging of coefficients approaches. It also allows the intercept, the short-run coefficients and the error variances to vary across the units, but constrains the long-run coefficients to be equal across the countries, that means parameters are homogeneous across countries.

According to Rafindadi & Yosuf (2013), the following are the main conditions for the validity, consistency and efficiency of the PMG methodology; failing to fulfil them, yields inconsistent estimators. First, a long-run relationship should exist among the variables of interest; this requires the coefficient on the error correction term to be negative and significant. Second, the resulting residuals of the error correction model must be serially uncorrelated and the explanatory variables should be treated as exogenous. Third, T and N should be large to avoid bias in the average estimators and resolve the issue of heterogeneity. Finally, the long-run equilibrium relationship between variables is expected to be similar across countries while the short-run adjustment relationships among individual countries are allowed to be country-specific.

# • Selection between MG, DFE and PMG

The practice of estimating ECMs commands the estimation of the three models (DFE, MG and PMG) because a priori, one does not know which hypothesis on coefficients holds, followed by the selection of the model that fits the data contemplating the assumptions. Pesaran et al. (1999) argue that the MG estimator is always consistent. Therefore the consistency of the PMG and DFE estimators is assessed comparatively to the MG estimator. This is done through the Hausman test with the null hypothesis of common coefficients between MG and PMG or DFE estimators. If the null hypothesis is rejected, the MG is selected because it is always consistent.

# 3.4.5 Data analysis

The ECM in Equation 3 assumes that variables are I(0) and/or I(1) and integrated. Before the estimation of the model some preliminary tests have to be carried out.

## Descriptive statistics

An exploratory analysis of variables was carried out throughout the descriptive statistics and the graphical representation. This provided the characteristics pertaining to the study dataset that must be kept in mind when the results are discussed.

# • Cross-sectional dependence test

A test for cross-sectional dependence was carried out to determine whether or not the panels in the study dataset are correlated. This is important because the choice of technique of estimation depends on whether or not the panels in the dataset are cross dependent. The study used the Pesaran CD (2004) test which is the most commonly used because of its facility in implementation.

# • Test for Unit Root

With respect to panel UR test, IPS and LLC tests were used. The reason for selecting these tests alongside a multitude of many other tests was that they are complementary for testing the UR. That means while in the test of UR the LLC test allows for the assumption of homogeneity of the UR process, the IPS test allows for the assumption of heterogeneity; and while the null hypothesis of UR is tested against the alternative of stationarity in the LLC test, in the IPS test the null of stationarity is tested against the alternative of UR (Baltagi, 2008). More, these two tests are also easy to implement as they are included in the available econometric software packages.

#### a. Levin, Lin, and Chu (LLC) unit root test

This test assumes the existence of a common unit root process across cross-sections. It sets a null hypothesis of a unit root and considers the following basic ADF specification:

$$\Delta y_{it} = \alpha y_{i,t-j} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + X_{it}' \delta + \varepsilon_{it}$$
(6)

Where  $\alpha = \rho - 1$  and the null and alternative hypotheses for the tests may be written as:  $H_0: \alpha = 0$  and  $H_1: \alpha < 0$ . Under the null hypothesis, the series has a unit root, while under the alternative it does not have a unit root.

### b. IPS unit root test

This test is from Im et al. (2003). It allows for individual unit root processes across cross-sections. The test is characterised by combining individual unit root tests to derive a panel-specific result. It also considers the ADF specification (3). The null hypothesis is:

 $H_0: \alpha = 0$ , for all *i*; whereas the alternative hypothesis is given by:

$$H_1: \begin{cases} \alpha_i = 0 & for \ i = 1, 2, \dots N_1 \\ \alpha_i < 0 & for \ i = N+, N+2, \dots N \end{cases}$$

Under the null hypothesis, the series has a unit root, while under the alternative it does not have a unit root.

These tests were followed by the presentation of cointegrating results to understand which factors determine access to health care in the long run by observing the coefficient on the error correction term.

#### • Test for Cointegration

For cointegration tests, Kao and Pedroni tests were used. The reason for the choice of these tests alongside many other tests is that they are the most commonly used due to their ease of implementation in the available software. The cointegrating relationship exists when these variables are all I(I) or when they are a mixt of I(1) and I(0) variables on the basis of the unit root test. After noting that the results were I(0) and I(1), the next step was panel cointegration analysis.

# a. Kao cointegration test

This test from Kao (1999) considers the following system of cointegrated regressions in the homogeneous panels.

$$\begin{cases} x_{it} = x_{it-1} + \varepsilon_{it} \\ y_{it} = y_{it-1} + v_{it} \\ y_{it} = \alpha_i + x_{it}\beta + \mu_{it} \end{cases}$$

$$(7)$$

Where  $\alpha_i$  are individual constant terms,  $\beta$  is the slope parameter,  $\mathcal{E}_{it}$ ,  $\mathcal{V}_{it}$  are stationary disturbance terms and so  $y_{it}$  and  $x_{it}$  are I(1) for all i.

Kao derives two types of panel cointegration tests based on residuals: the Dickey-Fuller (DF) using the model:  $\hat{u}_{it} = \rho \hat{u}_{it} + e_{it}$  and the Augmented Dickey-Fuller (ADF) using the model:  $\hat{u}_{it} = \rho \hat{u}_{it} + \sum_{j=1}^{p} \phi_j \Delta \hat{u}_{it-j} + e_{itp}$ . Kao proposes one type of ADF statistic and four DF-type statistics (two based on strict exogeneity of the regressors and two that allow for endogeneity of the regressors). Kao is the first author to suggest the test for cointegration in homogeneous panels.

# b. Pedroni cointegration test

Proposed by Pedroni (2004), this test allows for heterogeneous intercepts and trend coefficients across cross-sections. According to Murthy (2007), it is a better technique since it also overcomes the issue of a small sample size and multiple cointegrating relationships. This test is based on the estimated residuals from the following long-run model:

$$y_{it} = a_i + \sum_{i=1}^{m} \beta_{ji} X_{jit} + \mu_{it}$$
 (8)

Where  $\mu_{it} = \rho_i \mu_{i(t-1)} + w_{it}$  stands for the estimated residuals from the panel regression. The test provides seven test statistics (parametric and non-parametric) under a null of no cointegration in a heterogeneous panel with one or more nonstationary regressors.

# • Presentation of the regression results

The final step was the presentation of the demand-side determinants of access to health care derived from the estimation of the study model in Equation (3).

# 3.5 Chapter summary

This chapter described the methodology used in this study. It began by presenting an overview of the panel data in order to justify the methods selected because this study is based on data collected for 37 African countries during the period 1995 to 2012 in the WDI and WHO databases. The chapter then highlighted the modelling approach and the specification used, notably the ARDL model. The estimation techniques were presented, followed by the plan of analysis. The results of this plan are presented in the following chapter.

# Chapter Four: Empirical evidence and discussion of the results

This chapter presents and discusses the empirical evidence with respect to the research objectives. The chapter begins with the descriptive statistics of the variables used in the analysis. Section 2 presents the preliminary tests, while Section 3 presents the results on the long and short run demand-side determinants of access to health care services. In light of the literature reviewed in Chapter three, Section 4 discusses the research findings in detail.

# 4.1 Descriptive analysis and Preliminary tests

# 4.1.1 Descriptive statistics

This section presents a short review of the characteristics of the dependent variable, access to health care (ha), and the main covariates series. Table 4.3 provides some key statistics from these series for African countries during the period 1995 to 2012 where the variables are in level.

Table 4.3 Descriptive statistics of main variables, 1995-2012

Statistics		Access to health care index	GDP per capita	Fuel consumption	Out-of pocket payment share of health expenditure	Population aged over 65 years Share of total population	Under five population Share of total population	Urbanisation rate
Mean	overal1	0.25	1670	18	40.29	3.46	15.93	37.05
	overal1	0.10	2639	38	18.97	1.17	3.24	14.43
Standard deviation	between	0.09	2518	37	18.00	1.15	3.19	14.37
	within	0.04	884	9	6.65	0.26	0.76	2.62
	overal1	0.06	128	0	2.48	2.23	5.84	7.21
Minimum	between	0.11	152	0	9.61	2.46	7.74	9.09
	within	0.12	-6543	-29	14.49	2.05	10.96	28.84
	overal1	0.58	15096	210	80.91	8.38	20.69	68.87
Maximum	between	0.52	11638	166	71.72	7.65	20.56	62.58
	within	0.48	7874	78	64.82	5.23	19.30	44.89
Number of observations	overal1	666	666	666	666	666	666	666
	between	37	37	37	37	37	37	37
ouser various	within	18	18	18	18	18	18	18

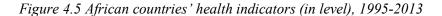
Source: Estimation

Table 4.3 reveals that during the period 1995 to 2013, the overall mean of the health access index is 0.25 and the overall standard deviation (SD) is 0.10. Compared to the overall mean, the overall SD is quite large, exhibiting significant dispersion around the mean. These features of distribution, central tendency and variability of data suggest that in Africa, the level of access to health care is more at the extremities, with countries with sound economies having high access to health care,

and those with struggling economies having lower levels of access. The main independent variables – GDP per capita and the consumption of fuel – also present large overall SDs from their overall means suggesting the same specificity as that from the health access index and showing the disparities in wealth among African countries. It could also be observed in Table 4.3 that the within SDs is low compared to the between SDs showing that within countries either the access to health care or its dependent variables are not varying too much within African countries.

# • Graphical presentations

Figure 4.5 depicts the evolution of the cross country mean values of the dependent variable – access to healthcare index – and the main covariates, namely GDP per capita, CPI and fuel consumption in African countries during the period 1995 to 2013.



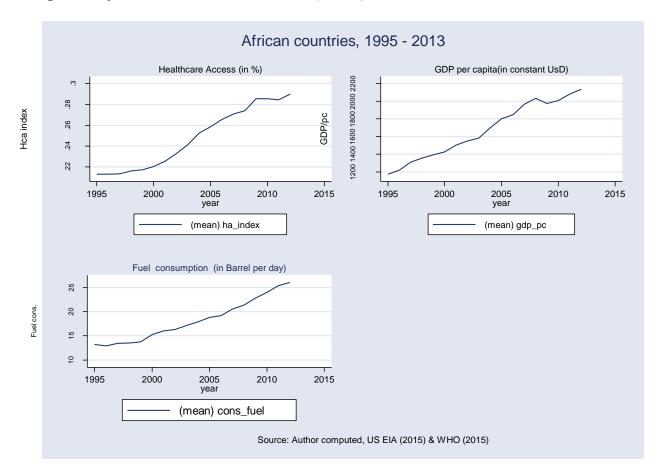


Figure 4.5 presents the average values of the healthcare access, the per capita GDP and the fuel consumption of the African countries during the period 1995-2013. It illustrates remarkably a similar behaviour of all these variables suggesting that they are positively co-trending across

African countries. Still while health care access and gdp per capita depict a flatter slope from 2008 to 2013, the fuel consumption seems not to be affected meaning that the consumption of fuel is not affected by the event that affects health access and gdp. The 2008 year relates to the global financial crisis - the debt crisis unfolding in the US and Europe – that has significantly and at different degrees affected the economies of most countries in Africa (African Development Bank (AfDB), 2012).

# 4.1.2 Preliminary tests

As per the methodology, the test for cross-sectional dependence was done, followed by the UR test and the cointegration test.

# • Test for cross section dependence

As outlined in Chapter three, the Pesaran CD test was used to examine if the panels in the dataset are correlated or not. The results from this test provided a CD-test of -0.29 with a P-value of 0.77. Under the null hypothesis of cross-sectional independence, the test fails to reject the null hypothesis. It is therefore concluded that the panels in the study dataset are independent.

# • Unit root Tests

Table 4.4 Unit root test of level variables (In logarithm)

	LLC	C test	Im Pes	aran Shin
		Individual effect &		Individual effect
	Individual	individual linear	Individual	& individual
	effect	Trend	effect	linear Trend
	(1)	(2)	(3)	(4)
lha	-2.04511**	-3.75020***	1.20053	-3.05778***
lgdp	-1.06317	-3.37957***	3.58340	-1.73292**
lconsf	0.04757	-4.49658***	3.41708	-2.79615***
loop	-0.98367	-2.53445 ***	-0.31722	-2.61746***
lpop65	-3.31016***	-4.26723***	1.06369	0.52137
lpopu5	-0.48802	-9.64860***	-1.68589**	-9.33809***
lurb	-24.8208***	8.70040	-2.76250 ***	10.7794

Source: Estimation legend: \*\* p < 0.05; \*\*\* p < 0.01

Table 4.4 reports the results of the unit root tests in level for all the study variables applying the LLC and the IPS tests both with individual effect (columns 1 and 3) as well as individual effect and

linear Trend (columns 2 and 4). In both tests the Schwarz information criterion was used for the lag length selection. The results from both the LLC and the IPS indicate that some variables are stationary at level, meaning that the null hypothesis of UR is rejected at 1 and 5 percent level of significance, and others are not. If stationary variables are I(0), there is no information showing that the non-stationary variables are I(1) in order to carry out the cointegration. Then, the unit root test should be conducted on first-differenced variables to determine if the non-stationary variables are I(1). The unit root results tests with first differenced variables are presented in Table 4.5.

Table 4.5 Unit root test of first-differenced variables (In logarithm)

	LLC	test	Im Pesaran Shin		
	Individual effect (1)	Individual effect & individual linear Trend (2)	Individual effect (3)	Individual effect & individual linear Trend (4)	
d.lha	-19.4362***	-19.0610***	-17.0888***	-14.7039***	
d.lgdp	-9.6902***	-13.1526***	-9.9982***	-11.0556***	
d.lconsf	-20.4261***	-20.7302***	-18.0300***	-15.8555***	
d.loop	-16.5042***	-16.1304***	-16.1259***	-14.4070***	
d.lpop65	-5.1139***	-7.3946***	-4.0853***	-5.3106***	
d.lpopu5	-8.2667***	-10.7269***	-7.2774***	-3.7696***	
d.lurb	0.6310	-20.8987***	1.8575	-9.0867***	

Source: Estimation legend: \*p<0.10; \*\*p<0.05; \*\*\*p<0.01

The unit root test results with first differenced variables presented in Table 4.5 clearly show that all the series are stationary. While in the unit root test with individual effect and individual linear trend (columns 2 and 4) the null hypothesis of unit root is rejected at all levels of significance, the unit root test with individual effect fails to reject the null hypothesis for the variable urb which was stationary at level. Therefore it can be concluded that the study dataset contains exclusively a mix

of I(0) and I(1) variables, then the cointegration test can be run.

# • Cointegration test

Following the results of unit root tests, the study variables are a mixture of I(0) and I(1) series. Therefore the cointegration test can be conducted. As per the methodology, the study used the Kao and Pedroni tests. The results from these tests are presented in Table 4.6.

Table 4.6 Cointegration test

Statistics	Kao (1999) test (1)	Pedroni (2004) Test (2)	
	. ,	Individual intercept	Individual intercept & trend
ADF	-3.294055***	-	-
Panel v-Statistic	-	-3.928033	-6.213108
Panel rho-Statistic	-	5.601776	7.318507
Panel PP-Statistic	-	-6.528842***	-7.832599***
Panel ADF-Statistic	-	-6.158719***	-6.119382***
Group rho-Statistic	-	7.673583	8.518998
Group PP-Statistic	-	-23.701770***	-27.376630***
Group ADF-Statistic	-	-9.167445***	-8.724750***

Source: Estimation legend: \*\*\* p<0.01

Column 1 reports the results of Kao tests and column 2 reports the results from the Pedroni test applied with the dependent and all the covariates. The null hypothesis of no cointegration is rejected at all levels of significance in both the Kao test and the Pedroni test, using the ADF statistic. Therefore it has been concluded that there is a cointegrating relationship between access to health care and the covariates; and next it has been estimated the magnitude of such long run relationship as well as the short run relationship between variables.

# 4.2 Determinants of access to health care

# 4.2.1 Main regression estimation

As outlined in Chapter three and the results of the test of cross-sectional dependence, the study model was estimated using the three estimators DFE, PMG and MG, respectively in columns 1, 2 and 3. The regression results are presented in Table 4.7, where the middle part "Ec" presents the cointegrating equation providing the long run relationship between the variables, and the lower part "SR" provides the short run relationship between the variables.

Table 4.7 Main regression estimation

X72-1-11		DFE	PMG	MG
Variables <sup>1</sup>		(1)	(2)	(3)
Ec				
	lgdp	0.1970***	0.1149***	0.4219
	lconsf	0.0961	0.0644***	-0.3757
	loop	-0.0472	0.0160*	0.1523
	lpop65	0.2747	0.0612	-9.7011
	lpopu5	-0.1123	0.4922***	-9.4735**
	lurb	1.0478***	1.0243***	-24.5040*
SR				
	ec	-0.2627***	-0.5466***	-1.0800***
	d.lgdp	0.0847*	0.1869	0.4593*
	d.lconsf	-0.0241*	0.0009	0.2293
	d.loop	0.0796*	0.0611	0.1812**
	d.lpop65	0.1510	2.7801	13.7843**
	d.lpopu5	-0.0123	-6.1638	-5.8649
	d.lurb	1.4560*	1.3458	31.5838
	_cons	-1.7080***	-4.0938***	50.6725***

Source: Estimation

legend: \*p<0.10; \*\*p<0.05; \*\*\*p<0.01

The cointegrating equation results from the three estimators are depicted in the Ec-part of table 4.7. Comparing the results from the three estimators, it can be noted that the coefficients on the main variables are all significant only in the PMG. No coefficient is significant in the MG; while only one coefficient (gdp) is significant in the DFE estimator. It is important to keep in mind that the PMG estimator constrains the long-run elasticities to be equal across all panels, such that when the restrictions are true, this "pooling" across countries yields efficient and consistent estimates (Blackburne & Frank, 2007).

Among the three models, the PMG was selected following the Hausman test. It was selected in the test against the MG estimator where the null hypothesis of no systematic difference in coefficients was not rejected since the p-value is equal to 0.4419. It was also selected in a test against the DFE where the null hypothesis of no systematic difference in coefficients was rejected since the p-value is equal to zero. Therefore the PMG estimator was used as the model of reference in the remainder of the study.

The long-run estimate equation indicates that the two main variables have slope coefficients (long run elasticities) statistically significant at all levels of significance. The GDP per capita long run

<sup>(1)</sup> Lhce is the dependent in the ER component and d.lhce in the SR component. Other variables listed are the independent variables.

elasticity of 0.1149 shows that in the long-run, a 1 percent increase in GDP per capita is expected to increase access to health care by 0.1149 percentage points, *ceteris paribus*, while the fuel consumption long run elasticity indicates that a 1 percent increase in fuel consumption is expected to increase access to healthcare by 0.0644 percentage points, *ceteris paribus*. The long-run estimate equation also shows that three control variables have statistically significant elasticities, the urban population and the under-five population at all levels of significance and the OOP at 5 percent level of significance. It should be noted that while the speed of adjustment (-0.5466) is negative and significant at all levels of significance no short run coefficient of the model is significant, except the constant. This implies that following a shock to the system causing disequilibrium, the system corrects its previous period disequilibrium at a speed of 54.66 percent annually, meaning that it returns to equilibrium after 1.83 years (22 months).

Following the main results of this study, it can be argued that access to health care services in African countries is driven by the GDP per capita proxy for income and the consumption of fuel proxy for distance to health care facilities, but only in the long-run.

# 4.2.2 Regression estimations by income class

In addition to the determinants of access to health care addressed above, it is likely that a country's medium to long-run access to health care services would also be influenced by other features of its macroeconomic environment such as its income levels. Therefore it has been conducted an assessment of the robustness of the main results focusing on the long-run relationship between access to health care services and the main variables (GDP, consf) using the country's income classes as framed and provided by the World Bank (2013). One reason for suggesting that a country's income class may matter is that a change in income should affect these groups of countries differently.

The regression estimations are presented by income class – low income (LI), lower middle income (LMI) and upper middle income (UMI) – as well as the full model specification (FULL). It should be noted that only one African country is classified in the high income countries group, namely the Equatorial Guinea; therefore this group could not be included in this analysis. The regression results are presented in Table 4.8.

Table 4.8 Regression Income class

x7 · 11 1		LI	LMI	UMI	FULL
Variables <sup>1</sup>		(1)	(2)	(3)	(4)
Ec					
	lgdp	0.3376***	0.6167***	0.5597***	0.1149***
	lconsf	0.0634***	0.0256	0.5240***	0.0644***
	loop	0.0097***	-0.2457***	0.1708***	0.0160*
	lpop65	-1.0278***	0.2226	0.1401***	0.0612
	lpopu5	0.3887**	-1.1067***	-0.0323***	0.4922***
	lurb	-0.0865***	0.4952	-0.8459***	1.0243***
SR					
	Ec	-0.6069***	-0.5372***	-0.3511***	-0.5466***
	d.lgdp	-0.1911	0.2878	-0.3120	0.1869
	d.lconsf	0.0265	-0.0411	0.0813	0.0009
	d.loop	0.0415	0.1650*	0.0809	0.0611
	d.lpop65	1.5889	3.6562	7.8653	2.7801
	d.lpopu5	-6.7220	-3.8537	-10.4865	-6.1638
	d.lurb	12.9077	12.1758	42.8224	1.3458
	_cons	-2.1671***	-2.3015***	3.2830	-4.0938***

Source: Estimation

legend: p<0.10; \*\* p<0.05; \*\*\* p<0.01

A quick perusal of Table 4.8 shows that only the GDP long run elasticity and the error correction coefficient are statistically significant across all the income and FULL specifications. However, GDP impacts access in the countries' income groups differently, with the highest impact in the LMI (0.6167) and the lowest in the LI (0.3376). Fuel consumption is significant only in the LI, the UMI and the FULL specifications. All the income class specifications (LI, LMI and UMI) show that in the long run access to health care in African countries is consistently driven by GDP per capita. However, other variables also play a role in particular specifications.

# 4.2.3 Regression at country level

This sub-section presents the regression coefficients from each individual country of the study dataset. These are outputs obtained from the selected PMG estimator and include the error correction mechanism coefficients and the short run coefficients or elasticities. The ECM regression results are presented in Tables AP1 and AP2 in appendix 1.

A quick examination of the tables AP1 and AP2 in appendix 1 focusing on the variables of interest, the income and the distance to health care services proxied respectively by the per capita GDP and the fuel consumption, shows that the GDP per capita short run elasticities are significant only for Congo Rep., Mali, Morocco, Mozambique and Seychelles at 1 percent level of significance; for

<sup>(1)</sup> Lhce is the dependent in the ER component and d.lhce in the SR component. Other variables listed are the independent variables.

Burundi, Ghana and Mauritius at 5 percent level of significance; and for Cabo Verde, Côte d'Ivoire and Rwanda at 10 percent level of significance. Except for Burundi, Ghana, Mozambique and Rwanda, the GDP per capita short run elasticities have positive expected sign for all the countries with significant coefficients; and these coefficients range from 0.2584 to 2.5079 with Congo Rep. having the highest value. More, the fuel consumption short run elasticity indicates are significant only for Cameroon and Mozambique at 1 percent level of significance; for Angola, Cabo Verde, Equatorial Guinea, Ethiopia, Gambia, Morocco and Zambia at 5 percent level of significance; and for Dem. Rep. of Congo, Tanzania and Togo. Except Angola, Dem. Rep. of Congo and Morocco, all the countries with significant short run coefficients have coefficients with the expected negative sign; and these coefficients range from -0.4015 to -0.0190 with Tanzania having the highest amplitude. The values of the error correction mechanism vary from one country to another. They are either positive or negative, either significant or insignificant, and range from -1.2256 to 0.1373. Given the PMG estimator hypothesizes common long-run coefficients, the error coefficient resulting from the cointegrating equation and the collective ECM (main regression) will be consider for the countries.

#### 4.3 Discussion of the results

Understanding the determinants of access to health care services has received increasing analytical attention in African countries where people are dying from diseases that are curable and preventive. This study used macroeconomic data on African countries and the dynamic ARDL panel model to investigate the demand side of the determinants of access to health care services. The study dataset was from 37 countries for the period 1995 to 2013. The additional feature of the data used was that it encompassed an index of access to health care based on the six health coverage indicators identified by Moreno-Serra & Smith (2008). Stressing on the main variables, the primary focus was on the long-run determinants of access to health care and the implications for these determinants in the short run.

The main findings of the study obtained by the PMG estimator indicate that in the long run, access to health care services in Africa is driven by the income and the distance to health care facilities, controlling for the OOP payments, elderly population, under-five population and the urbanisation. Moreover, the results indicate that after any shock to the long run equilibrium, the disequilibrium is corrected in approximately two years.

The PMG estimator was applied in this study because it has been found to be more suitable for investigating access to health care in the context of African countries. This estimator hypothesises common long-run variable coefficients across countries and country-specific short-run variable coefficients. For example, in terms of health or access to health care, on the one hand, African countries are engaged in many international strategies or programmes to combat health threats like HIV, tuberculosis and malaria (MDG objectives on health, Bamako initiative and Arusha Declaration) putting them together in the achievement of those objectives, and therefore justifying the commonness of the impact on access to health care in these countries. On the other hand, these countries are applying different national programmes or initiatives to comply with their international commitments by using specific legislation or economic policies.

The main regression results (Table 4.7) show that the sign of the long-run coefficients on the variables were not as expected. While the long-run distance to healthcare elasticity for access to health care has the positive unexpected sign, the long-run income elasticity for access to health care has the expected positive sign. The long run income elasticity of 0.1149 estimated in this study is positive and less than one. This positive long-run income elasticity suggests that access to health care is not a luxury good in Africa. This means that as a population's income increases they become worried about their health status and are more likely to pay and access better health care. This result is in line with the findings of a pioneering study by Newhouse (1977) in terms of the direction of the impact but not the magnitude of the elasticity which in this study is 1.4. However, some studies have found income elasticity of less than one (Kumagai, 2005; Farag et al., 2012). The income elasticity in this study is less than one, indicating that in African countries, some individuals have full health insurance (Ringel et al., 2002) or that a large part of fees for health care are sponsored by government or other sources (internal and external), such that, globally, the individual income does not play a significant role in accessing health care services. Moreover, this means that access to healthcare is inelastic; therefore, it is not a luxury good but a necessary good and it should thus receive more attention from policy makers. This finding is consistent with some empirical studies (Kumagai, 2005; Farag et al., 2012). The long-run coefficient on fuel consumption, the proxy for distance to health care facilities, exhibits a positive unexpected sign. This ambiguous positive sign on the distance to health care services could a priori mean that additional quantities of fuel consumed for longer distances travelled increases access to health facilities even if the cost of transport is increasing. This is not consistent with the demand theory which suggests that an increase in the cost or price of a good decreases the demand for that good. However, the positive long-run coefficient on fuel consumption could, under certain circumstances, mean that the

increasing means of transport captured by the increase in fuel consumption creates a decrease in the price or cost of transport because of competition among transporters; and a decrease in the cost of transport causes, in this case, access to health care services to increase as individuals can afford the lower cost of transport resulting from the competition. This finding (positive coefficient of price in a demand function) is consistent with some studies (Heller, 1982 and Akin et al., 1986) which found positive cost elasticities. Still, in this study, the positive elasticity on fuel consumption could indicate that fuel consumption is capturing other factors instead of the distance to health care; and is missing to capture, for example, people who walk to health care facilities. However, the majority of studies (Birdsall & Chuan, 1983; Dzator & Asafu-Adjaye, 2004, Okwaraji et al., 2012; Syed et al., 2013; Okwaraji et al., 2015) have found a negative relationship between access to health care and the distance to health care which is in line with demand theory. The main regression results, finally show, a negative speed of adjustment of -0.5466 meaning that 54.66 percent of the long-run system equilibrium is recovered each year after any shock.

The findings from samples split by income classes (Table 4.8) are dissimilar across the specifications (LI, LMI, and UMI). Still focusing on the main variables in the long-run relationship, the regression results suggest that the consistency (in sign and level of significance) of the results in the income class specifications and in the main regression for the error correction mechanism (speed of adjustment) and for all the long-run elasticities of the variables of interest except the long-run distance to health care elasticity in LMI specification which not significant. Still the speed of adjustment is high in LI countries (60.69 percent) compared with the UMI and LMI suggesting that the equilibrium is recovered quickly in the LI countries. The magnitudes of the long-run income elasticities in the income class specifications are diversely high compared to the main specification suggesting the income is affecting the health access differently in the income group of the countries meaning that each group of countries has a particular behaviour due to its own characteristics. While the fuel consumption has abnormal positive effect on access to health care in the LI and UMI specifications, it is not affecting health access in the LMI countries group. The speed of adjustments in all the income class specifications are consistent with the one in the main regression.

The findings from the individual regression (Tables AP1 and AP2 in appendix) provide quite interesting information. The results from the individual countries regression are not consistent with the regression from the main regression. The speeds of adjustment from individual countries exceed 100 percent for the Sudan, Cabo Verde, Malawi and Mozambique showing the long-run equilibrium is always recovered in these countries. Still in the Swaziland and Botswana the speed of adjustment

is positive meaning that the equilibrium is never recovered. As opposed to the results in the main regression where all the short-run elasticities are insignificant, the short-run income elasticities from the individual countries regression are significant for the Burundi, Cabo Verde, Congo Rep., Côte d'Ivoire, Ghana, Mali, Mauritius, Morocco, Mozambique, Rwanda and Seychelles; even though for the Burundi, Ghana, Mozambique and Rwanda they are negative meaning that in these countries income has a negative impact on access to health care. These results are consistent with the study from Clavero and González (2005) that related a negative effect of income on general practitioners. The short-run distance to health care elasticities from the individual countries regression are significant for Angola, Cabo Verde, Cameroon, Dem. Rep. of Congo, Equatorial, Guinea, Ethiopia, Gambia, The Morocco, Mozambique, Tanzania, Togo and Zambia while they are positive for Angola, Dem. Rep. of Congo and Morocco meaning in these countries the distance to health care has a positive impact on access to health care.

It should be noted that the elasticity presented in this study is related to a composite variable as a proxy for access to health care instead of the mono-indicator found in the majority of studies (Dor & Van Der Gaag, 1988; Kumagai, 2005; Drabo & Ebeke, 2011; Cisse, 2011; Sato, 2012; Wouterse & Tankari, 2015). The index built from various health care indicators indicates that the elasticities of the study are related at the same time to all of the indicators contained in the index. This is quite different from standard elasticities which relate to the single indicators used in many studies (Lalloo et al., 2004; Berthelemy and Seban, 2009; Mazumdar, 2012; Belasco et al., 2012). Moreover, the global impact of a covariate on the index should be normally decomposed based on the indicators' weight, to ascertain the impact of each indicator contained in the index that should be compared to the impact of the single indicator commonly used.

Income appears to be the key long-run demand-side determinant of access to health care facilities in African countries. It is significant and consistent across all the specifications even though in the sample split specification the magnitude differs across the specifications. Moreover, after any shock to the long run equilibrium is recovered.

# Chapter Five: Conclusion, recommendations and limitations of the study

#### 5.1 Conclusion

The purpose of this study was to investigate the demand side of the determinants of access to health care services in African countries. Using data from 37 countries for the period 1995 to 2012, the study applied the dynamic ARDL panel approach and used the PMG estimator to check whether long run relationships exist between access to health care and the main covariates (income and distance to medical facilities). The application of this estimator has been commanded by the nature of the data and this model suggests homogeneous long-run elasticity and heterogeneous short-run elasticities. The specific objectives of this study were to review the state of the literature on access to health care, to identify key demand-side factors influencing access to health care services in African countries, to determine whether a long-run relationship exists between access to health care and the identified factors, and to suggest policy options in order to enhance access to health care in Africa.

This study has quite a lot of implications for African countries, and its health care system. Despite the ambiguity of the distance to health care variable, this study has shown that in the long-run, access to health care service in Africa is driven by income, controlling for the OOP payments, elderly population, under-five population and the urbanisation; and after any shock the long-run equilibrium is recovered. While the long-run income elasticity has the positive expected sign meaning an increase in the income improves access to health care, the long-run distance to healthcare elasticity present positive unexpected sign meaning long distances - that relate to high costs – improve access to health care; that is questionable. This study has found a long-run income elasticity of 0.1149 suggesting that access to health care in Africa is a necessary good.

This study has also shown that the long-run income elasticity in the LMI is the highest among country income classes, meaning that an increase in income is more effective in improving access to health care services in the LMI countries. Based on the assumption of heterogeneity of countries' parameters, a perusal of findings from the short-run country specific regression indicates that the increase income is better improving access to health care in countries like Congo, Rep., Mali and

Mauritius where the short-run income elasticities are higher than one suggesting instead that in these countries access to health care services is a luxury goods in the short-run.

This study is noteworthy because it provides a new way to analyse access to health care, not by using a single indicator that does not properly capture the entire complexity of the access to health care concept, but instead by using an index built from various indicators that capture the complexity of access to health care. Moreover, this study explored the dynamic aspects of access to health care that provide information about the factors that persistently drive access to health care in Africa. To the best of our knowledge, no study on African countries has been carried out on access to health care services that consider these two aspects raised in this study.

These specific objectives were achieved in various parts of the study. Having provided an overview of the whole study in the introduction, it achieved the first and second objectives by reviewing the theoretical and empirical literature in relation to access to health care. The review revealed that in African countries, the demand-side determinants of access to health care services are socioeconomic, behavioural and environmental factors. Furthermore, it showed that there is insufficient evidence with respect to access, especially at macro level. In this respect the study contributed to the literature by analysing the dynamic aspect of access to health care at macro level. The study's third objective was achieved by using the appropriate methodology highlighted in Chapter three, the results of which were presented in Chapter four. Using ECM, it was shown that the main determinants of access to health care were income and distance to health care. These results were discussed in detail. The last objective of this study is achieved in this Chapter where evidence from the results are used to suggest policy implications.

### 5.2 Recommendations

Findings from this study provides evidence that policy makers could use to improve access to health care in the long run. While the study concluded that income was the main demand-side determinant of access to health care services, it has also shown that access to health care in Africa is a necessary rather than a luxury good, thus calling for policy interventions that specifically guarantee access to health care for the entire population

Drawing on the study's findings and given the key role of access to health care in the maintenance and improvement of a population's health, it is recommended that policy makers in all the African countries pay more attention to improving citizens' income which is the key demand-side determinant of access to health care services. The resulting increase in demand for health care could result in more utilisation of health care facilities – which are assumed underutilised in this study (supply side) – and therefore improved health status of population that has positive spillovers on the social and economic life of people across African countries.

# 5.3 Limitations of the study

Whereas findings materialized from this study are interesting, there are four noticeable limitations that must be considered. First, while access to health care could be investigate by type of access, meaning primary, secondary, and tertiary access to health care, this study conducted a global analysis gathering all these types of access. Each types of health care could inform on a particular access issue that could necessitate a particular attention as access to each of these types of health care could either be differently affected by the determinants of access or have different determinants of access resulting in the need for different strategies to address them. Second, this study has tackled only the demand-side of access to health care. As both the demand and the supply sides are interlinked it is always better to tackle simultaneously more information would have been gained by extending the analysis to the supply side determinants of access to health care. Third, while this study suggests the income as a key determinant of the demand-side of access to health care it did not go further in analysing the impact of the population's income on access as it is known that there some income categories (poor and rich) in the population and additional increase in income may have different effect in different population's income categories. The study would do better analysing access taking into account population's income classes. Finally, while this study emphasises on the cost aspect (implying financial burden for the population) of the distance to health care as a barrier and uses the quantities of fuel consumed as a proxy, this proxy may miss to capture other factors that would capture the distance to health care. Still at macro level the consumption of fuel appeared as a good proxy for the distance to health care.

These above weaknesses, which in general are due to data availability at macro level and time constraint, do not undermine the findings of this study, but instead they open areas where further research could also be conducted.

#### References

Aakvik, A., & Holmås, T. H. (2006). Access to primary health care and health outcomes: the relationships between GP characteristics and mortality rates. Journal of Health Economics, 25(6), 1139-1153.

Aday, L. A., & Andersen, R. M. (1974). A Framework for the Study of Access to Medical Care. Health Services Research, 9(3), 208-220.

Addae-Korankye, A. (2013). Challenges of financing health care in Ghana: the case of national health insurance scheme (NHIS). International Journal of Asian Social Science, 3(2), 511-522.

Adesiji, G., Dada, S., & Komolafe, S. (2012). problems faced by rural people in accessing health care facilities in Akure north and Akure south local government areas of Ondo State, Nigeria. J Appl Sci Res, 8(4), 2260-2266.

AfDB. (2012). African Development Bank.

http://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/brief%20impact%20of%20 US-Eng.pdf

Akin, J. S., Griffin, C. C., Guilkey, D. K., & Popkin, B. M. (1986). The demand for primary health care services in the Bicol region of the Philippines. Economic Development and Cultural Change, 755-782.

Akweongo, P., (2005). Measuring equity in access to health care: a case study of malaria control interventions in the Kassena-Nankana district of northern Ghana. PhD, thesis, Health Economics Unit, School of Public Health and Family Medicine, University of Cape Town.

Alderman, H., & Gertler, P. (1989). The substitutability of public and private health care for the treatment of children in Pakistan. Living Standards Measurement Survey Working Papers No. 57, Washington DC: World Bank.

Alsan, M., Bloom, D. E., & Canning, D. (2006). The effect of population health on foreign direct investment inflows to low-and middle-income countries. World Development, 34(4), 613-630.

Aluttis, C., Bishaw, T., & Frank, M. W. (2014). The workforce for health in Áglobal shortages and international migration. Global Health Action. <a href="http://www.who.int/workforcealliance/01.pdf?ua=1">http://www.who.int/workforcealliance/01.pdf?ua=1</a>

Andersen, R. M. & Newman, J. F. (1973). Societal and individual determinants of medical care utilization in the United States. Milbank Mem Fund Q Health Soc., 51(1), 95-124.

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: does it matter? Journal of health and social behavior, 1-10.

Angko, W. (2013). The Determinants of Healthcare Expenditure in Ghana. Journal of Economics and Sustainable Development, 4(15), 102-124.

Ashraf, Q. H., Lester, A., & Weil, D. N. (2008). When does improving health raise GDP? (No. w14449). National Bureau of Economic Research.

Asuo-Mante, E., Awoonor-Williams, J. K., Yelifari, L., Boyer, C., Schmitt, M. L., & Phillips, J. F. (2015). The Application of Geographic Information Systems (GIS) to Improving Health Systems in the Upper East Region of Ghana. The Journal of Global Health Care Systems, 6(1).

Audibert M, Dukhan Y, Grimaldi C, Korachais C, Mathonnat J. (2011). Amélioration de l'accessibilité financière aux soins et orientations pour des stratégies de financement de la gratuité, Vol. 1, Burkina Faso; Vol. 2, Mali, Vol. 3, Niger, CERDI, Institut d'Economie de la Santé et de Santé Publique (IESSP), Clermont-Ferrand.

Awaworyi, S., Yew, S. L., & Ugur, M. (2015). Effects of Government Education and Health Expenditures on Economic Growth: A Meta-analysis. <a href="https://mpra.ub.uni-muenchen.de/68007/1/MPRA paper 68007.pdf">https://mpra.ub.uni-muenchen.de/68007/1/MPRA paper 68007.pdf</a>

Audibert, M., & Mathonnat, J. (2013). Facilitating access to healthcare in low-income countries: a contribution to the debate. Field Actions Science Reports. The journal of field actions, (Special Issue 8).

Bai, J., & Ng, S. (2004). A PANIC attack on unit roots and cointegration. Econometrica, 72(4), 1127–1177.

Baltagi, B. (2008). Econometric analysis of panel data. John Wiley & Sons.

Baltagi, B. H., Griffin J.M. & Xiong W. (2000). To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand, Review of Economics and Statistics 82, 117-126.

Belasco, E., Philips, B. U., Gong, G., & Jr. (2012). The Health Care Access Index as a determinant of delayed cancer detection through principal component analysis. INTECH Open Access Publisher. <a href="http://cdn.intechopen.com/pdfs/30014.pdf">http://cdn.intechopen.com/pdfs/30014.pdf</a>

Berthelemy, J.-C. & Seban, J. (2009). Dépenses de santé et équité dans l'accès aux services de santé dans les pays en développement. Revue d'économie du développement, 23(1), 33–71.

Binder, M., & Offermanns, C. (2007). International investment positions and exchange rate dynamics: a dynamic panel analysis. Center for Financial Studies, Bundesbank.

Birdsall, N., & Chuan, P. (1983). Willingness to pay for health and water in rural Mali: Do WTP Questions work. In Three Studies on Cost Recovery in Social Sector Projects, Country Policy Department, Discussion Paper 1983-8, Washington DC, World Bank.

Blaauw, D., Ditlopo, P., Maseko, F., Chirwa, M., Mwisongo, A., Bidwell, P., & Normand, C. (2013). Comparing the job satisfaction and intention to leave of different categories of health workers in Tanzania, Malawi, and South Africa. Glob Health Action, 6, 19287.

Blackburne, E. F., & Frank, M. W. (2007). Estimation of nonstationary heterogeneous panels. Stata Journal, 7(2), 197.

Bloom, D. E., & Canning, D. (2005). Health and economic growth: reconciling the micro and macro evidence. Center on Democracy, Development and the Rule of Law Working Papers.

Boles, M., Pelletier, B., & Lynch, W. (2004). The relationship between health risks and work productivity. Journal of Occupational and Environmental Medicine, 46(7), 737-745.

Boman, C. K., & Isiaka, M. (2015). Government Health Care Financing and Workforce Productivity: Empirical Evidence From Nigeria. African Journal of Applied Research (AJAR), 1(1).

Breitung, J. (1999). 'The local power of some unit root tests for panel data', Discussion Papers 1999, 69, Humboldt University of Berlin.

https://www.econstor.eu/dspace/bitstream/10419/61764/1/722394276.pdf

Breitung, J., & Pesaran, M. H. (2005). Unit roots and cointegration in panels. Forthcoming in L. Matyas and P. Sevestre "The Econometrics of Panel Data".

Breitung, J., & Das, S. (2005). Panel unit root tests under cross-sectional dependence. Statistica Neerlandica, 59(4), 414-433.

Bryant, J. (1972). Santé publique et développement. Agence de santé publique. Canada.

Burstrom, B. (2002). Increasing inequalities in health care utilisation across income groups in Sweden during the 1990s? Health policy, 62(2), 117-129.

Carapinha, J. L., Ross-Degnan, D., Desta, A. T., & Wagner, A. K. (2011). Health insurance systems in five Sub-Saharan African countries: medicine benefits and data for decision making. Health policy, 99(3), 193-202.

Carrin, G., & Politi, C. (1996). Exploring the health impact of economic growth, poverty reduction and public health expenditure: technical paper.

Castro-Leal, F., Dayton, J., Demery, L., & Mehra, K. (2000). Social Determinants of Health. WHO, Geneva.

Choi, I. (2001). Unit root tests for panel data. Journal of international money and Finance, 20(2), 249-272.

Cisse, A. (2011). Analysis of health care utilization in Côte d'Ivoire. Nairobi, Kenya: The African Economic Research Consortium.

Clark, D. W. (1983). Dimensions of the concept of access to health care. Bulletin of the New York Academy of Medicine, 59(1), 5-8.

Clavero, A. and González, M.L. (2005): "La demanda de asistencia sanitaria en España desde la perspectiva de la decisión del paciente", in Muñoz de Bustillo, R., & Antón, J. I. (2009). Health care utilization and immigration in Spain. MPRA Paper No. 12382, <a href="http://mpra.ub.uni-muenchen.de/12382/">http://mpra.ub.uni-muenchen.de/12382/</a>

Corburn, Jand Hildebrand, C. (2015). Slum Sanitation and the Social Determinants of Women's Health in Nairobi, Kenya. Journal of Environmental and Public Health. <a href="http://dx.doi.org/10.1155/2015/209505">http://dx.doi.org/10.1155/2015/209505</a>

Cueto, M. (2004). The origins of primary health care and selective primary health care. American journal of public health, 94(11), 1864-1874.

Das, A., Chowdhury, M., & Akhtaruzzaman, M. (2012) Panel Cointegration and Pooled Mean Group Estimations of Energy-Output Dynamics in South Asia. Journal of Economics and Behavioral Studies, 4(5), 277-286.

Decroo, T., Rasschaert, F., Telfer, B., Remartinez, D., Laga, M., & Ford, N. (2013). Community-based antiretroviral therapy programs can overcome barriers to retention of patients and decongest health services in sub-Saharan Africa: a systematic review. International health, 5(3), 169-179.

Delamater, P. L., Messina, J. P., Shortridge, A. M., & Grady, S. C. (2012). Measuring geographic access to health care: raster and network-based methods. International Journal of Health Geographics, <a href="http://www.ij-healthgeographics.com/content/11/1/15">http://www.ij-healthgeographics.com/content/11/1/15</a>

Donabedian, A. (1972). Models for organizing the delivery of personal health services and criteria for evaluating them. The Milbank Memorial Fund Quarterly, 103-154.

Dor, A.J. and J. Van der Gaag. 1988. "The demand for medical care in developing countries: Quantity rationing in rural Côte d'Ivoire". Working Paper No. 35, Washington DC: World Bank.

Dora, C., Haines, A., Balbus, J., Fletcher, E., Adair-Rohani, H., Alabaster, G., & Neira, M. (2015). Indicators linking health and sustainability in the post-2015 development agenda. The Lancet, 385(9965), 380-391.

Drabo, A. & Ebeke, C. (2011). Remittances, Public Health Spending and Foreign Aid in the Access to Health Care Services in Developing Countries, Halshs.

Dzator, J., & Asafu-Adjaye, J. (2004). A study of malaria care provider choice in Ghana. Health Policy, 69(3), 389-401.

Enyioko, N. C., & Samuel, O. (2012). Under Utilization of Modern Health Facilities and the Practice of Alternative Medicine in Rural Areas of Rivers State. Available at SSRN 2187770.

Ezeh, O. K., Agho, K. E., Dibley, M. J., Hall, J., & Page, A. N. (2014). The Impact of Water and Sanitation on Childhood Mortality in Nigeria: Evidence from Demographic and Health Surveys, 2003–2013. International journal of environmental research and public health, 11(9), 9256-9272.

Field, K. (2000), Measuring the need for primary health care: an index of relative disadvantage, Applied Geography, 20, 305-332.

Fifield, A. (2015). A Mighty Purpose: How Jim Grant Sold the World on Saving Its Children, Other Press.

Foster, V., & Briceño-Garmendia, C. (Eds.). (2010). Africa's infrastructure: a time for transformation. World Bank Publications.

Franco, L. M., Diop, F. P., Burgert, C. R., Kelley, A. G., Makinen, M., & Simpara, C. H. T. (2008). Effects of mutual health organizations on use of priority health-care services in urban and rural Mali: a case-control study. Bulletin of the World Health Organization, 86(11), 830-838.

Frees, E. W., (1995). Assessing cross-sectional correlation in panel data. Journal of Econometrics 69: 393–414.

Frees, E. W., (2004). Longitudinal and Panel Data: Analysis and Applications in the Social Sciences. Cambridge: Cambridge University Press.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the american statistical association, 32(200), 675-701.

Gage, A. J. (2007). Barriers to the utilization of maternal health care in rural Mali. Social science & medicine, 65(8), 1666-1682.

Gallup, J. L., & Sachs, J. D. (2001). The economic burden of malaria. The American journal of tropical medicine and hygiene, 64(1 suppl), 85-96.

Ganesh, L. (2015). Impact of indirect cost on access to healthcare utilization. International Journal of Medical Science and Public Health, 4(9), 1255-1259.

Garcia-Subirats, I., Vargas, I., Mogollón-Pérez, A. S., De Paepe, P., da Silva, M. R. F., Unger, J. P., & Vázquez, M. L. (2014). Barriers in access to healthcare in countries with different health systems. A cross-sectional study in municipalities of central Colombia and north-eastern Brazil. Social Science & Medicine, 106, 204-213.

Gertler, P., & Gaag, J. V. D. (1990). The willingness to pay for medical care: evidence from two developing countries. Johns Hopkins University Press.

Gengenbach, C., Urbain, J.-P., & Westerlund, J. (2009). Error Correction Testing in Panels with Global Stochastic Trends (December 2009). Maastricht University: METEOR.

Goddard, M., & Smith, P. (2001). Equity of access to health care services: Theory and evidence from the UK. Social science & medicine, 53(9), 1149-1162.

Green, W.H. 2002. Econometric Analysis, 4th Edition, Upper Saddle River, NJ: Prentice Hall.

Green, W.H. 2002. Econometric Analysis, 5th Edition, Upper Saddle River, NJ: Prentice Hall.

Grossman, M. (1972). On the concept of health capital and the demand for health. The journal of political economy, 223-255.

Gu, D., Zhang, Z., & Zeng, Y. (2009). Access to healthcare services makes a difference in healthy longevity among older Chinese adults. Social Science & Medicine, 68(2), 210-219.

Gulliford M., Figueroa-Munoz J., Morgan M., Hughes D., Gibson B. Beech R. and Hudson M., (2002). What does 'access to health care' mean? Journal of Health Services Research & Policy, 7(3), 186–188

Gulliford, M., & Morgan, M. (Eds.). (2013). Access to health care. Routledge.

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. The Econometrics Journal, 148-161.

Heijink, R., Xu, K., Saksena, P., & Evans, D. (2011). Validity and comparability of out-of-pocket health expenditure from household surveys: a review of the literature and current survey instruments. World Health Organization.

Heller, P. S. (1982). A model of the demand for medical and health services in Peninsular Malaysia. Social science & medicine, 16(3), 267-284.

Hilaire, H. G. (2014). Does good governance improve public health expenditure-health outcomes nexus? New empirical evidence from Africa. <a href="http://www.ecoasso.org/articles/HOUENINVO Hilaire1.pdf">http://www.ecoasso.org/articles/HOUENINVO Hilaire1.pdf</a>

Hjortsberg, C. (2003). Why do the sick not utilise health care? The case of Zambia. Health economics, 12(9), 755-770.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of econometrics, 115(1), 53-74.

Iversen, T., & Kopperud G. S. (2005), Regulation versus practice - The impact of accessibility on the use of specialist health care in Norway, Health Economics, 14(12), 1231-1238

Jacobs, B., Ir, P., Bigdeli, M., Annear, P. L., & Van Damme, W. (2012). Addressing access barriers to health services: an analytical framework for selecting appropriate interventions in low-income Asian countries. Health Policy and Planning, 27(4), 288-300.

Jaffré, Y., & De Sardan O (ed.), (2003), Une medecine inhospitalière, Paris, APAD, Karthala.

Jamison, D. T., Breman, J. G., Measham, A. R., Alleyne, G., Claeson, M., Evans, D. B., & Musgrove, P. (Eds.). (2006). Disease control priorities in developing countries. World Bank Publications.

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. Journal of econometrics, 90(1), 1-44.

Kasilo, O. M. J., Trapsida, J. M., Mwikisa, C. N., & Samson, P. (2010). An overview of the traditional medicine situation in the African region. African Health Monitor, <a href="http://www.aho.afro.who.int/fr/ahm/issue/13/reports/overview-traditional-medicine-situation-african-region">http://www.aho.afro.who.int/fr/ahm/issue/13/reports/overview-traditional-medicine-situation-african-region</a>

Kasirye, I., Ssewanyana, S., Nabyonga, J., & Lawson, D. (2004). Demand for health care services in Uganda: implications for poverty reduction. Economic Policy Research Centre (EPRC), Research Series 40, <a href="http://purl.umn.edu/150529">http://purl.umn.edu/150529</a>

Kennedy, P. (2008). A Guide to Econometrics, 6th edition. Malden, MA: Blackwell Publishing.

KPMG (2012). The state of healthcare in Africa: A Progress Report, KPMG Africa, <a href="http://www.kpmg.com/africa/en/issuesandinsights/articles-publications/pages/the-state-of-healthcare-in-africa.aspx">http://www.kpmg.com/africa/en/issuesandinsights/articles-publications/pages/the-state-of-healthcare-in-africa.aspx</a>

Kumagai, N. (2005). Is Health Care a Necessity for the Elderly in Japan? Ikoma Journal of Economics, 2, 19-31.

Lalloo, R., Smith, M. J., Myburgh, N. G., & Solanki, G. C. (2004). Access to health care in South Africa-the influence of race and class: original article. South African Medical Journal, 94(8), 639-42.

Larson, P. S., Mathanga, D. P., Campbell, C. H., & Wilson, M. L. (2012). Distance to health services influences insecticide-treated net possession and use among six to 59 month-old children in Malawi. Malaria journal, 11(1), 1.

Le Grand, J. (1982). The Strategy of Equality. London, Allen and Unwin.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. Journal of econometrics, 108(1), 1-24.

Loef, M., & Walach, H. (2012). The combined effects of healthy lifestyle behaviors on all cause mortality: a systematic review and meta-analysis. Preventive medicine, 55(3), 163-170.

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and statistics, 61(S1), 631-652.

Makinen, M., Waters, H., Rauch, M., Almagambetova, N., Bitrán, R., Gilson, L., & Ram, S. (2000). Inequalities in health care use and expenditures: empirical data from eight developing countries and countries in transition. Bulletin of the World Health Organization, 78(1), 55-65.

Malmberg, B. (1994). Age structure effects on economic growth—Swedish evidence. Scandinavian Economic History Review, 42(3), 279-295.

Mazumdar, S. (2012). Assessing vulnerability to chronic undernutrition among under-five children in Egypt: contextual determinants of an individual consequence. International Journal of Population Research, 2012.

McCoskey, S., & Kao, C. (1998). A residual based test of the null of cointegration in panel data. Econometric Reviews, 17, 57-84.

McIntyre, D. I., Thiede, M., & Birch, S. (2009). Access as a policy-relevant concept in low-and middle-income countries. Health Economics, Policy and Law, 4(02), 179-193.

Mehmood, B., Raza, S. H., & Mureed, S. (2014). Health Expenditure, Literacy and Economic Growth: PMG Evidence from Asian Countries. Euro-Asian Journal of Economics and Finance, 2(4), 408-417.

Millman, M. (Ed.). (1993). Access to health care in America. National Academies Press.

Mitchell, R. J., Ozminkowski, R. J., & Serxner, S. (2013). Improving employee productivity through improved health. Journal of Occupational and Environmental Medicine, 55(10), 1142-1148.

Moon, H. R., & Perron, B. (2004). Testing for a unit root in panels with dynamic factors. Journal of econometrics, 122(1), 81-126.

Mooney GH (1983) Equity in health care: confronting the confusion. Effective Health Care 1, 179-185.

Moreno-Serra, R., & Smith, P. C. (2015). Broader health coverage is good for the nation's health: evidence from country level panel data. Journal of the Royal Statistical Society: Series A (Statistics in Society), 178(1), 101-124.

Morestin, F., & Ridde, V. (2009). The abolition of user fees for health services in Africa Lessons from the literature. Montreal: University of Montreal.

Morreale, M. C., Kapphahn, C. J., Elster, A. B., Juszczak, L., & Klein, J. D. (2014). Access to health care for adolescents and young adults. Journal of Adolescent Health, 35, 342-344.

Muftaudeen, O. & Bello, A. (2014). Public Healthcare Expenditure and Health Sector Performance in Nigeria: Implications for Sustainable Economic Development. IOSR Journal of Economics and Finance (IOSR-JEF), 4(3), 39-55.

Murthy, N.R.V. (2007), "Panel Cointegration Analysis: An Empirical Example, in Cointegration for the Applied Economist", In Das et al. (2012), Panel Cointegration and Pooled Mean Group Estimations of Energy-Output Dynamics in South Asia. Journal of Economics and Behavioral Studies, 4(5), 277-286.

Mwabu, G. M. (1991). Economic development and malaria prevalence: an empirical analysis with reference to Kenya. American Association for the Advancement of Science, 21:167-80.

Newhouse, J. P. (1992). Medical care costs: how much welfare loss? The Journal of Economic Perspectives, 6(3), 3-21.

Novignon, J., Nonvignon, J., & Arthur, E. (2015). Health Status and Labour Force Participation in Sub-Saharan Africa: A Dynamic Panel Data Analysis. African Development Review, 27(1), 14-26.

O'Connell, P. G. (1998). The overvaluation of purchasing power parity. Journal of international economics, 44(1), 1-19.

O'donnell, O. (2007). Access to health care in developing countries: breaking down demand side barriers. Cad. Saúde Pública, 23(12), 2820-2834.

Obrist, B., Iteba, N., Lengeler, C., Makemba, A., Mshana, C., Nathan, R., & Mshinda, H. (2007). Access to health care in contexts of livelihood insecurity: a framework for analysis and action. PLoS Med, 4(10), 1584-1588.

Odhiambo, S. A., & Wambugu, A. (2015). Convergence of Health Expenditure in Sub-Saharan Africa: Evidence from a Dynamic Panel. Journal of Economics and Sustainable Development, 6(6), 185-205.

Okwaraji, Y. B., Cousens, S., Berhane, Y., Mulholland, K., & Edmond, K. (2012). Effect of geographical access to health facilities on child mortality in rural Ethiopia: a community based cross sectional study. PLoS One, 7(3), e33564.

Okwaraji, Y. B., Webb, E. L., & Edmond, K. M. (2015). Barriers in physical access to maternal health services in rural Ethiopia. BMC health services research, 15(1), 1.

Oliver, A., & Mossialos, E. (2004). Equity of access to health care: outlining the foundations for action. Journal of epidemiology and community health, 58(8), 655-658.

Olsen, E. O., & Rogers, D. L. (1991). The welfare economics of equal access. Journal of public economics, 45(1), 91-105.

Oni, L. B. (2014). Analysis of the growth impact of health expenditure in Nigeria. IOSR Journal of Economics and Finance, 3(1), 77-84.

Park, H. M. (2011). Practical guides to panel data modelling: a step-by-step analysis using stata. Public Management and Policy Analysis Program, Graduate School of International Relations, International University of Japan.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61(Special Issue), 653-670.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric theory, 20(3), 597-625.

Penchansky, R. (1977). The concept of access: a definition. National Health Planning Information Center.

Penchansky, R., & Thomas, J. W. (1981). The concept of access: definition and relationship to consumer satisfaction. Medical care, 19(2), 127-140.

Pesaran, M. H. (2003). Estimation and inference in large heterogenous panels with cross section dependence.

Pesaran, M. H. (2004). "General Diagnostic Tests for Cross Section Dependence in Panels" IZA Discussion Paper No. 1240.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967-1012.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1997). Pooled estimation of long-run relationships in dynamic heterogeneous panels. University of Cambridge, Department of Applied Economics.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621-634.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. Journal of econometrics, 68(1), 79-113.

Peters, D. H., Garg, A., Bloom, G., Walker, D. G., Brieger, W. R., & Hafizur Rahman, M. (2008). Poverty and access to health care in developing countries. Annals of the New York Academy of Sciences, 1136(1), 161-171.

Rafindadi, A. A., & Yosuf, Z. (2013). An application of panel ARDL in analysing the dynamics of financial development and economic growth in 38 Sub-Saharan African continents. In Proceeding - Kuala Lumpur International Business, Economics and Law Conference. <a href="http://www.academia.edu/5473419/AN\_APPLICATION\_OF\_PANEL\_ARDL\_IN\_ANALYSING-THE\_DYNAMICS\_OF\_FINANCIAL\_DEVELOPMENT\_AND\_ECONOMIC\_GROWTH\_INGERO

Ricketts, T. C., & Goldsmith, L. J. (2005). Access in Health Services Research: The Babble of the Frameworks. Nursing Outlook 53(6):274–80.

Ringel, J. S., Hosek, S. D., Vollaard, B. A., & Mahnovski, S. (2002). The Elasticity of Demand for Health Care. A review of the literature and its application to the military health system (No. MR-1355-OSD). Rand National Defense Research Inst Santa Monica Ca.

Rutherford, M. E., Mulholland, K., & Hill, P. C. (2010). How access to health care relates to underfive mortality in sub-Saharan Africa: systematic review. Tropical medicine & international health, 15(5), 508-519.

Sanglimsuwan, K. (2011). The Relationship between Health and Environment: Econometric analysis. Conference on Interdisciplinary Research and Development, Thailand.

Sarafidis, V., & Wansbeek, T (2010). Cross-sectional Dependence in Panel Data Analysis. Online at <a href="http://mpra.ub.uni-muenchen.de/20815/">http://mpra.ub.uni-muenchen.de/20815/</a>

Sato, A. (2012). Does socio-economic status explain use of modern and traditional health care services?. Social Science & Medicine, 75(8), 1450-1459.

Sauerborn, R., Nougtara, A., & Latimer, E. (1994). The elasticity of demand for health care in Burkina Faso: differences across age and income groups. Health Policy and Planning, 9(2), 185-192.

Smith, K. V., & Sulzbach, S. (2008). Community-based health insurance and access to maternal health services: evidence from three West African countries. Social science & medicine, 66(12), 2460-2473.

Sotiriadou, K., Sarafis, P., & Malliarou, M. (2015). Economic development and improving health status. Nursing Care and Research, 6(34).

Sun, S., Chen, J., Johannesson, M., Kind, P., & Burström, K. (2015). Subjective well-being and its association with subjective health status, age, sex, region, and socio-economic characteristics in a Chinese population study. Journal of Happiness Studies, 1-41.

Syed, S. T., Gerber, B. S., & Sharp, L. K. (2013). Traveling towards disease: transportation barriers to health care access. Journal of community health, 38(5), 976-993.

Tanaka, S. (2010). Access to Health Infrastructure and Child Health Development: Evidence from Post-Apartheid South Africa. Institute of Social and Economic Research, Osaka University. DP 768.

Theuring, S., Mugenyi, K., Rubaihayo, J., Busingye, P., & Harms, G. (2015). Antiretroviral therapy programme retention and outcomes after 12 months in a retrospective patient cohort in Fort Portal, Uganda: the ongoing challenge of male ART performance. Journal of AIDS & Clinical Research, 2015.

Soors W., Waelkens, M.-P., & Criel, B. (2008). Community health insurance in sub-Saharan Africa: Opportunities for improving access to emergency obstetric care? [http://www.itg.be/itg] website, Studies in HSO&P 2008.

Tompa, E. (2002). The impact of health on productivity: empirical evidence and policy implications. The review of economic performance and social progress, 2.

U. N. Habitat, (2010). The State of African Cities 2010, Governance, Inequality and Urban land Markets. United Nations Human Settlements Programme (UN-HABITAT) Nairobi.

Vos, R. & Sánchez, V. M. (2014). Financing Human Development in Africa, Asia and the Middle East. The United Nations Series on Development, A&C Black.

Wang, F., & Luo, W. (2005). Assessing spatial and non-spatial factors for healthcare access: towards an integrated approach to defining health professional shortage areas. Health & place, 11(2), 131-146.

Westerlund, J. (2007). Testing for Error Correction in Panel Data. Oxford Bulletin of Economics and Statistics, 69(6), 709-748.

WHO. (2005). Health and the millennium development goals. World Health Organization.

WHO. (2014). World health statistics 2014. World Health Organization.

WHO. (2015). World health statistics 2015. World Health Organization.

Wooldridge, J. (2009). Introductory econometrics: A modern approach. 4th Ed., Cengage Learning.

Wouterse, F., & Tankari, M. (2015). Household Out-of-Pocket Expenses on Health: Does Disease Type Matter?. Journal of African Economies, ejv001.

Wright, J., Williams, R., & Wilkinson, J. R. (1998). Health needs assessment: Development and importance of health needs assessment. BMJ: British Medical Journal, 316(7140), 1310. Yao, J., Murray, A. T., Agadjanian, V., & Hayford, S. R. (2012). Geographic influences on sexual and reproductive health service utilization in rural Mozambique. Applied Geography, 32(2), 601-607.

Zheng, X., & Zimmer, D. M. (2008). Farmers' health insurance and access to health care. American Journal of Agricultural Economics, 90(1), 267-279.

# Appendix I. INDIVIDUAL COUNTRY REGRESSION RESULTS

Table AP1: PMG estimator results by country

ID	Countries <sup>1</sup>	ec	d.ln_gdp	d.ln_consf	d.ln_oop	d.ln_pop65	d.ln_popu:	d.ln_urb	cons
1	Algeria	-0.9260***	-0.4533	0.0362	-0.0072	5.7528***	-0.6389*	-78.6283***	-6.4099*
2	Angola	-0.7694***	0.3816	0.4647**	0.4257***	25.8491	-9.9633	-16.2111	-5.7015***
3	Benin	-0.7516***	1.3951	-0.0018	-0.0029	0.1327	-1.1691	-25.0884	-5.5649 <sup>**</sup>
4	Botswana	0.1373	-0.0049	0.0168	-0.1091**	-2.6698	-0.0175	-0.1648	1.0956
5	Burkina Faso	-0.3267	-3.7261	0.3147	-0.9745	-15.3697	-34.3251	-4.1175	-2.3758
6	Burundi	-0.4376*	-0.8710**	-0.0150	0.0571	1.6621	1.0090	-32.7864*	-1.6934
7	Cabo Verde	-1.1198 <sup>***</sup>	0.2584*	-0.2394**	0.0183*	-3.1467*	-9.0476 <sup>**</sup>	-10.2349	-8.7774 <sup>***</sup>
8	Cameroon	-0.3946**	0.0352	-0.0797***	0.4005***	-6.7100 <sup>**</sup>	7.9972***	-27.5555*	-2.6565**
9	Central African	**							**
	Rep.	-0.3940	0.8573	-0.2194	-0.0013	36.4675	-6.3496	27.9683	-3.1480
10	Chad	-0.7765***	-0.0680	0.4909	0.5297	-4.5197	0.7012	122.1504*	-6.2181***
11	Congo, Rep.	-0.9638***	2.5079***	0.0378	-0.1150	13.3738	-45.8029*	86.4550	-8.4282***
12	Côte d'Ivoire	-0.9041***	0.8440*	0.0010	0.0613	24.3034**	-10.8411**	-12.6775	-7.1173***
13	D.R. of Congo	-0.5018***	0.3109	0.3186*	0.3239	5.3706	-26.2899	76.1611***	-5.4442***
14	Egypt, Arab Rep.	-0.5704***	-0.6929	-0.0140	-0.1608	-2.2024	0.0736	7.7610	-4.2183 <sup>***</sup>
15	Equatorial Guinea	-0.7155***	0.0969	-0.2209**	0.1596	15.7416	36.0271***	-41.1432	-4.6344***
16	Ethiopia	-0.1618*	0.1603	-0.1198**	-0.0377	-0.4183	-1.4442	4.8454**	-1.2202**
17	Gambia, The	-0.2255*	0.2097	-0.1493**	0.0861	-0.6707	-7.9801	4.6792	-1.8155*
18	Ghana	-0.7839***	-1.1257**	0.0244	-0.0517	-4.7879	11.8274	10.6459	-6.0451***
19	Kenya	-0.1774	-0.2795	0.0369	-0.1474	-1.3602	-0.3822	-9.7012	-1.0824
20	Madagascar	-0.6160**	0.2043	0.0480	-0.0059	-11.6418*	-15.9877***	-0.0284	-4.7523 <sup>**</sup>

Source: Estimation

 $(1)\ d.lhce$  is the dependent variable for the model

Legend: \*p<0.10; \*\*p<0.05; \*\*\* p<0.01

Table AP2: PMG estimator results by country

ID	Countries <sup>1</sup>	ec	d.ln_gdp	d.ln_consf	d.ln_oop	d.ln_pop65	d.ln_popu5	d.ln_urb	cons
21	Malawi	-1.0664***	-1.0913	0.0487	0.0503	7.1743**	7.5169*	7.6710***	-6.9147***
22	Mali	-0.3081***	1.1528***	0.0830	0.4659***	-9.5670***	-43.4123***	0.3819	-2.3765***
23	Mauritania	-0.5157**	0.4326	-0.0620	-0.0709	-15.8826	-89.0556	-7.4969	-4.6182**
24	Mauritius	-0.0349	1.1523**	0.0477	0.1754*	-1.6156	-1.0487*	-17.4952	-0.3211
25	Morocco	-0.5608***	0.4977***	0.0882**	0.3991***	-6.0828***	-0.6616*	-5.5331	-4.1516***
26	Mozambique	-1.0619***	-0.1842***	-0.0586***	-0.0041	3.8342***	6.1610***	-3.4699***	-7.8446
27	Niger	-0.2378	0.2471	-0.0567	0.2270	-4.0899	-12.3158	13.4281	-1.7383
28	Nigeria	-0.7396**	0.9833	-0.1570	0.8223	22.9581	41.9738	-11.2072	-5.8744**
29	Rwanda	-0.8638***	-1.3294*	0.1431	-0.0783	-3.4229**	1.5519	7.7147***	-6.0651***
30	Senegal	-0.0945	0.8345	0.0194	0.3153***	-0.7169	25.3621***	-42.3361	-0.4624
31	Seychelles	-0.0153	0.4929***	0.0083	-0.0821**	1.8176***	-0.5115	4.8439	-0.1690
32	South Africa	-0.4865***	0.2071	0.0271	0.1364***	-0.2433	-0.1352	27.0950	-3.8425***
33	Sudan	-1.2256***	0.4153	-0.1104	-0.2786	4.6715	-47.0448 <sup>***</sup>	44.9594	-9.6934***
34	Swaziland	0.0529	1.0639	-0.1456	-0.0369	0.2560	-0.5313	-4.9049 <sup>*</sup>	0.3310
35	Tanzania	-0.8877***	2.1771	-0.4015*	-0.0975	10.0264	5.7825	1.9846	-6.6187***
36	Togo	-0.5625***	0.0382	-0.0190*	-0.0352	1.4829	-3.3436*	-45.4279***	-3.2276***
37	Zambia	-0.2354	-0.2161	-0.1525**	-0.0944	17.1063***	-5.7447	-2.7411**	-1.6768

Source: Estimation
(1) d.lhce is the dependent variable for the model.

Legend: \*p<0.10; \*\*p<0.05; \*\*\*p<0.01

# Appendix II. REGRESSION AND TEST OUTPUTS

# 1. Test for cross section independence (STATA 13)

. xtcd mg\_res, resid

Average correlation coefficients & Pesaran (2004) CD test

Residual series tested: mg res

Group variable: id Number of groups: 37

Average # of observations: 18.50

Panel is: unbalanced

Variable	CD-test	p-value	corr	abs(corr)
mg_res	-0.29	0.774	-0.003	0.221

Notes: Under the null hypothesis of cross-section independence CD ~ N(0,1)

# 2. Unit root test: ILC and IPS - Level variables (Eviews-9)

# a. Individual effects

Panel unit root test: Summary Series: LN\_HA Date: 11/01/15 Time: 22:23 Sample: 1995 2012 Exogenous variables: Individual effects Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

Panel unit root test: Summary Series: LN\_GDP Date: 11/01/15 Time: 22:26 Sample: 1995 2012 Exogenous variables: Individual effects

Method

Levin, Lin & Chu t\*

PP - Fisher Chi-square

Panel unit root test: Summary

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

Null: Unit root (assumes common unit root process)

Null: Unit root (assumes individual unit root process)Im, Pesaran and Shin W-stat3.583400.9998ADF - Fisher Chi-square77.26350.3748

Method	Statistic	Prob.**	Cross- sections	Obs
Null: Unit root (assumes comm	on unit root p	process)		
Levin, Lin & Chu t*	-2.04511	0.0204	37	610
Null: Unit root (assumes individ Im, Pesaran and Shin W-stat ADF - Fisher Chi-square	1.20053 83.9114	0.8850 0.2018	37 37	610 610
PP - Fisher Chi-square	63.2239	0.8098	37	629

PP - Fisher Chi-square	63.2239	0.8098	37	62
** Probabilities for Fisher tests -square distribution. All oth				

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Statistic

-1.06317

Prob.\*\*

0.1439

0.0000

Cross-

sections

608

608

629

Panel unit root test: Summary Series: LN\_CONSF Date: 11/01/15 Time: 22:30 Sample: 1995 2012

ADF - Fisher Chi-square

Method

Exogenous variables: Individual effects

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2

Null: Unit root (assumes common unit root process)

Null: Unit root (assumes individual unit root process)
Im, Pesaran and Shin W-stat 3.41708 0.9997

Newey-West automatic bandwidth selection and Bartlett kernel

-		
าร	Obs	Met
	617	<u>Nul</u> Lev
	617	<u>Nul</u> Im,
	617	ADF
	000	

Cross

37

\*\* Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Statistic

0.04757

54.3738

Prob.\*\*

0.5190

0.9579

Series: LN\_OOP Date: 11/01/15 Time: 22:31 Sample: 1995 2012 Exogenous variables: Individual effects Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	process)		
Levin, Lin & Chu t*	-0.98367	0.1626	37	613
Null: Unit root (assumes individ	ual unit roo	t process)		
Im, Pesaran and Shin W-stat	-0.31722	0.3755	37	613
ADF - Fisher Chi-square	109.451	0.0047	37	613
PP - Fisher Chi-square	109.573	0.0046	37	629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

Panel unit root test: Summary Series: LN\_POP65 Date: 11/01/15 Time: 22:34 Sample: 1995 2012 Exogenous variables: Individual effects

Automatic selection of maximum lags Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	process)		
Levin, Lin & Chu t*	-3.31016	0.0005	37	578
Null: Unit root (assumes individ	lual unit root	process)		
Im, Pesaran and Shin W-stat	1.06369	0.8563	37	578
ADF - Fisher Chi-square	174.044	0.0000	37	578
PP - Fisher Chi-square	91.8558	0.0781	37	629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: LN\_URB

Date: 11/01/15 Time: 22:36 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

Statistic	Prob.**	Cross- sections	Obs
on unit root p	process)		
-24.8208	0.0000	37	589
dual unit root	process)		
-2.76250	0.0029	37	589
644.139	0.0000	37	589
1747.06	0.0000	37	629
	non unit root p -24.8208 dual unit root -2.76250 644.139	non unit root process) -24.8208 0.0000  dual unit root process) -2.76250 0.0029 644.139 0.0000	Statistic         Prob.**         sections           non unit root process)         -24.8208         0.0000         37           dual unit root process)         -2.76250         0.0029         37           644.139         0.0000         37

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: LN\_POPU5 Date: 11/01/15 Time: 22:35 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	non unit root	process)		
Levin, Lin & Chu t*	-0.48802	0.3128	37	554
Null: Unit root (assumes indivi	<u>d</u> ual unit roo	t process)		
Im, Pesaran and Shin W-stat	-1.68589	0.0459	37	554
ADF - Fisher Chi-square	172.493	0.0000	37	554
PP - Fisher Chi-square	188.609	0.0000	37	629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

# b. Individual effect and linear Trend

Panel unit root test: Summary Series: LN\_HA Date: 11/01/15 Time: 22:01 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross- sections	Obs	
Null: Unit root (assumes comm			300000113	CDS	
	on unit root p	nocess,			
Levin, Lin & Chu t*	-3.75020	0.0001	37	601	
Breitung t-stat	0.39388	0.6532	37	564	
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat	-3.05778	0.0011	37	601	
ADF - Fisher Chi-square	115.387	0.0015	37	601	
PP - Fisher Chi-square	89.9808	0.0997	37	629	

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: LN\_CONSF Date: 11/01/15 Time: 22:05 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root p	process)		
Levin, Lin & Chu t*	-4.49658	0.0000	37	611
Breitung t-stat	-2.91344	0.0018	37	574
Null: Unit root (assumes individed in Pesaran and Shin W-stat ADF - Fisher Chi-square PP - Fisher Chi-square	dual unit root -2.79615 107.572 103.920	process) 0.0026 0.0066 0.0125	37 37 37	611 611 629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

Panel unit root test: Summary Series: LN\_GDP Date: 11/01/15 Time: 22:02 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-		
Method	Statistic	Prob.**	sections	Obs	
Null: Unit root (assumes common unit root process)					
Levin, Lin & Chu t*	-3.37957	0.0004	37	586	
Breitung t-stat	0.67395	0.7498	37	549	
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat	-1.73292	0.0416	37	586	
ADF - Fisher Chi-square	102.506	0.0158	37	586	
PP - Fisher Chi-square	74.5205	0.4612	37	629	

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: LN\_OOP Date: 11/01/15 Time: 22:07 Sample: 1995 2012

PP - Fisher Chi-square

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-		
Method	Statistic	Prob.**	sections	Obs	
Null: Unit root (assumes comm	on unit root	process)			
Levin, Lin & Chu t*	-2.53445	0.0056	37	595	
Breitung t-stat	2.80131	0.9975	37	558	
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat	-2.61746	0.0044	37	595	
ADF - Fisher Chi-square	124.099	0.0002	37	595	

98.0127

0.0324

629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

Panel unit root test: Summary Series: LN\_OOP
Date: 11/01/15 Time: 22:31 Sample: 1995 2012 Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	orocess)		
Levin, Lin & Chu t*	-0.98367	0.1626	37	613
Null: Unit root (assumes individ	<u>d</u> ual unit root	process)		
Im, Pesaran and Shin W-stat	-0.31722	0.3755	37	613
ADF - Fisher Chi-square	109.451	0.0047	37	613
PP - Fisher Chi-square	109.573	0.0046	37	629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: LN\_URB Date: 11/01/15 Time: 22:11

Sample: 1995 2012 Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	orocess)		
Levin, Lin & Chu t*	8.70040	1.0000	37	582
Breitung t-stat	-3.28457	0.0005	37	545
Null: Unit root (assumes individ	ual unit root	process)		
Im, Pesaran and Shin W-stat	10.7794	1.0000	37	582
ADF - Fisher Chi-square	76.8485	0.3875	37	582
PP - Fisher Chi-square	166.433	0.0000	37	629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

Panel unit root test: Summary Series: LN\_POPU5 Series. LN\_FOFOS Date: 11/01/15 Time: 22:10 Sample: 1995 2012 Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross- sections	Obs
Null: Unit root (assumes comm	non unit root	process)		
Levin, Lin & Chu t*	-9.64860	0.0000	37	565
Breitung t-stat	2.68512	0.9964	37	528
Null: Unit root (assumes indivi Im, Pesaran and Shin W-stat ADF - Fisher Chi-square PP - Fisher Chi-square	dual unit roo -9.33809 286.412 55.4514	0.0000 0.0000 0.0000 0.9472	37 37 37	565 565 629

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

# 3. Unit root test: ILC and IPS-First-differenced variables (Eviews-9)

# a. Individual effects

Panel unit root test: Summary Series: D(LN HA) Date: 11/01/15 Time: 23:04 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	process)		
Levin, Lin & Chu t*	-19.4362	0.0000	37	577
Null: Unit root (assumes individ	<u>l</u> ual unit root	process)		
Im, Pesaran and Shin W-stat	-17.0888	0.0000	37	577
ADF - Fisher Chi-square	386.789	0.0000	37	577
PP - Fisher Chi-square	455.880	0.0000	37	592

<sup>\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN GDP) Date: 11/01/15 Time: 23:05 Sample: 1995 2012

Exogenous variables: Individual effects
Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root	process)		
Levin, Lin & Chu t*	-9.69018	0.0000	37	569
Null: Unit root (assumes individ	dual unit root	process)		
Im, Pesaran and Shin W-stat	-9.99824	0.0000	37	569
ADF - Fisher Chi-square	247.093	0.0000	37	569
PP - Fisher Chi-square	387.880	0.0000	37	592

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_CONSF) Date: 11/01/15 Time: 23:07 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3 Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross- sections	Obs				
Null: Unit root (assumes comm	on unit root	process)						
Levin, Lin & Chu t*	-20.4261	0.0000	37	576				
Null: Unit root (assumes individual unit root process)								
Im, Pesaran and Shin W-stat	-18.0300	0.0000	37	576				
ADF - Fisher Chi-square	404.145	0.0000	37	576				
PP - Fisher Chi-square	840.877	0.0000	37	592				

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality

Panel unit root test: Summary Series: D(LN\_OOP) Date: 11/01/15 Time: 23:08 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-				
Method	Statistic	Prob.**	sections	Obs			
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu t*	-16.5042	0.0000	37	567			
Nivita I lada a a 4 /a a a como a a da alta d							
Null: Unit root (assumes individ							
Im, Pesaran and Shin W-stat	-16.1259	0.0000	37	567			
ADF - Fisher Chi-square	380.621	0.0000	37	567			
PP - Fisher Chi-square	666.745	0.0000	37	592			

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_POP65) Date: 11/01/15 Time: 23:09 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

	0	D 1 ++	Cross-	01			
Method	Statistic	Prob.**	sections	Obs			
Null: Unit root (assumes comm	on unit root p	process)					
Levin, Lin & Chu t*	-5.11394	0.0000	37	550			
Null: Unit root (assumes individual unit root process)							
Im, Pesaran and Shin W-stat	-4.08531	0.0000	37	550			
ADF - Fisher Chi-square	170.791	0.0000	37	550			
PP - Fisher Chi-square	198.725	0.0000	37	592			

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_URB) Date: 11/01/15 Time: 23:10 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes commo	n unit root p	process)		
Levin, Lin & Chu t*	0.63104	0.7360	37	566
Null: Unit root (assumes individu	al unit root	process)		
Im, Pesaran and Shin W-stat	1.85747	0.9684	37	566
ADF - Fisher Chi-square	111.279	0.0033	37	566
PP - Fisher Chi-square	114.741	0.0017	37	592

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_POPU5) Date: 11/01/15 Time: 23:09 Sample: 1995 2012

Exogenous variables: Individual effects Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 3

Newey-West automatic bandwic			tt kernel	
Method	Statistic	Prob.**	Cross- sections	Obs

Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu t*	-8.26665	0.0000	37	529			
Null: Unit root (assumes individ	Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	-7.27738	0.0000	37	529			
ADF - Fisher Chi-square	226.717	0.0000	37	529			
PP - Fisher Chi-square	69.2076	0.6359	37	592			

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi square distribution. All other tests assume asymptotic normality.

# b. Individual effect and linear Trend

Panel unit root test: Summary Series: D(LN\_HA) Date: 11/01/15 Time: 22:53 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 2 Newey-West automatic bandwidth selection and Bartlett kernel Panel unit root test: Summary Series: D(LN\_GDP)
Date: 11/01/15 Time: 22:55
Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags Automatic lag length selection based on SIC: 0 to 2

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-					Cross-	
Method	Statistic	Prob.**	sections	Obs	Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	non unit root	orocess)			Null: Unit root (assumes comm	non unit root	process)		
Levin, Lin & Chu t*	-19.0610	0.0000	37	584	Levin, Lin & Chu t*	-13.1526	0.0000	37	579
Breitung t-stat	-8.43831	0.0000	37	547	Breitung t-stat	-6.25397	0.0000	37	542
Null: Unit root (assumes individual unit root process)			Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	-14.7039	0.0000	37	584	Im, Pesaran and Shin W-stat	-11.0556	0.0000	37	579
ADF - Fisher Chi-square	309.872	0.0000	37	584	ADF - Fisher Chi-square	242.050	0.0000	37	579
PP - Fisher Chi-square	385.920	0.0000	37	592	PP - Fisher Chi-square	339.118	0.0000	37	592

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_CONSF)
Date: 11/01/15 Time: 22:57
Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2
Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-	
Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes comm	on unit root p	process)		
Levin, Lin & Chu t*	-20.7302	0.0000	37	581
Breitung t-stat	-13.6999	0.0000	37	544
Null: Unit root (assumes individe	ual unit root	process)		
Im, Pesaran and Shin W-stat	-15.8555	0.0000	37	581
ADF - Fisher Chi-square	331.782	0.0000	37	581
PP - Fisher Chi-square	453.688	0.0000	37	592

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_OOP)
Date: 11/01/15 Time: 22:57
Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 2 Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-				
Method	Statistic	Prob.**	sections	Obs			
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu t*	-16.1304	0.0000	37	580			
Breitung t-stat	-5.69650	0.0000	37	543			
Null: Unit root (assumes individ	<u>l</u> ual unit root	process)					
Im, Pesaran and Shin W-stat	-14.4070	0.0000	37	580			
ADF - Fisher Chi-square	303.430	0.0000	37	580			
PP - Fisher Chi-square	398.703	0.0000	37	592			

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary Series: D(LN\_POPU5) Date: 11/01/15 Time: 23:00

Im, Pesaran and Shin W-stat ADF - Fisher Chi-square PP - Fisher Chi-square

Automatic selection of maximum lags

Panel unit root test: Summary Series: D(LN\_POP65) Date: 11/01/15 Time: 22:59 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends

Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 2 Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross- sections	Obs		
Null: Unit root (assumes common unit root process)						
Levin, Lin & Chu t*	-7.39460	0.0000	37	570		
Breitung t-stat	3.35619	0.9996	37	533		
Null: Unit root (assumes indivious) Im, Pesaran and Shin W-stat ADF - Fisher Chi-square PP - Fisher Chi-square	dual unit root -5.31059 178.389 178.192	0.0000 0.0000 0.0000	37 37 37	570 570 592		

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Method Statistic Prob.\*\*
Null: Unit root (assumes common unit root process) Levin, Lin & Chu t\* Null: Unit root (assumes individual unit root process)

-10.7269

-3.76958 168.722

0.0000

0.0001 0.0000

Obs

552 515

552 552

Sample: 1995 2012 Exogenous variables: Individual effects, individual linear trends

Automatic lag length selection based on SIC: 0 to 2
Newey-West automatic bandwidth selection and Bartlett kernel

Panel unit root test: Summary Series: D(LN\_URB)
Date: 11/01/15 Time: 23:02 Sample: 1995 2012

Exogenous variables: Individual effects, individual linear trends Automatic selection of maximum lags

Automatic lag length selection based on SIC: 0 to 2

Newey-West automatic bandwidth selection and Bartlett kernel

			Cross-				
Method	Statistic	Prob.**	sections	Obs			
Null: Unit root (assumes common unit root process)							
Levin, Lin & Chu t*	-20.8987	0.0000	37	584			
Breitung t-stat	2.30117	0.9893	37	547			
Mode De Season Commence Season							
Null: Unit root (assumes individ		,					
Im, Pesaran and Shin W-stat	-9.08673	0.0000	37	584			
ADF - Fisher Chi-square	161.235	0.0000	37	584			
PP - Fisher Chi-square	172.960	0.0000	37	592			

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

# 4. Cointegration test - The Kao & Pedroni Tests (Eviews-9)

#### a. 1 Pedroni test – Individual Intercept

Pedroni Residual Cointegration Test

Series: LN\_HALN\_GDP LN\_CONSF LN\_OOP LN\_POP65 LN\_POPU5

LN\_URB

Date: 11/22/15 Time: 19:44 Sample: 1995 2012 Included observations: 666 Cross-sections included: 37 Null Hypothesis: No cointegration Trend assumption: No deterministic trend

Automatic lag length selection based on SIC with a max lag of 2 Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

#### Weighted Statistic Statistic Prob. Prob -3.928033 1.0000 -6.579377

Panel v-Statistic 1.0000 Panel rho-Statistic 5.601776 1.0000 5.549288 1.0000 Panel PP-Statistic -6.528842 0.0000 -16.93079 0.0000 Panel ADF-Statistic -6.158719 0.0000 -9.267855 0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.	
Group rho-Statistic	7.673583	1.0000	
Group PP-Statistic	-23.70177	0.0000	
Group ADF-Statistic	-9.167445	0.0000	

<sup>\*\*</sup> Probabilities for Fisher tests are computed using an asymptotic Chi square distribution. All other tests assume asymptotic normality.

# a.2 Pedroni test - Individual Intercept and individual trend

Pedroni Residual Cointegration Test

Series: LN\_HALN\_GDP LN\_CONSF LN\_OOP LN\_POP65 LN\_POPU5

LN\_URB

Date: 11/22/15 Time: 19:47 Sample: 1995 2012 Included observations: 666 Cross-sections included: 37 Null Hypothesis: No cointegration

Trend assumption: Deterministic intercept and trend

Automatic lag length selection based on SIC with a max lag of 1 Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

•		Weighted		
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-6.213108	1.0000	-8.835486	1.0000
Panel rho-Statistic	7.318507	1.0000	6.979584	1.0000
Panel PP-Statistic	-7.832599	0.0000	-21.81196	0.0000
Panel ADF-Statistic	-6.119382	0.0000	-9.183890	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	8.518998	1.0000
Group PP-Statistic	-27.37663	0.0000
Group ADF-Statistic	-8.724750	0.0000

# b.1 Kao test - Dependent and all variables

Kao-Residual Cointegration Test

Series: LN\_HALN\_GDP LN\_CONSF LN\_OOP LN\_POP65 LN\_POPU5

LN\_URB

Date: 11/22/15 Time: 19:48
Sample: 1995 2012
Included observations: 666
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend

Automatic lag length selection based on SIC with a max lag of 3 Newey-West automatic bandwidth selection and Bartlett kernel

ADF	<u>t-Statistic</u> -3.294055	Prob. 0.0005
Residual variance HAC variance	0.009550 0.008784	

# 5. Main regression estimation: Long-run and Short-run outputs (STATA 13)

. est table DFE PMG MG, p stats(N 11)

Variable	DFE	PMG	MG
ec			
ln gdp	.19699233	.11491196	.42188157
	0.0000	0.0011	0.5672
ln consf	.09612911	.06437702	37565777
_	0.2139	0.0000	0.4228
ln_oop	04716085	.01598559	.15232392
	0.7051	0.0690	0.7040
ln_pop65	.27467354	.06116057	-9.7011023
	0.3125	0.4689	0.1823
ln_popu5	11230031	.49215301	-9.4734667
	0.6510	0.0000	0.3323
ln_urb	1.0477554	1.0243155	-24.503985
	0.0020	0.0000	0.0979
SR	+ 		
ec	26271056	54655858	-1.0799791
	0.0000	0.0000	0.0000
ln gdp			
D1.	.08467574	.18686037	.45934042
	0.0769	0.2790	0.0560
ln consf			
- D1.	02414016	.00088825	.02293149
	0.0514	0.9760	0.7886
ln oop			
D1.	.07957716	.06114904	.18120034
	0.3036	0.1996	0.0467
ln_pop65			
D1.	.15103018	2.7800726	13.784343
	0.6183	0.1391	0.0373
ln_popu5			
D1.	01226182	-6.1638028	-5.864923
	0.9478	0.1071	0.5979
ln_urb			
D1.	1.4560975	1.3458196	31.583757
	0.3414	0.8219	0.5017
_cons		-4.0938246	
	0.0003	0.0000	0.2806
Statistics	+ 		
N	i I	629	629
11	İ		1751.7952

legend: b/p

# 6. Hausman test (STATA 13)

# a.1 MG vs PMG

#### . hausman MG PMG

	Coeffic	cients ——		
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	MG	PMG	Difference	S.E.
ln_gdp	.4218816	.114912	.3069696	.7364437
ln_consf	3756578	.064377	4400348	.4684355
ln_oop	.1523239	.0159856	.1363383	.4007914
ln_pop65	-9.701102	.0611606	-9.762263	7.27323
ln_popu5	-9.473467	. 492153	-9.96562	9.770783
ln_urb	-24.50398	1.024315	-25.5283	14.80344

 $\label{eq:beta} b = consistent \ under \ Ho \ and \ Ha; \ obtained \ from \ xtpmg \\ B = inconsistent \ under \ Ha, \ efficient \ under \ Ho; \ obtained \ from \ xtpmg$ 

Test: Ho: difference in coefficients not systematic

$$chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)$$
  
= 5.83  
Prob>chi2 = 0.4419

# a.2 PMG vs DFE

#### . hausman PMG DFE

	Coeffi	cients		
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	PMG	DFE	Difference	S.E.
ln_gdp	.114912	.1969923	0820804	.0267
ln_consf	.064377	.0961291	0317521	-
ln_oop	.0159856	0471609	.0631464	
ln_pop65	.0611606	.2746735	213513	
ln_popu5	. 492153	1123003	. 6044533	
ln_urb	1.024315	1.047755	0234399	-

b = consistent under Ho and Ha; obtained from xtpmg B = inconsistent under Ha, efficient under Ho; obtained from xtpmg

Test: Ho: difference in coefficients not systematic

# 7. Regression by Income class: Long-run and short-run outputs (STATA 13)

. est table PMG\_LI PMG\_LMI PMG\_UMI, p stats(N 11)

Variable	PMG_LI	PMG_LMI	PMG_UMI
ec			
ln gdp	.33757299	.61667758	.5596759
9	0.0000	0.0000	0.0118
ln consf	.06233706	.02562399	.52398303
	0.0020	0.2839	0.0037
ln oop	.00967342	24571881	.17078686
	0.3844	0.0001	0.0003
ln pop65	-1.0278237	.22257711	.14009942
	0.0000	0.5506	0.6723
ln popu5	.38874008	-1.1067069	03232908
	0.0000	0.0087	0.9205
ln urb	0864753	.49520487	8459437
_	0.5453	0.2662	0.5520
	+		
SR			
ec	60693541	53716741	43053253
	0.0000	0.0001	0.0007
ln_gdp			
D1.	19114343	.28775659	04913462
	0.5306	0.3639	0.8839
ln_consf			
D1.	.0265362	04108927	02569185
	0.5405	0.3056	0.6894
ln_oop			
_D1.	.04152518	.16498224	.05356534
	0.5842	0.0805	0.4823
ln_pop65			
D1.	1.5889053	3.6562496	6.2127381
1	0.5832	0.2790	0.3079
ln_popu5	6 500000	0.0506060	0 4005605
D1.	-6.7220016	-3.8536861	-3.4005697
1	0.1309	0.6380	0.0373
ln_urb D1.	   12.90774	12 125205	13.582282
DI.	0.1795	12.175785 0.3554	0.6273
	-2.1671369		-2.4232665
_cons	0.0000	0.0001	
		0.0001	0.0260
Statistics	 		<b></b>
N	1 289	221	102
11	555.7262		
			1 1 - 1 - /

legend: b/p

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