Demand-side determinants of access to healthcare services: Empirical evidence from Africa

Wa Ntita Serge Kabongo and Josue Mbonigaba

ERSA working paper 641

October 2016

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

Demand-side determinants of access to healthcare services: Empirical evidence from Africa

Wa Ntita Serge Kabongo and Josue Mbonigaba*

October 12, 2016

Abstract

This study identifies the key determinants of access to healthcare in Africa and estimates the short-run and long-run effects of these determinants. Panel data from 37 African countries, collected from the World Bank Development Indicators and World Health Organisation databases for the period 1995-2012, were analysed using the pooled mean group estimators. Income appeared the strongest determinant of access in the long run in countries in Africa included in the sample. Access to healthcare was a necessity with the long-run income elasticity for access to healthcare being 0.1149. The short-run effects of income on access were, however, only significant in four of the countries in the sample. The difference in the effects of income in the short run and the long run was generally applicable to other variables. These findings imply that policy makers should focus on income to increase access to healthcare while taking cognisance of country-specific conditions in the short run to mitigate varying levels of shocks.

Keywords: Access to healthcare, Dynamic panel data, Africa

JEL Classification: I-11, I-15, I-18, C-23

1 Introduction

Improved health status is one of the most important items on the international development agenda because of the economic and social benefits that it provides. The importance of better health status is reflected in the presence of health-related items in the Millennium Development Goals (MDG) as well as in the more recently adopted Sustainable Development Goals (SDG). Theoretically, better health status promotes economic development through improved productivity and learning capabilities, reduces the treatment burden, and contributes

*Department of Economics, University of KwaZulu-Natal. Corresponding author - e-mail: Mbonigaba@ukzn.ac.za

to well-being as a source of enjoyment of life and happiness for households and individuals (Grossman, 1972).

These theoretical benefits of enhanced health status have been supported by empirical evidence both at micro and macro levels (Mitchell et al., 2013; Boman & Isiaka, 2015; Goetzel, et al., 2004; Oni, 2014; Bloom & Canning, 2015; Peters et al., 2008). At a micro level, a recent study showed that healthier individuals are more productive through mechanisms such as fewer days of absence from work, and fitness while at work (Goetzel, et al., 2004). At macro levels, better health status was found to be positively associated with economic growth (Oni, 2014; Bloom & Canning, 2015), and in recent evidence, better health status has also been linked to poverty reduction (Peters, et al., 2008).

Despite the positive association between health status, productivity and well-being, health status has remained relatively poor in low-income countries (LIC). In Africa especially, the situation has been alarming. Statistics from the World Health Organisation (WHO) show that in 2012, people in Africa had the lowest life expectancy at birth and suffered about a third of the world deaths (WHO, 2014). The evidence further reveals that 60.7 percent of these deaths were caused by preventable or curable diseases such as malaria, diarrhoea and pneumonia (Loef & Walach, 2012; Corburn & Hildebrand, 2015), raising the issue of access to basic healthcare. This situation prevails despite evidence that access to available health facilities is effectively improving health among the most vulnerable (Tanaka, 2010). The evidence is also that these facilities are underutilised (Enyioko & Samuel, 2012; Adorka et al.,2013; Astale & Chenault, 2015). Indeed, studies estimate that millions of individuals on the continent suffer and even perish as a result of the underutilisation of healthcare resources (Theuring, Mugenyi, Rubaihayo, Busingye, & Harms, 2015).

The importance of access to healthcare, and the prevailing underutilisation of healthcare facilities in Africa has prompted an interest among researchers (O'Donnel, 2007) and policy makers (Rutherford et al., 2010; Morreale et al., 2014; Ganesh, 2015) in assessing demand-side factors related to access to healthcare. Theoretically, access to healthcare can be affected by supply- and demand-side factors, ranging from social, economic and behavioural factors to environmental factors. Although evidence on access remains insufficient, demand-side factors have been relatively less investigated, especially at macro levels (Drabo & Ebeke, 2011), as most studies focused on supply-side factors (Gulliford, et al., 2002; Zheng & Zimmer, 2008; Gulliford & Morgan, 2013). Furthermore, in spite of the existence of multiple indicators of access to healthcare, such as availability of facilities, out-of-pocket payment, health status levels, affordability, and government budget allocations, most analyses (Oliver & Mossialos, 2004; Peters, et al., 2008; Delamater et al., 2012) focused on supply-side factors and used separate indicators of access to healthcare (Aakvik & Holmås, 2006; Delamater et al., 2012; Moreno-Serra & Smith, 2015; Leegwater et al., 2015). Thus, not only did these studies overlook demand-side factors but they also ignored the use of a composite indicator of access to healthcare. Studies that considered demand-side factors of access to healthcare (Berthelemy & Seban, 2009; O'Donnel, 2007) did not use a composite index of access either. To the best of our knowledge studies by Belasco et al. (2012) and Leegwater et al. (2015) are the only studies that used a composite index of access although they did not focus on demand-side determinants of that access. Furthermore, these studies did not distinguish short-run (SR) and long-run (LR) effects of these determinants. This paper contributes to the literature by identifying demand-side determinants of access, and distinguishing SR and LR effects of these determinants in the context of an autoregressive distributed lag (ARDL) model. Given the importance of access to healthcare, this evidence is relevant for policy making in Africa.

The remainder of the paper is structured as follows: The next section presents the methodology employed to conduct this study. Section 3 presents the results, while Section 4 discusses the study's results and conclusion.

2 Methods

2.1 Theoretical framework

Since the 1970s, access to healthcare has been conceptualised in different ways encompassing demand and supply facets (Donabedian, 1972; Aday & Andersen, 1974; Penchansky, 1977; Gulliford, et al., 2002; Oliver & Mossialos, 2004; Peters, et al., 2008). This paper focuses on the demand-side conception of access by Delamater et al. (2012) and follows the framework of Peters et al. (2008) where access or utilisation was also conceived in terms of financial accessibility (price of care, income) and the geographical accessibility (distance to health facilities).

2.2 Contributing factors indicating access to healthcare

Based on the conception of access adopted, an index of access (HA) is constructed and used as a dependent variable. This index represents the following three indicators of access (Moreno-Serra & Smith, 2015): government health expenditure per capita, voluntary health insurance expenditure per capita, and an aggregate immunisation rate constructed from six immunisation rates (diphtheria, tetanus toxoid and pertussis; polio; measles; haemophilus influenza type b; Bacillus Calmette–Guérin (BCG); and hepatitis B). The methodology was borrowed from that used by the Colorado Health Institute (2015).

Following the methodology, each series of the above variable indicators is normalised using its maximum value, assumed to represent the best score of access. Thereafter, the average value of the indicators is used for each observation to constitute the index of access to healthcare. The estimation of the index does not take into account the weights of indicators because of the absence of weighting criteria. To circumvent this issue, the study unsuccessfully attempted the use of the principal component analysis (PCA) as an alternative. Indeed, while the sampling adequacy of PCA requires a Kaiser-Meyer-Olkin (KMO) test statistic of greater than 0.5 (Zuo et al., 2015), running this test on our data resulted in a test statistic of 0.4, suggesting that PCA was not appropriate for our data. Thus, the index of access was used, following the methodology of the

Colorado Health Institute.

Following Peters et al. (2008) and confining our analysis to data availability, our main covariates are income, measured as constant gross domestic product (GDP) in United States (U.S.) dollars (2005), and distance to healthcare facilities (DHF), measured in terms of fuel consumption (CFC). In the absence of the price of healthcare data in Africa, we thought that the distance to facility (DHF) could act as a proxy. This was then estimated in terms of the volume of fuel consumption, using the number of barrels of fuel consumed in each country. According to the demand theory, the increase in the GDP is expected to increase access to healthcare. With respect to the volume of fuel consumed, it can be positively related to access in the case that the volume increases with the number of those commuting to healthcare facilities. The opposite, however, is true if the volume increases because of distances travelled. So the sign on the distance measure used in this study is a matter of empirical outcome.

Based on the literature on health and its relevance to this study, some covariates have been included in the study model in order to control for the effects of health systems, the structures of the population, and the environments. The study used out-of-pocket payment (OOP) as a share of total expenditure on health to proxy the health system (Heijink et al., 2011) and this variable was expected to have a negative sign. The elderly and the under-five section of the total population was included to control for the effects of the structure of the population as in Malmberg (1994), and is expected to have a positive sign because in Africa, the aged and children under five have a high disease burden. The urban population section of the total population (URB) was included to control for the spatial distribution (urban-rural) of the population as in Sanglimsuwan (2011). This indicator is measured as a percentage share of the total population and is expected to have a positive sign.

2.3 Data

2.3.1 Data collection

Data on 37 African countries (list in Appendix 7) from 1995 to 2012 were collected from the World Health Organisation (WHO) and World Development Indicators (WDI) online databases, except for the data on fuel consumption, which were obtained from the U.S. Energy Information Administration (EIA). While Africa is made up of 54 countries, 17 countries were excluded from the analysis due to missing data. Countries remaining in the sample are still a good representation of Africa as whole as they include countries with different levels of incomes, burdens of diseases and geographical locations. Thus, the exclusion of 17 countries would not bias the estimates and conclusions.

2.3.2 Descriptive Statistics

The panel data of this study has a large T (T>10) suggesting the use of dynamic panel data modelling (Breitung & Pesaran, 2008). In large T, non-stationarity and spurious regressions are resolved by this type of modelling (Wooldridge, 2009). The modelling also takes care of potential cross-sectional dependence that can arise from these types of data (Sarafidis & Wansbeek, 2012).

Appendix 1 provides descriptive statistics for the variables used in this study. Appendix 2 presents the graphs of level and first-differenced variables of interest, showing that level variables are not stationary but first-differenced variables are stationary. Still, formal stationarity tests and cross-section dependence tests are required for further diagnostics on the data. The correlation matrices between study variables are provided in Appendices 3-6 for both the "global" sample (all 37 African countries included in this study) and the country income class (income groups as per World Bank classification). From these correlation matrices, a number of correlations are found. In the "global" sample, access to healthcare is positively correlated with the GDP, the cost of fuel consumption and the elderly, while it is negatively correlated with the OOP. However in the income class sub-samples, access to healthcare and the number of elderly people are positively correlated with GDP only in the lower middle-income countries (LMIC) and upper middle-income countries (UMIC). Thus the correlation of access to healthcare with the number of elderly people and the GDP in the low-income countries (LIC) is not consistent with that of the full sample.

2.3.3 Preliminary data diagnostics

The following tests were carried out to determine whether the study variables have unit root (UR) or the panels in data are cross dependent. The modelling depends on whether these issues are present or not.

Cross-section dependence (CSD) test The Pesaran cross-section dependence (CSD) test is used to test for correlations among the panels. The p-value of 0.77 observed under the null hypothesis of cross-sectional independence suggests that this hypothesis cannot be rejected. Thus there is statistical evidence that the study panels are independent.

Unit root (UR) tests Following the independence of the panels, the study assumes individual unit root process and uses the Augmented Dickey-Fuller (ADF), Philip Perron (PP) and Im-Pesaran-Shin (IPS) tests because they allow testing the UR under the assumption of heterogeneity (Baltagi et al., 2010). These tests are, furthermore, easy to implement using standard software packages. Table 1 reports the results of the UR tests on level variables applying the ADF-Fisher, PP-Fisher and IPS tests with individual effects for exogenous variables (columns 1, 2 and 3).

In all three tests the Schwarz information criterion has been used for the lag length selection. The results from all the tests indicate that only the variables "under-five" and "urban populations" are consistently stationary (the null hypothesis of UR is rejected at 1% and 5% levels of significance). While stationary variables "under-five mortality, popu5", and "urban populations, urb" are I(0), there is no information showing that the remaining non-stationary variables are

I(1) in order to carry out the cointegration test that requires the variables to be I(1) or a mix of I(1) and I(0). Thus, the UR tests for first-differenced variables are carried out to determine if the non-stationary variables are I (1). The UR tests results with first-differenced variables are presented in Table 2.

The results from the three tests depicted in Table 2 show that all the series are stationary, except for the IPS test result on the variable *urb* which was stationary at level. The results of all these tests reject the null hypothesis of UR at all levels of significance. The fact that we fail to reject the null hypothesis on the first difference on the *urb* is due to power issues with unit root tests Therefore, we can conclude that the study data has a mix of I (0) and I (1) variables. This feature allows for the cointegration test.

Cointegration test Following the results from the CSD and the UR tests, the Kao and Pedroni tests were used to test whether the study variables are cointegrated or not. The results from these tests are presented in Table 3.

The Kao test in column 1 shows that the study variables are cointegrated since the null hypothesis of no cointegration is rejected at all levels of significance. The results of the Pedroni (2004) cointegration test are presented in columns 2 and 3. Except for group rho-statistic, panel rho-statistic and panel v-statistic, the remaining statistics significantly reject the null hypothesis of no cointegration. In fact, performing Monte Carlo simulations, Pedroni (2004) demonstrates that the group-rho, panel-rho and panel-v tests have lower power than the panel ADF statistic and group ADF statistic. Thus, using higher power tests in our results, the null hypothesis of UR is rejected at all levels of significance by the panel-ADF, panel-PP statistic, and group-ADF and group-PP statistics. Hence, it can be concluded that variables in our behavioural equation trend together in the long run.

2.3.4 Modelling approach

The diagnostics on the data conducted above suggest that the study can use a dynamic ARDL panel model derived from the general model of health access (Dor & Van Der Gaag, 1988), which is re-parameterised into an error correction model (ECM) using the study variables. This allows modelling both the SR and LR effects of the variables on access to healthcare. The ECM is specified as follows:

$$\begin{aligned}\Delta ha_{it} = \phi_i(ha_{i,t-1} - \theta_{1i} gdp_{i,t-1} - \theta_{2i} cfc_{i,t-1} - \theta_{3i} oop_{i,t-1} - \theta_{4i} pop\ 65_{i,t-1} \\ -\theta_{5i} popu\ 5_{i,t-1} - \theta_{6i} urb_{i,t-1}) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta ha_{i,t-j} + \sum_{j=0}^{q-1} \delta_{1ij} \Delta gdp_{i,t-j} \\ + \sum_{j=0}^{q-1} \delta_{2ij} \Delta cfc_{i,t-j} + \sum_{j=0}^{q-1} \delta_{3ij} \Delta oop_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4ij} \Delta pop\ 65_{i,t-j} \\ \sum_{j=0}^{q-1} \delta_{5ij} \Delta popu\ 5_{i,t-j} + \sum_{j=0}^{q-1} \delta_{6ij} \Delta urb_{i,t-j} + \omega_i + u_{it} \\ i = 1, 2, ...37 \qquad t = 1, 2, ...18\end{aligned} \tag{1}$$

Where for any country i at time t, ha is access to healthcare, gdp is the per capita GDP, cfc is the cost of fuel consumption, oop is the out-of-pocket payment share of health expenditure, *pop65* and *popu5* are the elderly and under-five populations, and *urb* is the urban population as a share of total population. All the variables in Equation (1) are either lagged or first-differenced. The parameters θ and δ are the coefficients on the LR and SR independent variables, respectively, (k = *1... 6*), λ are the coefficients on lagged access to healthcare, ϕ is the speed of adjustment, ω is the unobserved fixed effects and μ the idiosyncratic error terms. The model in Equation (1) is a log-log model, the most popular ?exible functional form to guarantee the linearity of the model that allows it to interpret the coefficient as elasticities (Green, 2002).

The parameters of interest are θ_{1i}, θ_{2i}, and $\phi_{i,}$ which measure, respectively, the LR income elasticity for access to healthcare, the LR effect of fuel consumption on access to healthcare, and the speed of adjustment. The θ_{1i} is expected to have positive signs, while θ_{2i} and ϕ_i are expected to be negative. A negative coefficient of the speed of adjustment term, combined with the lagged variables, provides us with an "error correction mechanism" that will allow the system to move back to equilibrium after a shock. The inclusion of the unobserved factor (μ_i) seeks to capture the heterogeneity across African countries.

The results of the CSD suggested that the panels in the study dataset are independent. These results prompted the use of three estimators: the mean group (MG), the pooled mean group (PMG) and the dynamic fixed effect (DFE) estimators to evaluate the ECMs in this context (Blackburne & Frank, 2007).

The MG estimator was suggested by Pesaran & 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 LR parameters for the panels by averaging the LR parameters from ARDL models for individual countries. The coefficients are heterogeneous in the LR and in the SR. 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.

The DFE estimator restricts not only the coefficient of the cointegrating vector to be identical across all panels in the LR, but also the speed of adjustment coefficient and the SR coefficients. The DFE allows panel-specific intercepts and calculates the standard error allowing the 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 et al., 2000).

Suggested by Pesaran et al. (1997), the PMG aims at detecting the LR and SR association between variables while taking into account possible heterogeneity across countries. It combines both pooling and averaging of coefficients. It also allows the intercept, the SR coefficients and the error variances to vary across the units, while constraining the LR coefficients to be equal across countries. The PMG requires large T and large N to avoid the bias in the average estimators.

The practice of estimating ECMs in the context of cross-section independence of the panel data induces the estimation of the three models DFE, MG and PMG (Blackburne & Frank, 2007) because a priori, the hypothesis that holds on coefficients of the model is unknown. The model, between the three, that best suits the data is thus selected post estimation applying the Hausman test.

3 Regression results

3.1 Model selection

Table 4 provides the regression results of the three models. The EC part includes the LR elasticities and the SR part includes both the SR elasticities and the speed of adjustment.

The regression results show that the LR elasticities are statistically significant for our variables of interest only in the PMG model. These elasticities are significant for GDP only in the DFE while for the MG they are all insignificant. The Hausman tests for model selection supports the choice of the PMG model, since they provide the p-value of 0.4419 (test against MG) and the p-value of zero (test against DFE) supporting the choice of the model. Thus the PMG suits the data best and is used as a reference model. When LR coefficients are the same but SR coefficients are different, the PMG estimator constraints are met for it to produce efficient and consistent estimators (Blackburne & Frank, 2007). In the context of African countries, the suitability of PMG can be justified in that these countries are engaged in common international and local programmes to combat health threats (HIV, tuberculosis, malaria), to achieve MDG and SDG objectives for health, such that they are trending together (common LR effect). They might, however, achieve these objectives at a different pace (SR effect) given their different characteristics and approaches to dealing with issues of access to healthcare.

3.2 Global and income class specific estimates

This subsection presents the regression results from the "global" model as well as from the income class specifications. The income class specifications results are presented in order to assess the robustness of the results from the main model. That is, it is assumed that aside from the identified factors, access to healthcare could also be in?uenced by other features of countries' macroeconomic environments such as income levels. 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. Hence, regressions by the country's income classes have been carried out. The selected countries include 17 LIC, 13 LMIC and 7 UMIC. Table 5 presents LR homogeneous regression coefficients ("global" and by income class, that is, LIC, LMIC and UMIC). The SR coefficients that differ across countries according to models assumptions are in Appendices 7-10.

3.2.1 Long-run estimates

Table 5 shows that in the "global" specification, the LR elasticities of the main variables are statistically significant at all levels. The income elasticity of 0.1149 shows that in the LR, a 1% increase in GDP per capita increases access to healthcare by 0.1149 percentage points, other things remaining the same, while the CFC variable indicates that a 1% increase in fuel consumption increases access to healthcare by 0.0644 percentage points. This model also shows that three control variables have significant LR elasticities: the URB and the POPU5 at all levels of significance and the OOP at a 10% level of significance.

In income class specifications, only the LR income elasticity is consistently significant across all the specifications as in the global model. However, income impacts differently on access across different income groups, with the highest impact in the LMIC (0.6167) and the lowest in the LIC (0.3376). In income classes, the LR income elasticities of access are positive as in the "global" model, although its magnitude differs from one group to another: 0.3376 for LIC, 0.5597 for UMIC, and 0.6167 LMIC. The LR CFC elasticity is statistically significant only in the LIC and the UMIC specifications. It is worth noting that an income elasticity of 0.1149 in the "global" model is closer to the one from the LIC group than any other income class, probably because of more LICs in the sample (17 countries precisely).

3.2.2 Short-run or country-specific estimates

Short-run coefficients are presented in Appendices 7-10. Considering significance levels of 1% and 5%, the "global" model (Appendix 7) suggests that income (GDP) is a strong determinant of access to healthcare with the expected sign only for a few countries, notably, Congo Republic, Mali, Mauritius, Morocco and Seychelles. The income elasticity of access to healthcare varies from 0.4929 percentage points in Seychelles to 2.5079 percentage points in Congo Republic. Unexpected negative effects of income on access are observed in Burundi, Ghana and Mozambique, and a possible explanation for this observation is provided in the discussion section. Results in the SR are also different from those in the LR for fuel consumption (CFC), which had negative and significant effects for four countries (at 1% and 5% significant level), except in Angola.

4 Discussion

This paper set out to identify demand-side determinants of access to healthcare in Africa and to estimate the SR and LR effects of these determinants. The scant evidence on demand-side factors, the recent and increasing interest in these factors by researchers and policy makers, the underutilisation of available facilities (Enyioko & Samuel, 2012), and the need to expand healthcare coverage (Harris, et al., 2011) motivated this analysis. On the basis of the theory and literature, the study identified income (GDP) and distance to health facilities (additional cost of accessing healthcare) as the main determinants of access to healthcare, with the health system, structure of the population, and environment, as control variables. SR and LR effects of these variables on access to healthcare were analysed by applying a PMG model on these variables. Data for 37 African countries spanning the period 1995-2012 for these variables were collected from the World Health Organisation (WHO), World Development Indicators (WDI) and U.S. Energy Information Administration (EIA) online databases.

The study found that income is the strongest LR determinant of access to healthcare in Africa with a common income elasticity of 0.1149. The evidence of income elasticity being less than 1 implied also that access to healthcare is a necessity. The study found further that the distance to health facilities, measured by the volume of fuel consumption (CFC) was positively associated with access to healthcare in the LR with a coefficient of 0.0644. This finding is unexpected in case the volume of fuel consumption is a result of more distances travelled. However, this result can be expected in case more fuel consumption is a result of more commuting, which might ease access and reduce transport fares as a result of competition. The interpretation of the result in this manner remains only valid inasmuch as more access to transport services more generally translates into easiness of access to transport services towards healthcare facilities.

The plausibility of the latter explanation can indeed be argued in terms of the fact that the transport sector is one of the most lucrative sectors in Africa. Over time, the investments in the sector might have contributed to an increase in transport services more generally, which in tum increased access to healthcare services.

Unlike LR effects of income in the "global" and income class models, the SR (country-specific) effects of income was not very significant. Of the 37 countries covered by the study, SR income effects were significant only in five countries, notably Seychelles, Mali, Mauritius, Morocco and Congo Republic. Income elasticity ranged from 0.4929 in Seychelles to 2.5079 in Congo Republic. Unexpected findings in the SR included a negative effect of income on access in some countries. While this result is difficult to explain theoretically, in the context of healthcare, health outcomes such as seriousness of illness and the high burden of diseases among under-five children might drive the necessity to seek healthcare, overshadowing the effect of income. In fact, the lower the income people have, the more they suffer from these health outcomes from time to time, and the more they see the need to get to facilities, achieving access through means such as selling the few assets they have or by borrowing. Another explanation might be that in some countries, higher incomes might imply better living conditions, better health status and limited need to access healthcare. Results in the SR are also different from those in the LR for CFC, which had negative and significant effects for four countries (at 1% and 5% significant level), except in Angola. The result in Angola could be justified by the high level of subsidisation of fuel consumption in this country (International Monetary Fund (IMF), 2013).

Our results were similar to results obtained in previous studies. For instance, our LR estimates of income elasticity of 0.1149 in Africa resembled the result of a pioneering study by Newhouse (1977) analysing medical expenditure in the United States, which also reported a positive estimate (0.14) of income elasticity for health expenditure. More recently, other studies reported the income elasticity for healthcare access of 0.112 and 0.122 (Kumagai, 2005; Farag, et al., 2012). With respect to income elasticity for healthcare access or usage, the question has been whether healthcare is a luxury good (elasticity >1) or a necessity good (elasticity <1). In line with most findings in this area, our study found that healthcare was a necessity in Africa. Furthermore, even if the distance to health facilities appeared in an unexpected manner to increase access to healthcare, this result is consistent with the findings from some studies (Heller, 1982; Akin et al., 1986). The unexpected result finds explanation in the possibility that higher volume of fuel might be a result of more transport (quantity rather than the price of fuel). Higher availability of transport services as a result of competition might lower the costs of transport and increase access. This is a possibility given the fact that the transport sector is lucrative in Africa. It is, however, worth acknowledging that many studies (Okwaraji et al., 2012; Syed et al., 2013; Okwaraji et al., 2015) found negative effects resulting from the distance to health facilities on access to healthcare. The finding in SR estimates that income is negatively associated with access is also not unique to this study. Clavero and González (2005) arrived at the same finding in analysing access to healthcare where access to health care was proxied by the number of general practitioners.

While the results of this study conform to the previous literature, this study showed that the SR effects of various variables might not be the same as their LR effects. Not only does it show that long-run average elasticities for access to healthcare are common for African countries in the study, but it also hints at the fact that this evidence can mask some country-specific realities about access. Specifically, the study revealed evidence that although variables might have common effects in the LR in countries covered by the study, the effects of these variables might vary from one country to another in Africa. This contribution to the literature stemmed from the use of the PMG estimator in the context of panel data that allowed the estimation of LR common effects coefficients and SR country-specific coefficients. Another contribution of the study was the use of a composite index to measure access to healthcare and analysing its determinants from the demand-side perspective. Other studies in the literature focused either on supply-side factors of access, did not use the composite indicators (Drabo & Ebeke, 2011; Belasco et al., 2012; Sato, 2012; Wouterse & Tankari, 2015) or did not use an estimation technique that produces both SR and LR estimates.

The findings from this study have significant policy implications. On the one hand, policy makers, whether at an international level or at a country level, should consider income-related policies or policies targeting other significant variables found in this study as the policies most likely to improve access to healthcare in the long run. On the other hand, they should take cognisance of the fact that African countries respond differently to shocks and that policies that produce effects in the LR might have limited effects in the short run, requiring some mitigation of SR policies.

A word of caution on the conclusions reached by this study is in order. The variables used in this study were limited to the variables for which data were available. For example, a theoretically important variable, the price of healthcare, was not available. This price could not be proxied by the consumer price index because the cost of healthcare is usually free for patients using public facilities in Africa. Patients only pay for transport costs and other non-medical costs while accessing healthcare. The assumption adopted by this study that the costs of transport to health facilities would act as proxy for the DHS could not result in the theoretically expected effect of cost of healthcare on access to healthcare in many countries. The study refers for future investigation the question of how best to measure the price of healthcare and the DHS at a macro level.

5 Summary

This study identified the determinants of access to healthcare and produced SR and LR estimates using a PMG estimator in the context of panel ARDL. The study found that LR effects (common effects) were different from SR effects (country-specific effects) and that income was the strongest determinant of access to healthcare. The study found further that access to healthcare remained a necessity in Africa. As an implication, due care should be taken to account for SR country-specific effects while formulating polices targeting improvement of access to healthcare in the LR.

Acknowledgement

The authors would like to acknowledge the English editing services provided by Carol Brammage. They accept, however, responsibility for any remaining English errors. The authors are also grateful to an anonymous referee at ERSA for useful comments which assisted in the improvement of the paper. Last but not least, the funding support from ERSA is gratefully acknowledged.

References

[1] Aakvik, A., & Holmås, T. (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.

[2] Aday, L. A., & Andersen, R. M. (1974). A framework for the study of access to medical care. *Health Services Research*, 9(3), 208–220.

[3] Adorka, M., Dikokole, M., Mitonga, K. H., & Allen, K. (2013). Healthcare providers' attitudes and perceptions in infection diagnosis and antibiotic prescribing in public health institutions in Lesotho: a cross sectional survey. *African Health Sciences*, 13(2), 344-350.

[4] 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*, 34(4) 755–782.

[5] Astale, T., & Chenault, M. (2015). Help-Seeking Behavior for Children with Acute Respiratory Infection in Ethiopia: Results from 2011 Ethiopia Demographic and Health Survey. *PloS one*, 10(11), e0142553.

[6] 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.

[7] Baltagi, B. H., Jung, B. C., & Song, S. H. (2010). Testing for heteroskedasticity and serial correlation in a random effects panel data model. *Journal of Econometrics*, 154(2), 122-124.

[8] Belasco, E., Philips, B. U., Gong, G., Gong, J., & Gong, G. (2012). *The Health Care Access Index as a determinant of delayed cancer detection through principal component analysis.* Retrieved from INTECH Open Access Publisher: http://cdn.intechopen.com/pdfs/30014.pdf

[9] 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'Economie du Développement*, 23(1), 33–71.

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

[11] Bloom, D. E., & Canning, D. (2015, November 08). *Health and economic growth: reconciling the micro and macro evidence'.* Retrieved from Stanford Institute on International Studies: http://iis-db.stanford.edu/pubs/20924/BloomCanning_42.pdf

[12] Boman, C. K., & Isiaka, M. (2015). Government Health Care Financing and Workforce Productivity: Empirical Evidence From Nigeria. *African Journal of Applied Research* , 1(1), 25-40.

[13] Breitung, J., & Pesaran, M. H. (2008). *Unit roots and cointegration in panels.* Berlin Heidelberg: Springer.

[14] Clavero, A., & González, M. (2005). La demanda de asistencia sanitaria en España desde la perspectiva de la decisión del paciente. *Estadística Española*, 47(158), 55-87.

[15] Colorado Health Institute. (2015). *The Colorado Access to Care Index: Measuring Access, Equity and the Effects of Policy Change.* Retrieved from Colorado Health Institute: http://www.coloradohealthinstitute.org/uploads/postfiles/Acces_to_Care_Index_brief_v3.pdf

[16] Corburn, J., & Hildebrand, C. (2015). Slum Sanitation and the Social Determinants of Women's Health in Nairobi, Kenya. *Journal of Environmental and Public Health*, http://dx.doi.org/10.1155/2015/209505.

[17] 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*, 11(1), 1.

[18] Donabedian, A. (1972). Models for organizing the delivery of personal health services and criteria for evaluating them. *The Milbank Memorial Fund Quarterly*, 50(4), 103-154.

[19] Dor, A., & Van Der Gaag, J. (1988). The demand for medical care in developing countries: quantity rationing in rural Cote d'Ivoire. *LSMS Working Paper 35, World Bank.*

[20] Drabo, A., & Ebeke, C. (2011). Remittances, Public Health Spending and Foreign Aid in the Access to Health Care Services in Developing Countries. Retrieved from, https://hal.archives-ouvertes.fr/halshs-00552996/document.

[21] 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.*

[22] Farag, M., NandaKumar, A. K., Wallack, S., Hodgkin, D., Gaumer, G., & Erbil, C. (2012). The income elasticity of health care spending in developing and developed countries. *International Journal of Health Care Finance and Economics*, 12(2), 145-162.

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

[24] Goetzel, R., Long, S. R., Ozminkowski, R., Hawkins, K., Wang, S., & Lynch, W. (2004). Health, absence, disability, and presenteeism cost estimates of certain physical and mental health conditions affecting U.S. employers. *Journal of Occupational Environmental Medicine*, 46(4):398-412.

[25] Green, W. (2002). *Econometric Analysis, 5th Edition.* Upper Saddle River, NJ: Prentice Hall.

[26] Grossman, M. (1972). On the concept of health capital and the demand for health. *The Journal of Political Economy*, 80(2), 223-255.

[27] Gulliford, M., & Morgan, M. (2013). *Access to health care.* Routledge. UK .

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

[29] Harris, B., Goudge, J., Ataguba, J. E., McIntyre, D., Nxumalo, N., Jikwana, S., & Chersich, M. (2011). Inequities in access to health care in South Africa. *Journal of Public Health Policy*, S102-S123.

[30] Heijink, R., Xu, K., Saksena, P., & Evans, D. (2011, Sepember 12). *Validity and comparability of out-of-pocket health expenditure from household surveys: a review of the literature and current survey instrument.* Retrieved from WHO: http://www.who.int/health_financing/documents/dp_e_11_01-oop_errors.pdf

[31] Heller, P. S. (1982). A model of the demand for medical and health services in Peninsular Malaysia. *Social Science and Medicine*, 16(3), 267–284.

[32] IMF. (2013). *Energy subsidy reform in Sub-Saharan Africa: experiences and lessons.* Retrieved from International Monetary Fund: https://www.imf.org/external/pubs/ft/dp/2013/afr1302.pdf

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

[34] Leegwater, A., Wong, W., & Avila, C. (2015). A concise, health service coverage index for monitoring progress towards universal health coverage. *BMC Health Services Research*, 15(1), 1.

[35] 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.

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

[37] 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.

[38] 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*, 178(1), 101–124.

[39] 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.

[40] Newhouse, J. P. (1977).). Medical-care expenditure: a cross-national survey. *The Journal of Human Resources*, 12(1) 115–125.

[41] O'Donnel, O. (2007). Access to health care in developing countries: breaking down demand side barriers. *Cad Saude Publica Rio de Janeiro*, 23(12): 2820-2834.

[42] 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.

[43] 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.

[44] 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.

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

[46] 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**,** 597-625.

[47] Penchansky, R. (1977). *The concept of access: a definition.* Hyattsville, Md: National Health Information Center.

[48] Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79–113.

[49] 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.

[50] 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.

[51] Rutherford, M. E., Mulholland, K., & Hill, P. C. (2010). How access to health care relates to under-five mortality in sub-Saharan Africa: systematic review. *Tropical Medicine and International Health*, 15(5), 508–519.

[52] Sanglimsuwan, K. (2011). *The relationship between health and environment: Econometric Analysis.* Bangkok: Bangkok University.

[53] Sarafidis, V., & Wansbeek, T. (2012). Cross-sectional dependence in panel data analysis. *Econometric Reviews*, 31(5), 483-531.

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

[55] 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.

[56] Tanaka, S. (2010). *Access to health infrastructure and child health development: evidence from post-apartheid South Africa.* Colchester: ISER Discussion Paper 0768, Institute for Social and Economic Research.

[57] 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,* 15(3): 256-267.

[58] WHO. (2014). *World health statistics 2014.* Retrieved from World Health Organization: http://apps.who.int/iris/bitstream/10665/112738/1/9789240692671_eng.pdf

[59] Wooldridge, J. (2009). *Introductory Econometrics: A Modern Approach, 4th Edition.* Mason, Ohio: Cengage Learning.

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

[61] Zheng, X., & Zimmer, D. M. (2008). Farmers' Health Insurance and Access to Health Care. *American Journal of Agricultural Economics*, 90(1), 267-279.

[62] Zuo, A., Wheeler, S. A., Bjornlund, H., Edwards, J., & Xu, W. (2015). Exploring Generational Differences Towards Water Resources and Policy Preferences of Water Re-Allocation in Alberta, Canada. *Water Resources Management*, 29(14), 5073-5089.

Tables and appendices

TABLE 1

Unit root test of level variables (In logarithm)

Variables	ADF test	PP test	IPS test
	(1)	(2)	(3)
ha	83.911	63.224	1.201
gdp	77.264	323.309***	3.583
cfc	54.374	50.317	3.417
oop	109.451***	109.573***	-0.317
pop65	174.044	91.856	1.064
popu5	172.493***	188.609***	-1.686**
urb	644.139***	1747.060***	-2.763***

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

Note that ADF and PP test are in fact "ADF-Fisher" and "PP-Fisher" used in the context of panel data

TABLE 2

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

Variables	ADF test	PP test	IPS test
	(1)	(2)	(3)
ha	386.789***	455.880***	-17.089***
gdp	247.093***	387.880***	-9.998***
cfc	404.145***	840.877***	-18.030***
oop	380.621***	666.745***	-16.126***
pop65	170.791***	198.725***	-4.085***
popu5	226.717***	69.208***	-7.277***
urb	111.279***	114.741***	1.857

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

Note that ADF and PP test are in fact "ADF-Fisher" and "PP-Fisher" used in the context of panel data

TABLE 3

Cointegration test

Statistics	Kao test (1)	Pedroni Test (2)	
		Individual intercept	Individual intercept & trend
ADF	-3.29***	-	-
Panel v-Statistic	-	-3.93	-6.21
Panel rho-Statistic	-	5.60	7.32
Panel PP-Statistic	-	-6.56***	-7.83***
Panel ADF-Statistic	-	-6.16***	-6.12***
Group rho-Statistic	-	7.67	8.52
Group PP-Statistic	-	-23.70***	-27.38***
Group ADF-Statistic	-	-9.17***	-8.72***

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

TABLE 4

DFE, PMG and MG model selection

	DFE (1)	PMG (2)	MG (3)
Dependent variable: ha			
EC			
gdp	0.1970***	0.1149***	0.4219
cfc	0.0961	0.0644***	-0.3757
oop	-0.0472	0.0160*	0.1523
pop65	0.2747	0.0612	-9.7011
popu5	-0.1123	0.4922***	-9.4735**
urb	1.0478***	1.0243***	-24.5040*
SR			
ec	-0.2627***	-0.5466***	-1.0800***
d.gdp	0.0847*	0.1869	0.4593*
d.consf	-0.0241*	0.0009	0.2293
d.oop	0.0796*	0.0611	0.1812**
d.pop65	0.151	2.7801**	13.7843**
d.popu5	-0.0123	-6.1638	-5.8649
d.urb	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*

Estimations were carried out using data in logarithmic form.

TABLE 5

Global and Income class specific PMG long-run estimates

Variables		GLOBAL (1)	LIC (2)	LMIC (3)	UMIC (4)
Dependent variable: ha					
Ec					
	gdp	0.1149***	0.3376***	0.6167***	0.5597***
	cfc	0.0644***	0.0634***	0.0256	0.5240***
	oop	0.0160*	0.0097***	-0.2457***	0.1708***
	pop65	0.0612	-1.0278***	0.2226	0.1401***
	popu5	0.4922***	0.3887**	-1.1067***	-0.0323***
	urb	1.0243***	-0.0865***	0.4952	-0.8459***

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

Estimations were carried out using data in logarithmic form

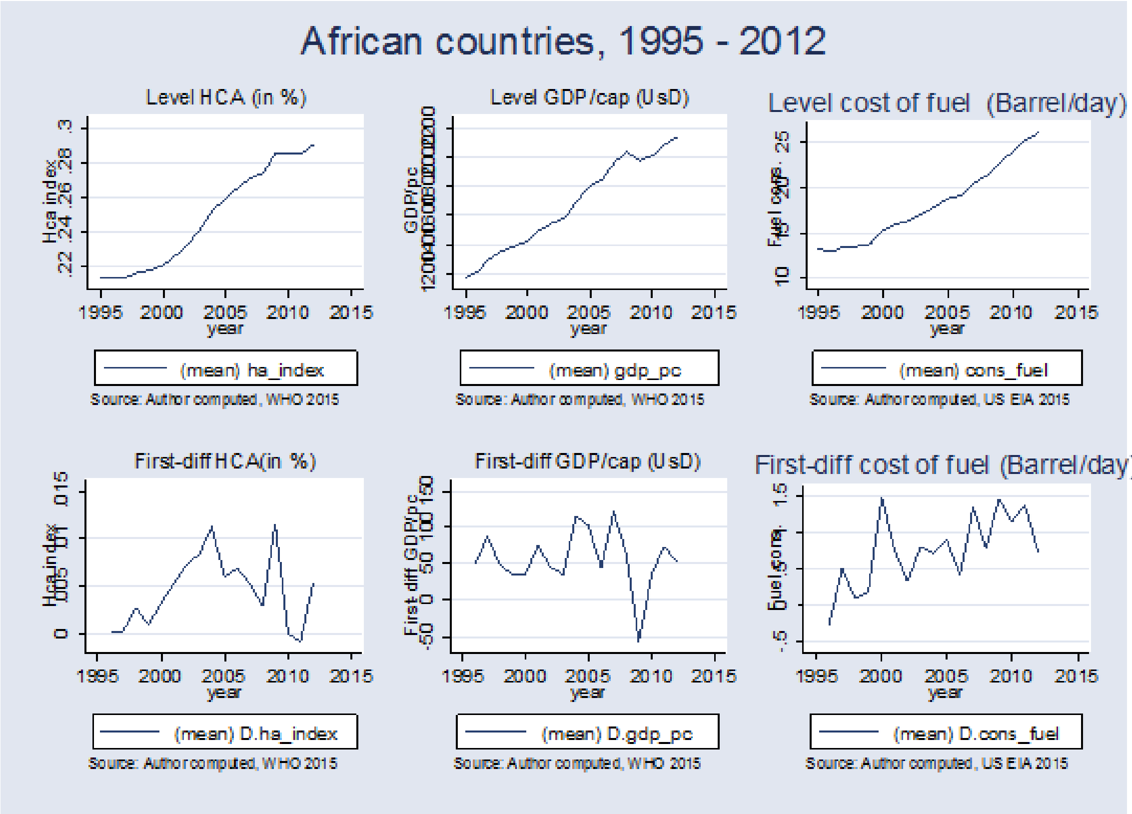
I. Appendices

Appendix 1. Descriptive statistics of variables, 1995-2012

Variable		Mean	Std. Dev.	Min	Max	Observations	
ln_ha	overall	-1.4762	0.4104	-2.8235	-0.5518	N =	666
	between		0.3704	-2.2467	-0.6595	n =	37
	within		0.1864	-2.4564	-0.8492	T =	18
ln_gdp	overall	6.6882	1.1148	4.8481	9.6222	N =	666
	between		1.1080	5.0234	9.3553	n =	37
	within		0.2157	4.3993	7.5024	T =	18
ln_consf	overall	1.5641	1.5578	-1.1712	5.3486	N =	666
	between		1.5385	-0.8764	5.1046	n =	37
	within		0.3469	0.2888	2.6995	T =	18
ln_oop	overall	3.5373	0.6349	0.9083	4.3933	N =	666
	between		0.5980	2.1286	4.2707	n =	37
	within		0.2337	2.2737	4.3013	T =	18
ln_pop65	overall	1.1982	0.2718	0.8020	2.1258	N =	666
	between		0.2680	0.8998	2.0344	n =	37
	within		0.0622	0.9681	1.4763	T =	18
ln_popu5	overall	2.7424	0.2413	1.7647	3.0297	N =	666
	between		0.2369	2.0335	3.0231	n =	37
	within		0.0598	2.3981	2.9954	T =	18
ln_urb	overall	3.5180	0.4661	1.9755	4.2322	N =	666
	between		0.4642	2.1985	4.1345	n =	37
	within		0.0852	2.9478	3.9152	T =	18

Source: author compilation

Appendix 2. Level and first-differenced graphs of variable of interest



Source: computed by author using data from WHO, WDI and US EIA

Appendix 3. Global sample correlation matrix

	ln_ha	ln_gdp	ln_consf	ln_oop	ln_pop65	ln_popu5	ln_urb
ln_ha	1						
ln_gdp	0.6253*	1					
ln_consf	0.3296*	0.2896*	1				
ln_oop	-0.4664*	-0.4144*	-0.0602	1			
ln_pop65	0.4963*	0.6119*	0.2361*	-0.2366*	1		
ln_popu5	-0.6857*	-0.7161*	-0.3904*	0.3431*	-0.8514*	1	
ln_urb	0.4138*	0.6456*	0.3873*	-0.1236*	0.4635*	-0.4914*	1

Source: Estimation *legend: * p<0.01*

Appendix 4. LIC correlation matrix

	ln_ha	ln_gdp	ln_consf	ln_oop	ln_pop65	ln_popu5	ln_urb
ln_ha	1						
ln_gdp	-0.0641	1					
ln_consf	0.1700*	0.2536*	1				
ln_oop	-0.2971*	0.2904*	-0.1382*	1			
ln_pop65	-0.268*	-0.0703	-0.0556	-0.0351	1		
ln_popu5	-0.3654*	0.0440	-0.2303*	0.1685*	-0.2533*	1	
ln_urb	0.0870	0.7204*	0.1481*	0.0626	0.2091*	-0.1320*	1

Source: Estimation *legend: * p<0.01*

Appendix 5. UMIC correlation matrix

	ln_ha	ln_gdp	ln_consf	ln_oop	ln_pop65	ln_popu5	ln_urb
ln_ha	1						
ln_gdp	0.6859*	1					
ln_consf	0.1945*	0.1280	1				
ln_oop	-0.3933*	-0.3767*	0.2055*	1			
ln_pop65	0.6161*	0.5873*	0.3861*	-0.0666	1		
ln_popu5	-0.6744*	-0.5791*	-0.4636*	0.1031	-0.8604*	1	
ln_urb	0.1572*	0.1586*	0.1507*	0.2332*	0.4896*	-0.3113*	1

Source: Estimation *legend: * p<0.01*

Appendix 6. LMIC correlation matrix

	ln_ha	ln_gdp	ln_consf	ln_oop	ln_pop65	ln_popu5	ln_urb
ln_ha	1						
ln_gdp	0.7856*	1					
ln_consf	0.1296	-0.3535*	1				
ln_oop	-0.3825*	-0.6256*	0.0454	1			
ln_pop65	0.6177*	0.7567*	-0.3624*	-0.1161	1		
ln_popu5	-0.7046*	-0.7009*	0.1812	0.1205	-0.8885*	1	
ln_urb	0.5930*	0.4275*	0.4955*	-0.5102*	0.2200*	-0.4080*	1

Source: Estimation *legend: * p<0.01*

Appendix 7. Global country short-run estimates

	Country	ec	D.ln_gdp	D.ln_cfc	D.ln_oop	D.ln_pop65	D.ln_popu5	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**
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*	-0.8713*	-0.0150	0.0571	1.6621	1.0090	-32.7864	-1.6934
7	Cabo Verde	-1.1198***	0.2584	-0.2394**	0.0183	-3.1467	-9.0476*	-10.2349	-8.7774***
8	Cameroon	-0.3946**	0.0352	-0.0797***	0.4005***	-6.7100*	7.9972**	-27.5555	-2.6565**
9	Central African Republic	-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	Dem. Rep. 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***
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*
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	-17.4951	-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**:	44.9594	-9.6934***
34	Swaziland	0.0529	1.0639	-0.1456	-0.0369	0.2560	-0.5313	-4.9049	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 *legend: * p<0.10; ** p<0.05; *** p<0.01*

Appendice 8. LIC Specific short-run estimates

	Country	ec	D.ln_gdp	D.ln_cfc	D.ln_oop	D.ln_pop65	D.ln_popu5	D.ln_urb	_cons
1	Benin	-0.5854*	0.9506	0.0128	-0.0123	0.0569	5.3839	38.3974	-2.3554*
2	Burkina Faso	-0.3054	-3.8110	0.3201	-0.9764	-15.7663	-44.5017	-3.3841	-1.2405
3	Burundi	-0.7581**	-0.5925	-0.0551	0.0909	-0.7038	3.9394	-44.6804**	-1.1922
4	Central African Republic	-0.3729*	0.8261	-0.2232	0.0023	36.8838	-6.1357	26.3786	-1.2793
5	Chad	-0.7237**	-0.1463	0.3745	0.5510	-3.9944	26.3179	117.0523	-3.2288**
6	Dem. Rep. of Congo	-0.3398**	-0.0919	0.3628	0.0920	2.0784	-35.9233	65.6264**	-2.5021**
7	Ethiopia	-0.1596*	0.1332	-0.1129*	-0.0548	-0.4971	-2.0803	6.0606**	-0.6740*
8	Gambia, The	-0.4096**	0.2064	-0.1635**	0.1012*	0.6963	-3.0078	1.3650	-1.3548**
9	Kenya	-0.8446***	-0.8833	0.0431	-0.0414	1.0460	-1.5001	28.4482	-3.5229*
10	Madagascar	-0.6976**	0.0804	0.1307	0.2359	-12.9006*	-16.3024**	7.7848	-2.7121**
11	Malawi	-0.8913***	-1.1886	0.0574	0.0418	8.9535*	7.2726	4.5883	-2.7844**
12	Mali	-0.4109***	1.0287***	0.0533	0.4496***	-8.3756***	-39.7569**	-1.5755	-1.4136***
13	Mozambique	-1.1146***	-0.2773***	-0.0616**	0.0096	5.2919***	6.6806***	-2.7907***	-3.6871***
14	Niger	-0.1944	0.2594	-0.0557	0.2082	-3.9446	-11.9190	13.8044	-0.8003
15	Rwanda	-1.3950***	-1.6083**	-0.0902	0.0533	-1.7644	-0.1874	2.7679	-4.6259***
16	Tanzania	-0.7181**	1.8310	-0.1271	-0.0163	18.0217	-2.3959	23.6639	-3.2412**
17	Togo	-0.3968***	0.0340	-0.0143	-0.0288	1.9296	-0.1579	-64.0755**	-0.2266

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

Appendix 9. LMIC Specific short-run estimates

	Country	ec	D.ln_gdp	D.ln_cfc	D.ln_oop	D.ln_pop65	D.ln_popu5	D.ln_urb	_cons
1	Cabo Verde	-0.4278**	0.0202	-0.3353**	0.1107*	7.8977**	11.9033*	23.8940	-2.0989
2	Cameroon	-0.3500**	-0.7417	-0.0699**	0.4788***	-6.3175*	5.0559*	-10.9023	-1.1003
3	Congo, Rep.	-0.6476**	3.4031**	0.2008	-0.0841	20.3468	16.1899	92.9080	-3.2256
4	Côte d'Ivoire	-1.0178***	0.8889*	0.0318	0.2607	20.1486*	-14.0985**	113.1058*	-5.2570
5	Egypt, Arab Rep.	0.4350*	0.3038	0.1547	-0.4967**	3.7303*	1.6092	-27.4440**	1.8175
6	Ghana	-0.9260***	-1.4587**	0.0136	0.1325	7.4318	-12.6727	43.1780*	-4.2224
7	Mauritania	-0.5071*	0.2485	-0.0378	-0.0375	-18.7785	-85.6131	6.5149	-2.6374
8	Morocco	-0.5108***	0.0634	0.0355	0.4488***	7.8833**	1.7476*	2.3801	-2.4029
9	Nigeria	-0.7764*	0.8182	-0.2041	0.9096	6.4661	35.4624	-10.4363	-2.8866
10	Senegal	0.0027	0.7237	0.0271	0.3463***	-3.3751	24.0298**	-63.8535	0.3677
11	Sudan	-1.4117***	-0.4240	-0.0681	0.0485	-13.1869	-25.5016**	-5.0451	-4.9386
12	Swaziland	-0.7467***	0.2302	-0.1238**	0.0852*	-2.4446	-1.4864*	-3.2040	-3.0915
13	Zambia	-0.0990	-0.3349	-0.1586	-0.0578	17.7292**	-6.7238	-2.8106*	-0.2435

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

Appendix 10. UMIC Specific short-run estimates

	Country	ec	D.ln_gdp	D.ln_cfc	D.ln_oop	D.ln_pop65	D.ln_popu5	D.ln_urb	_cons
1	Algeria	-0.3533	-1.2941**	-0.0219	-0.0594	5.4089*	-1.1383**	-62.8304*	-1.0864
2	Angola	-0.8931***	0.2716	0.2468	0.3899***	35.7614*	-11.1489	142.5399	-7.2848
3	Botswana	-0.4174	-0.0344	-0.1327	-0.0923**	-5.4111*	-3.8651	-6.3045	-1.4638
4	Mauritius	-0.1612	0.9704*	-0.0136	0.1221	-1.6636	-1.0615	-4.1728	-0.6673
5	Seychelles	-0.0783	0.4874***	-0.0122	-0.0965*	1.9513***	-0.4383	-3.3733	-0.3135
6	South Africa	-0.6798***	-0.6958	-0.2205	0.0576	1.2296	-2.7514	15.6348	-3.7239

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