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Exploring the relationship between healthcare expenditure, income, medical technology, and aging: A pooled mean group analysis of African countries

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ABSTRACT

This paper empirically examines the short and long-run relationships among healthcare expenditure, income, medical technology, and an aging population in a panel of 45 African countries over the period 1995-2018. We test for cross-sectional dependence among different countries and employ the pooled mean group estimator. The results support the presence of cross-sectional dependence in African countries and reveal that healthcare expenditure, income, medical technology, and aging population have a long-run relationship. Medical technology and an aging population are key drivers of healthcare expenditure in the low-income group as well as the middle-income group. The long-run income elasticities of healthcare expenditure are less than one for both income groups. Finally, we found bidirectional causality between healthcare expenditure and its determinants. Healthcare expenditure is considered a necessity for African countries. Nevertheless, low-income countries have higher income elasticities for private health expenditure compared to middle-income countries. We suggest that African governments should increase public healthcare spending since healthcare spending is a necessity. This increase will lead to growth in income and medical technology development, which will have a beneficial impact on health status.

Contribution/ Originality: To the authors' best knowledge, this paper is the first to investigate the determinants of healthcare expenditure (HCE) dynamics in the African context and take into account medical technology as an important driver of HCE growth. Income heterogeneity among African countries and the nature of HCE are also considered.

1. INTRODUCTION

Over the last two decades – 1995-2018 – Africa has seen an improvement in health indicators such as maternal, infant, and child mortality rates and life expectancy at birth (World Bank, 2021). However, Africa still lags behind the rest of the world. In the same period, healthcare expenditure (HCE) per capita increased from $US119.23 (1995) to $US324.70 (2018) in Africa. However, many leading health economists and development agencies have argued that healthcare funding remains insufficient to meet healthcare needs. Moreover, the United Nations' (2014) projection shows that Africa is expected to see the largest relative increase in the size of its population over the coming 15 years, with a median projection of 1.68 billion people in 2030. The aging population is also expected to increase. This picture poses a serious concern due to the growing healthcare demands in the region and explains why African economies are searching for innovative and sustainable strategies to increase HCE, particularly public HCE, as a means to

provide quality healthcare to its growing population and achieve universal health coverage (World Bank, 2021). The starting point of such health financing reform is to have a better understanding of the driving factors of HCE.

Many models have tried to explain the questions related to the determinants of HCE dynamics in developed countries (Barros, 1998; Chernew & Newhouse, 2011; Newhouse, 1992). However, less is known concerning this issue in developing countries, including those in Africa (Barkat, Sbia, & Maouchi, 2019; Kouassi, Akinkugbe, Kutlo, & Brou, 2018). A wide range of factors has been taken into consideration, including the demographic structure of the population, income, and medical technology (Llorian & Mann, 2022; Pammolli, Riccaboni, & Magazzini, 2012; You & Okunade, 2017).

Previous studies differ in terms of the level of aggregation of the data, the independent variables used, the specification adopted, the estimation methods, the countries included, and the period studied. Consequently, their findings with respect to the core determinants of HCE are conflicting, and the magnitude of their effects shows that the issue is largely unresolved. For instance, the issue of whether healthcare is a luxury good or a necessity good remains largely unresolved (Getzen, 2000; Pammolli et al., 2012). Furthermore, the income elasticity of health spending increases with the level of aggregation; the income elasticity of HCE at the individual level is typically near zero or negative (for insured people), whereas at the national level, it is typically greater than one (Dormont, Martins, Pelgrin, & Suhrcke, 2020; Getzen, 2000). The leading health economists also perceive medical technology as one of the key drivers of the long-run growth in HCE (Barros, 1998; Newhouse, 1992; Weisbrod, 1991; You & Okunade, 2017); however, the extent to which medical technology affects HCE continues to be challenging and controversial on the empirical front (Chernew & Newhouse, 2011; Llorian & Mann, 2022; Okunade & Murthy, 2002).

As far as African countries are concerned, the literature on HCE determinants has focused only on demand-side factors, particularly income. The authors have shown that national income is a core HCE driver (Barkat, Mrabet, & Alsamara, 2016; Byaro, Kinyondo, Michello, & Musonda, 2018; Farag et al., 2012; Ke, Saksena, & Holly, 2011; Murthy & Okunade, 2009).

To the authors' best knowledge, this paper is the first to investigate the determinants of HCE dynamics in the African context and to take into account medical technology as an important driver of HCE growth, as hypothesized by Newhouse (1992). This paper fills the gap in the literature by revisiting the determinants of HCE dynamics in the African context, considering the roles of income, aging population, and medical technology. We also account for income heterogeneity among African countries and examine how this relationship changes with the level of development by dividing African countries into two income groups: a low-income and a middle-income group. Unlike Kouassi et al. (2018), we use a large sample of African countries and reduce income heterogeneity among these countries by using the World Bank classification of African economies. The relationship between HCE and its determinants may change with individual countries or income groups. Omitting this could bias the relative contribution of the predictors of HCE (Barkat et al., 2016; Ogundipe, Alege, & Ogundipe, 2014). Health policy derived from the average effect of the determinants of HCE may also be misleading if this effect varies with the distinction between private and public health spending. As in Pammolli et al. (2012) and Llorian and Mann (2022), we go a step further by performing separate econometric analyses of the total, public, and private HCE to obtain more relevant policy implications. This distinction is imperative because a large share of health expenditure is financed through the private sector in African countries, and by ignoring this the opportunity to propose specific policies could be missed. We apply a pooled mean group (PMG) estimator that assumes heterogeneity in the long-run slope coefficients, cross-sectional dependence, and non-stationarity (Pesaran, Shin, & Smith, 1999). Ignoring those attributes would have severe implications for the standard estimators' biasness and consistency properties. Finally, we examine the direction of the relationships between HCE and income, medical technology, and aging.

The rest of the paper is organized as follows. Section 2 reviews the literature on the determinants of HCE. Section 3 outlines the model specification and estimation strategy. Section 4 presents the data and main findings. The results are discussed in Section 5. The study concludes in Section 6 with some recommendations and policy implications.

2. HEALTHCARE EXPENDITURE DETERMINANTS: AN OVERVIEW

The literature on HCE determinants has recognized national income as the key factor that explains variations in HCE among countries (Newhouse, 1992; Okunade, 2005; Smith, Newhouse, & Freeland, 2009). However, the magnitude of HCE's elasticity with respect to income varies substantially across studies (Kouassi et al., 2018; Rodríguez & Nieves Valdes, 2019). For instance, Gbesemete and Gerdtham (1992) found an income elasticity of HCE of between 0.88 and 1.07 using cross-sectional data on 30 African countries for the year 1984 and weighted least squares corrected for heteroskedasticity. Similarly, Okunade (2005) used a flexible Box-Cox model regression method and 1995 post-Structural Adjustment Program cross-sectional data of 26 African countries and concluded that the income elasticity of HCE is 0.65. Murthy and Okunade (2009) reached similar results using large cross-sectional data from 44 African countries for the year 2001 and ordinary least squares and robust least absolute error estimators. They also found that many countries have an income elasticity of HCE greater than one, except for Mauritania, Kenya, Malawi, and South Africa. Sahn (1992) used a panel of 23 Sub-Saharan African countries covering 1974-1987 and a fixed effects estimator to show that the income elasticity of HCE was slightly elastic (1.17 for 1974-79, 1.06 for 1980-84, and 1.17 for 1985-89). However, the aggregate expenditure elasticity of health spending was slightly below one (respectively 0.67 (1974-79), 0.67 (1980-84), and 0.96 (1985-89)). Lv and Zhu (2014) conducted a semi-parametric panel data analysis for 42 African countries over the period 1995-2009 and found that the income elasticity of health spending varies with income level and that healthcare is a necessity for African countries. Kouassi et al. (2018) used a heterogeneous panel data model on a panel of 14 Southern African Development Community member countries over the period 1995-2012 and found that health expenditure and GDP per capita are non-stationary and co-integrated, and the estimated income elasticity is below unity.

Medical technology is another important driver of HCE. It is conceptualized as any change in the procedures, equipment, and processes by which healthcare is delivered to the population (Chernew & Newhouse, 2011). It includes, for example, the introduction of new diagnostic testing methods, new drugs, new applications of existing procedures, and the development and diffusion of technologies (Willemé & Dumont, 2015). Economic theory does not predict a clear-cut effect of medical technology on HCE. The effect of medical technology on HCE depends on the relative importance of the treatment substitution effect and treatment expansion effect (Cutler & McClellan, 2001). The treatment substitution effect, which depends on a change in relative prices, refers to replacing the old medical technology with a new one that is more efficient and cost-effective and improves the treatment provided to the citizen. On the other hand, the treatment expansion effect is the diffusion of new technology, allowing more patients to be treated for a disease. This may help explain how a new medical technology with lower unit costs at the micro level sometimes results in higher total HCE (Chernew & Newhouse, 2011). The empirical studies focusing on the effect of medical technology on HCE use different approaches to measure medical technology. Some studies use a residual approach that entails estimating the impact of the relevant time-varying factors of HCE. The part of changing HCE that is not accounted for by the explanatory variables (i.e., the residual) is then interpreted as an estimate that captures the impact of medical technology (Rossen & Faroque, 2016; Smith et al., 2009; You & Okunade, 2017). A positive residual is interpreted to indicate that medical technology has increased HCE, whereas a negative residual can be interpreted to mean that technology has reduced HCE (Doessel, 1986; You & Okunade, 2017). Researchers that use the residual approach find that medical technology may explain between 17 and 55% of HCE increases in Organisation for Economic Cooperation and Development (OECD) countries (Barros, 1998; Newhouse, 1992; Okunade & Murthy, 2002; You & Okunade, 2017). Other authors use a proxy approach in which medical technological proxy variables are directly included in the HCE function (Okunade & Murthy, 2002; Willemé & Dumont, 2015; You & Okunade, 2017). For instance, health outcomes such as life expectancy at birth (Barkat et al., 2019; Dreger & Reimers, 2005) and infant mortality (De Mello-Sampayo & Vale, 2014; Rodríguez & Nieves Valdes, 2019; You & Okunade, 2017) are used as a proxy for medical technology. According to Llorian and Mann (2022), these studies found that the estimated effects are around 30%. Innovation inputs such as total research and development expenditure on healthcare and surgical

procedures are also used as proxy variables (Okunade & Murthy, 2002; Weil, 1995; Willemé & Dumont, 2015) These studies suggest that technological change is a statistically significant long-term driver of increasing HCE. Time trends have been used to capture medical technology (Di Matteo, 2005; Nghiem & Connelly, 2017). They found that the effects of medical technology on HCE range from 3 to 65%. However, a trend variable may capture the effects of all kinds of non-stationary variables (Roberts, 1999).

In recent studies, various researchers have investigated the relationship between medical technology and HCE. You and Okunade (2017) used Australian annual aggregate data from 1971-2011 to explore this relationship, finding that Australia's healthcare is a technical necessity with estimated technology effects ranging from 0.30 to 0.35%. Similarly, Willemé and Dumont (2015) analyzed the effect of medical technology on HCE using a panel data model for 18 OECD countries between 1981 and 2012. Their results suggest that medical technology has a statistically significant effect, accounting for as much as 43% of the explained growth of HCE. Llorian and Mann (2022) also explored the effect of medical technology on HCE using a panel of 21 OECD countries between 1981 and 2019 using dynamic common correlated mean group estimators. Their findings suggest that the HCE-technology relationship differs significantly within the group of OECD member countries. Using the pooled mean group estimator and common correlated effects estimator, Barkat et al. (2019) investigated the effect of medical technology on HCE in 18 Arab countries for the period 1995-2015, measuring medical technology by the infant mortality rate and life expectancy at birth. Their results suggest that medical technology plays an important role in increasing HCE.

Changes in the age structure of the population have also been considered a potential driver of HCE, as population aging tends to increase the demand for publicly and privately financed healthcare services (Lichtenberg, 2014). Moreover, the elderly population is more likely to develop chronic illnesses that can lead to functional disabilities, which can further increase the demand for healthcare services. While an increase in population size and changes in age structure can put pressure on HCE, it is also possible that reductions in mortality and morbidity and increases in life expectancy could lower HCE by creating healthier cohorts that require less expensive medical treatments. Nonetheless, an increase in the share of HCE spent on elderly care can shift HCE to a higher rate. However, aging alone does not contribute significantly to the growth rate of HCE. In fact, most research suggests that the impact of the age structure or population aging on HCE is small or non-significant (Gerdtham & Löthgren, 2000; Hitiris & Posnett, 1992; Lv & Zhu, 2014; Murthy & Okunade, 2009).

To sum up, most of the works on the link between HCE and its determinants have revealed that the core drivers of HCE are income, medical technology, and population aging. The magnitude of their respective effects varies across studies. The medical technology elasticity of HCE largely depends on different measures of medical technology. All in all, the literature reports contrasting results.

3. MODEL SPECIFICATION AND ESTIMATION STRATEGY

The objective of this article is to investigate the relationship between HCE, per capita real GDP, medical technology, and aging population in African economies, as well as to understand how this relationship depends on the level of development of the studied countries. Therefore, based on the above discussion on aggregate HCE models, we expect a positive and significant relationship between HCE per capita and income per capita. Like Dreger and Reimers (2005), You and Okunade (2017), Barkat et al. (2019), and Llorian and Mann (2022), we use proxies for the medical technology variable: infant mortality rate (IMR) and life expectancy at birth (LEB). Our preferred medical technology measure is mortality rate rather than life expectancy at birth because the life expectancy variable includes the effect of population aging and longevity and is highly correlated with these (Barkat et al., 2019; Murthy & Ketenci, 2017). We hypothesize that new medical technologies, after a certain time lag, will be commonly used by physicians and thus represent changes in treatment decisions. Medical technology makes a positive contribution to the health of the population, which is frequently measured using these health indicators. Therefore, we expect a positive coefficient

for life expectancy at birth, while the mortality rate coefficient is expected to be negative. Finally, we add the aging population (POP65).

As the literature on aggregate HCE models does not give clear guidance on the functional form of the relationship between the HCE (HEXP) and its determinants, we assume the general linear panel model.

$$HEXP = g(GDP, IMR, LEB, POP65) \quad (1)$$

Where $HEXP$ indicates a vector of health expenditure per capita [total HCE (THEXP), private HCE (PRHEXP), and public HCE (PUHEXP)].

Assuming that y_{it} is a vector of HCE per capita ($HEXP$), and X_{it} is a vector of regressors (GDP, IMR, LEB, POP65), and HCE and its determinants are cointegrated, the general form of the long-run HCE equation can be given as:

$$y_{it} = \alpha + \beta_i X_{it} + \varepsilon_{it} \quad (2)$$

To separately capture the relative contribution of the long-run effect of the different measures of medical technology on HCE growth, four long-run expenditure functions are specified as follows:

$$(S\ 1): LHEXP_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LIMR_{it} + \varepsilon_{it} \quad (3)$$

$$(S2): LHEXP_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LLEB_{it} + \varepsilon_{it} \quad (4)$$

$$(S3): LHEXP_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LPOP65_{it} + \varepsilon_{it} \quad (5)$$

$$(S4): LHEXP_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LIMR_{it} + \beta_3 LPOP65 + \varepsilon_{it} \quad (6)$$

Equation 3 uses the infant mortality rate (LIMR) as a measure of medical technology, while Equation 4 uses life expectancy at birth (LLEB) as an alternative measure of medical technology. In Equation 5, the elderly population (LPOP) is interpreted as a demographic variable. It is important to note that in the sixth specification (Equation 6), the infant mortality rate (LIMR) is considered a medical technology proxy, while the aging population variable (LPOP65) is a demographic measure (You & Okunade, 2017). We run different sets of regressions for total, private, and public HCE. The dependent variables are total health expenditure per capita (THEXP), private health expenditure per capita (PRHEXP), and public health expenditure per capita (PUHEXP).

To avoid spurious regression, we first conduct the Pesaran cross-sectional dependence (CD) test (Pesaran, 2004) to test for cross-sectional dependence among the variables considered. If the null hypothesis of the cross-sectional dependence is confirmed, we proceed to conduct panel unit root tests with cross-sectional dependence, specifically, the cross-section augmented Dickey-Fuller (CADF) and cross-section augmented Im-Pesaran-Shin (CIPS) tests (Pesaran, 2007). If the results show that the series are integrated of the same order, we move on to the next step, which is to use the Westerlund (2007) co-integration test to determine the existence of a long-term relationship between health expenditure and its determinants. The Westerlund co-integration test is a simple residual-based panel co-integration test that accommodates cross-sectional dependence among different groups in the panel. The co-integration statistics provide four panel co-integration tests (Gt, Ga, Pt, and Pa) based on the error correction model (ECM) to test the null hypothesis of no co-integration. While Ga (among groups) and Gt (between groups) test the co-integration for each country individually, Pt and Pa test the co-integration of the panel as a whole.

Next, we test the homogeneity of the co-integration coefficients because incorrectly ignoring slope heterogeneity leads to biased results (Pesaran & Smith, 1995). This test is also important for selecting the appropriate heterogeneous panel Granger causality test. We use the test developed by Swamy (1970) and enhanced by Pesaran and Yamagata (2008) to test whether the slope coefficients in the co-integration equation are homogeneous or not. Based on Equation 2, the tests are specified in Equations 7 and 8 as follows:

$H_0: \beta_i = \beta$ for all i, slope coefficients are homogeneous. (7)

$H_1: \beta_i \neq \beta$ for some i, slope coefficients differ across sections. (8)

Equations 9 and 10 below present the delta test statistics of Pesaran and Yamagata (2008):

$$\widehat{\Delta} = \sqrt{\mathrm{N}}\ \frac{N^{-1}\hat{S} - \mathrm{K}}{\sqrt{2\mathrm{K}}} \quad (9)$$

$$\widehat{\Delta}_{adj} = \sqrt{N}\ \frac{N^{-1}\hat{S} - K}{\sqrt{var(T,K)}} \quad (10)$$

Where N is the number of countries, S is the Swamy test statistics, k is the number of explanatory variables, and $var(T, K)$ indicates the standard error.

Based on Pesaran et al. (1999), the error correction model of the dynamic heterogeneous panel regression of Equation 2 using the autoregressive distributed lag panel ARDL (p, q) technique is as follows:

$$\Delta y_{it} = \sum_{j=1}^{p-1} \gamma_{ij} \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta X_{it-j} + \varphi_i [y_{it-1} - (\alpha_{0i} - \beta_i X_{it-1})] + \varepsilon_{it} \quad (11)$$

Where γ_{ij} and δ_{ij} represent the country-specific short-run coefficients of the lagged dependent and independent variables, respectively, β are the long-run coefficients, φ_i is the coefficient of the speed of adjustment to the long-run equilibrium, and ϵ_{it} is a white noise error. Equation 11 is a panel error correction model in which short-run and long-run effects are estimated jointly.

We applied the pooled mean group (PMG) estimator proposed by Pesaran et al. (1999) to estimate Equation 11 for three reasons. First, this estimator makes it possible to control for unobserved heterogeneity at the country level and the presence of unit roots. Second, it allows for differences among short-run coefficients and the speed of adjustment to the long-run equilibrium values to vary across countries while constraining the long-run coefficient to be identical. The PMG estimator is efficient at estimating under the assumption of long-run homogeneity. Third, the PMG estimator provides consistent coefficients in the presence of endogeneity because it includes lags of dependent and independent variables (Pesaran et al., 1999). We expect the long-run equilibrium relationship between the HCE and its determinants to be similar across groups due to budgetary constraints, arbitrage conditions, or common technologies similarly influencing all the groups (Okunade, You, & Koleyni, 2018).

As suggested by Pesaran et al. (1999), we perform the Hausman test to verify whether there are significant differences among PMG, mean group (MG), and dynamic fixed effect (DFE) estimators. Under the null hypothesis of equation long-run coefficients, the difference between PMG and MG should be insignificant, and the PMG is efficient. When comparing the MG and DFE estimators, the null hypothesis is that the DFE estimations are preferred.

To better understand the relationship between HCE and its determinants, we applied the panel causality test of Dumitrescu and Hurlin (2012) in heterogeneous panels.

4. DATA AND MAIN FINDINGS

We employ annual data extracted from 45 African countries between 1995 and 2018. Data are sourced from the World Bank (2021). Table 1B in Appendix 1 shows the list of countries included in the study. The dependent variables are total health expenditure per capita (THEXP), private health expenditure per capita (PRHEXP), and public health expenditure per capita (PUHEXP). The independent variables are gross domestic product per capita (GDPPC), medical technology measured by life expectancy at birth (LEB) and infant mortality rate (IMRI), and the population aged 65 and above (POP65). THEXP, PRHEXP, PUHEXP, and GDPPC are measured in $US in purchasing power parity (PPP) at 2005 prices. The definitions of the study variables are presented in Table 1A in Appendix 1.

Given the heterogeneity among African countries, we divide our sample into two subgroups, low-income level and middle-income level countries, using the World Bank country classification of 2017. This strategy allows us to control for income heterogeneity among the countries under study and to know how the elasticities of each component of health spending change across income groups. While the first sub-group includes low-income countries with a gross national income (GNI) per capita equal to or less than $1,045 (a group of 20 countries), the second sub-group is composed of middle-income countries with a GNI per capita of between $1,045 and $12,746 (a group of 25 countries). Table 1 provides summary statistics of the variables used in our analysis.

The descriptive statistics reported in Table 1 show a large variation in the data. For instance, the mean values of total HCE range from 291.8$US to 331.8$US, with the low-income countries group having the highest mean value.

For all income groups, the mean values of private HCE are higher than those of public HCE. However, in the low-income countries group, private HCE is 3.58 times higher than public HCE (184.2$US versus 51.40$US). The standard deviation of private HCE is larger than that of public HCE for low-income group countries, 803.7$US versus 220.9$US. GDP per capita ranges from 327.5$US (Mozambique) to 38,408$US (Equatorial Guinea), with a mean value of 3,909$US and a standard deviation of 4,793$US. The mean values of the infant mortality rates are higher in the low-income countries group compared to the middle-income countries group, 78.27‰ versus 55.76‰. In contrast, the mean values of life expectancy at birth are lower in the low-income countries group compared to the middle-income countries, 54.33 years versus 59.13 years. Concerning the aging population variable, the mean values are 813,759 persons older than 65 years for the middle-income countries group and 528,015 persons older than 65 years for the low-income countries group.

Table 1. Summary statistics for the whole sample and for low-income and middle-income groups.

Income groups and variables	Mean	Standard deviation	Minimum	Maximum	N
Whole sample (45 countries)					
THEXP	309.6	992.5	6.623	12.643	1.080
PUHEXP	97.01	189.0	0.282	3.181	1.080
PRHEXP	158.3	543.7	4.114	6.538	1.080
GDPPC	3.909	4.793	327.5	38.408	1.080
IMRI	65.76	27.79	13.60	164	1.080
LEB	56.99	7.872	31.04	76.69	1.080
POP65	686.762	966.372	14.665	5.381e+06	1.080
Low-income countries (20 countries)					
THEXP	331.8	1.461	6.623	12.643	480
PUHEXP	51.40	220.9	0.282	3.181	480
PRHEXP	184.2	803.7	4.114	6.538	480
GDPPC	1.261	661.8	327.5	5.048	480
MRI	78.27	26.11	27.30	164	480
LEB	54.33	6.230	31.04	68.70	480
POP65	528.015	650.204	28.071	3.824e+06	480
Middle-income countries (25 countries)					
THEXP	291.8	257.3	27.65	1.129	600
PUHEXP	133.5	149.5	5.304	843.5	600
PRHEXP	137.6	122.8	15.49	687.9	600
GDPPC	6.028	5.559	1.007	38.408	600
MRI	55.76	24.92	13.60	130.8	600
LEB	59.13	8.386	42.52	76.69	600
POP65	813.759	1.144e+06	14.665	5.381e+06	600

Note: The variables LTHEXP, LPUHEXP, and LPRHEXP represent the logarithm of per capita health expenditure for total health expenditure (THEXP), private health expenditure (PRHEXP), and public health expenditure (PUHEXP), respectively. LGDPPC stands for GDP per capita, LMRI represents the infant mortality rate, LEB indicates life expectancy at birth, and LPOP65 denotes the proportion of the population aged over 65 years old.

Table 2 summarizes the results of the cross-sectional dependence tests. The results reported in Table 2 support the presence of cross-sectional dependence for the panel, as the p-values of the CD test are statistically significant at the 1% level.

We also perform panel unit-root tests using the CADF and CIPS tests suggested by Pesaran (2007), which account for cross-sectional dependence. The results are reported in Table 3. For the whole sample and the two subgroups of countries, the findings in Table 3 suggest that nearly all the variables provide evidence for the presence of unit root among the data, except for infant mortality rate, life expectancy at birth, and aging population.

Table 2. Cross-sectional dependence test.

Variables	Whole sample		Low-income countries		Middle-income countries	
	CD test	P-value	CD test	P-value	CD test	P-value
LTHEXP	107.016	0.000	47.020	0.000	58.459	0.000
LPUHEXP	47.556	0.000	14.757	0.000	33.082	0.000
LPRHEXP	59.378	0.000	21.915	0.000	37.291	0.000
LGDPPC	130.490	0.000	56.569	0.000	72.540	0.000
LMRI	138.996	0.000	66.557	0.000	70.881	0.000
LLEB	132.350	0.000	64.367	0.000	67.934	0.000
LPOP65	143.414	0.000	60.739	0.000	80.928	0.000

Table 3. Panel unit root test with cross-sectional dependence.

Income groups and variables	Level		Difference	
	CADF	CIPS	CADF	CIPS
Whole sample				
LTHEXP	-2.431	-2.702	-3.033***	-4.610***
LPUHEXP	-1.903	-2.427	-3.610***	-5.151***
LPRHEXP	-2.403	-2.614	-3.395***	-4.686***
LGDPPC	-2.158	-2.098	-3.285***	-4.144***
LMRI	-2.698***	-2.791***	-	-
LLEB	-11.295***	-3.632***	-	-
LPOP65	-3.335***	-2.675**	-	-
Low-income countries				
LTHEXP	-2.418	-2.320	-2.853***	-4.375***
LPUHEXP	-2.263	-2.552	-4.097***	-5.190***
LPRHEXP	-1.768	-2.153	-3.466***	-4.892***
LGDPPC	-2.187	-1.934	-3.593***	-4.300***
LMRI	-2.405	-2.763	-2.643*	-3.230***
LLEB	-7.010***	-2.440*	-	-
LPOP65	-2.812***	-2.222*	-	-
Middle-income countries				
LTHEXP	-2.354	-2.513	-2.880***	-4.278***
LPUHEXP	-2.002	-2.460	-3.460***	-5.025***
LPRHEXP	-2.494	-2.802	-3.239***	-4.692***
LGDPPC	-2.385	-2.197	-3.051***	-3.942***
LMRI	-2.582*	-2.496*	-	-
LLEB	-14.569***	-3.901***	-	-
LPOP65	-2.600*	-2.127*	-	-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The variables LTHEXP, LPUHEXP, and LPRHEXP represent the logarithm of per capita health expenditure for total health expenditure (THEXP), private health expenditure (PRHEXP), and public health expenditure (PUHEXP), respectively. LGDPPC stands for GDP per capita, LMRI represents the infant mortality rate, LEB indicates life expectancy at birth, and LPOP65 denotes the proportion of the population aged over 65 years old.

The results of the homogeneity tests are summarized in Table 4. Based on Table 4, we reject the null homogeneity statement of the slope coefficients; therefore, we accept the alternative hypothesis of heterogeneity of the slope coefficients for the whole sample, the four specifications, and the three types of health expenditure. Concerning the two subgroups of countries, the findings of the homogeneity test vary according to the specifications and the components of health expenditure.

The findings in Table 5 suggest, for the whole panel and the subgroups, the rejection of the null hypothesis of no co-integration and acceptance of the alternative hypothesis of the existence of a long-run relationship between total health expenditure and its determinants for the four specification models. On these grounds, there is a panel indication of a stable long-run connection within the studied variables. As expected, the Hausman test used to select the appropriate model for estimating the long-run coefficients shows that when comparing PMG and MG, the p-values are insignificant at the 5% level (p-values equal 0.14, 0.32, and 0.09 for the whole sample, low-income countries, and middle-income group, respectively). The null hypothesis of the homogeneity restriction on the regressors in the

long run is accepted and indicates that PMG is a more efficient estimator than MG. Comparing the results of DFE and MG, the Hausman tests have significant p-values at the 1% level, suggesting that the MG estimator is preferred over the DFE. Consequently, the PMG estimation is more relevant for this analysis. The main econometric results discussed are exclusively based on the PMG model.

Table 4. Slope homogeneity tests.

Models	Whole sample $\hat{\Delta}_{adj}$	Low-income $\hat{\Delta}_{adj}$	Middle-income $\hat{\Delta}_{adj}$
Total health expenditure			
(S1): GDP-LMRI	5.101***	2.346**	3.400***
(S2): GDP-LLEB	8.500***	3.300***	7.710***
(S3): GDP-LPOP65	3.936***	0.441	3.764***
(S4): GDP-LMRI-LPOP65	6.468***	3.913***	4.395***
Public health expenditure			
(S1): GDP-LMRI	1.674*	0.782	1.250
(S2): GDP-LLEB	2.025**	-0.874	3.277***
(S3): GDP-LPOP65	1.563	0.959	1.168
(S4): GDP-LMRI-LPOP65	2.619***	2.426**	1.095
Private health expenditure			
(S1): GDP-LMRI	4.840***	1.512	2.165**
(S2): GDP-LLEB	5.565***	1.933*	3.054***
(S3): GDP-LPOP65	4.355***	1.967**	1.351
(S4): GDP-LMRI-LPOP65	5.288***	4.244***	1.602

Note: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5. Westerlund co-integration test.

Income groups and models	G_t		G_a		P_t		P_a	
	z-value	p-value	z-value	p-value	z-value	p-value	z-value	p-value
Whole sample								
(S1): MRI	-2.200	0.000	-3.126	1.000	-10.994	0.000	-2.706	0.388
(S2): LEB	-2.500	0.000	-4.075	0.984	-11.996	0.000	-2.580	0.456
(S3): POP65	-1.604	0.078	-3.268	0.999	-7.135	0.261	-2.881	0.301
(S4): MRI-POP65	-2.333	0.000	-2.479	1.000	-11.751	0.013	-2.290	0.982
Low-income countries								
(S1): MRI	-2.142	0.001	-2.279	0.998	-7.193	0.012	-2.038	0.663
(S2): LEB	-2.555	0.000	-3.371	0.978	-8.325	0.001	-2.153	0.624
(S3): POP65	-1.478	0.341	-2.191	0.999	-4.186	0.501	-2.670	0.438
(S4): MRI-POP65	-2.129	0.033	-2.181	1.000	-9.040	0.008	-1.978	0.948
Middle-income countries								
(S1): MRI	-2.247	0.000	-3.803	0.968	-8.770	0.001	-3.619	0.127
(S2): LEB	-2.456	0.000	-4.638	0.861	-10.035	0.000	-5.120	0.004
(S3): POP65	-1.705	0.062	-4.130	0.939	-7.877	0.008	-3.506	0.152
(S4): MRI-POP65	-2.496	0.000	-2.717	1.000	-8.167	0.114	-2.803	0.877

Tables 6, 7, and 8 show the results of the pooled mean group long-run coefficients for total, public, and private HCE functions, respectively. With few exceptions, the estimates have the expected signs. In general, the estimated coefficients suggest that the long-run relationships between HCE, GDP, medical technology, and aging population change with the income groups, a component of HCE and the models' specifications. The long-run estimates of GDP are positive and statistically significant at the 5% level for total, public, and private HCE regressions. Irrespective of the income group of the countries, the elasticities of HCE with respect to income (GDP) are less than one for each of the models, ranging from 0.214 to 0.426 for total HCE, 0.203 to 0.559 for public HCE, and 0.448 to 0.958 for private HCE. The elasticities of private HCE with respect to income are higher than those of public HCE. However, when we consider the two sub-groups, the findings suggest that, in most regressions, the income elasticities of public HCE are higher for middle-income countries than for low-income countries. One possible reason is that increases in income

raise the demand for health services due to an increase in the marginal utility of healthcare in the middle-income group more than in the low-income group (Hall & Jones, 2007). As countries grow, they have more resources to invest in their health system to improve the health of the population. In contrast, the income elasticities of private health expenditure are higher for low-income countries than for middle-income countries. One possible explanation is that in low-income countries, people perceive private healthcare to be of higher quality than public healthcare.

Table 6. Pooled mean group long-run estimation of total health expenditure.

Models	Whole sample	Low-income	Middle-income
(S1)			
LGDPPC	0.406***	0.346**	0.418***
	(0.082)	(0.157)	(0.106)
LMRI	-0.354***	-0.380***	-0.346***
	(0.083)	(0.122)	(0.121)
(S2)			
LGDPPC	0.337***	0.808***	0.347***
	(0.056)	(0.161)	(0.058)
LLEB	1.429***	0.943*	1.365***
	(0.194)	(0.512)	(0.207)
(S3)			
LGDPPC	0.426***	0.032	0.459***
	(0.062)	(0.159)	(0.076)
LPOP65	0.590***	0.722***	0.544***
	(0.118)	(0.181)	(0.148)
(S4)			
LGDPPC	0.214**	0.237	0.181
	(0.091)	(0.175)	(0.113)
LMRI	0.317***	0.237	0.289**
	(0.120)	(0.280)	(0.142)
LPOP65	1.521***	1.101***	1.564***
	(0.150)	(0.357)	(0.150)
N	1,035	460	575

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses.

Concerning the estimated coefficients of the medical technology variable, we note that in most regressions, the estimates on infant mortality rates have the expected negative sign with statistical significance at the 1% level. Also, the estimated coefficients on life expectancy at birth have the expected positive signs with statistical significance at the 5% level. Life expectancy elasticities of HCE are similar in absolute value for the low-income countries (1.886 for public HCE versus 1.710 for private HCE). However, for middle-income countries, the life expectancy elasticities of public HCE are greater than those of private HCE (1.669 versus 0.070). The infant mortality elasticities of health expenditure are lower in absolute value than the life expectancy elasticities of health expenditure in the two subgroups of countries. For instance, in low-income countries, these elasticities are 0.796 versus 1.886 for public HCE and 0.029 versus 1.710 for private HCE. It must be noted that the long-run elasticities of HCE (total, public, and private) with respect to life expectancy at birth are greater than those of GDP.

With respect to the variable aging population, the coefficients estimated on this variable in the total HCE function are positive and statistically significant at 1%, both for the whole sample and the two subgroups of countries. More importantly, the effect of the aging population varies according to the income group and the component of health expenditure. For example, the elasticities of public HCE with respect to the aging population are slightly lower in low-income countries than in middle-income countries. Similar results are noted for private HCE.

Table 7. Pooled mean group long-run estimation of public health expenditure.

Models	Whole sample	Low-income	Middle-income
(S1)			
LGDPPC	0.532***	0.183	0.837***
	(0.103)	(0.161)	(0.102)
LMRI	-0.157*	-0.796***	0.133
	(0.095)	(0.141)	(0.098)
(S2)			
LGDPPC	0.203**	1.148***	0.148
	(0.096)	(0.196)	(0.108)
LLEB	3.161***	1.886***	1.669***
	(0.315)	(0.503)	(0.377)
(S3)			
LGDPPC	0.350***	0.186	1.588***
	(0.102)	(0.177)	(0.163)
LPOP65	0.771***	1.073***	-1.430***
	(0.187)	(0.301)	(0.280)
(S4)			
LGDPPC	0.559***	-0.110	1.276***
	(0.121)	(0.154)	(0.128)
LMRI	-0.378***	-0.607**	-0.125
	(0.118)	(0.276)	(0.091)
LPOP65	-0.391**	0.762*	-0.996***
	(0.191)	(0.420)	(0.218)
N	1,035	460	575

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses.

Table 8. Pooled mean group long-run estimation of private health expenditure.

Models	Whole sample	Low-income	Middle-income
(S1)			
LGDPPC	0.487***	0.537***	0.310***
	(0.066)	(0.110)	(0.089)
LMRI	-0.387***	0.029	-0.597***
	(0.075)	(0.088)	(0.102)
(S2)			
LGDPPC	0.958***	1.462***	0.814***
	(0.071)	(0.151)	(0.068)
LLEB	-0.505*	-1.710***	0.070
	(0.269)	(0.474)	(0.261)
(S3)			
LGDPPC	0.624***	0.721***	-0.116
	(0.077)	(0.077)	(0.107)
LPOP65	0.234	0.083	1.683***
	(0.151)	(0.153)	(0.203)
(S4)			
LGDPPC	0.565***	0.592***	-0.133
	(0.076)	(0.100)	(0.105)
LMRI	-0.287***	1.008***	-0.347***
	(0.101)	(0.202)	(0.120)
LPOP65	-0.006	1.339***	1.410***
	(0.171)	(0.299)	(0.197)
N	1,035	460	575

Note: *** p < 0.01, * p < 0.1. Standard errors in parentheses.

As regards the short-run estimates, the findings are presented in Tables 2A, 2B, and 2C in Appendix 2. The coefficients on the error-correction term are negative and statistically significant at the 1% level and are lower than

1 for all specifications, both whole sample and subgroups. This shows the existence and stability of the dynamic of the adjustment to the long-run equilibrium between each component of HCE and its determinants. The adjustment speed from the short-run disequilibrium toward the long-run equilibrium between HCE and its determinants ranges from 31.9% to 51.1% for public HCE and from 26.4% to 36.8% for private HCE. We also notice that only the short-run coefficients on GDP are positive and statistically significant at the 5% level for all types of HCE in the low-income countries group. Moreover, the short-run coefficients on GDP in public HCE functions are higher than those of private HCE functions. For example, for specification S1, the short-run coefficients are 0.882 for public HCE and 0.592 for private HCE. HCE reacts to short-run income fluctuations in low-income African countries. Concerning the medical technology variables, the estimated short-run coefficients on the proxy's variables are statistically insignificant at the conventional 5% level for the whole panel as well as for the subgroups.

With respect to the causality test, Table 9 suggests the existence of long-run bidirectional causality between each type of health expenditure, GDP, infant mortality rate, and aging population.

Table 9. Pairwise Dumitrescu-Hurlin panel causality.

Models	Whole sample		Low-income		Middle-income	
Causality direction	**W-stat**	**Zbar-stat**	**W-stat**	**Zbar-stat**	**W-stat**	**Zbar-stat**
LTHEXP						
LGDPPC → LTHEXP	4.221	15.280***	2.416	4.479***	5.665	16.494***
LTHE → LGDPPC	3.224	10.550***	2.826	5.775***	3.542	8.989***
LMRI → LTHEXP	4.084	14.630***	3.280	7.209***	4.728	13.180***
LTHE → LMRI	12.237	53.301***	13.402	39.219***	11.304	36.431***
LLEB → LTHEXP	4.076	14.592***	3.563	8.106***	4.487	12.328***
LTHE → LLEB	38.168	176.304***	10.751	30.836***	60.102	208.957***
LPOP65 → LTHEXP	4.018	14.314***	2.848	5.845***	4.953	13.977***
LTHE → LPOP65	4.495	16.580***	2.865	5.899***	5.799	16.968***
LPUHEXP						
LGDPPC → LPUHEXP	3.497	11.846***	2.631	5.159***	4.190	11.279***
LPUHE → LGDPPC	2.463	6.940***	2.340	4.238***	2.561	5.520***
LMRI → LPUHE	3.503	11.872***	3.872	9.081***	3.208	7.806***
LPUHE → LMRI	10.613	45.597***	6.103	16.137***	14.220	46.741***
LLEB → LPUHEXP	4.331	15.800***	4.466	10.962***	4.223	11.393***
LPUHE → LLEB	27.509	125.742***	8.951	25.144***	42.355	146.211***
LPOP65 → LPUHEXP	3.164	10.265***	3.932	9.272***	2.550	5.478***
LPUHE → LPOP65	4.772	17.894***	2.752	5.539***	6.389	19.054***
LPRHEXP						
LGDPPC → LPRHEXP	5.971	23.579***	3.943	9.306***	7.593	23.311***
LPRHE → LGDPPC	2.151	5.459***	1.796	2.516**	2.435	5.074***
LMRI → LPRHEXP	7.145	29.148***	4.021	9.552***	9.645	30.563***
LPRHE → LMRI	10.125	43.286***	12.076	35.025***	8.565	26.747***
LLEB → LPRHE	5.855	23.031**	3.747	8.688***	7.542	23.128***
LPRHE → LLEB	22.271	100.898***	14.088	41.389***	28.817	98.349***
LPOP65 → LPRHEXP	5.627	21.947***	3.477	7.833***	7.347	22.439***
LPRHE → LPOP65	6.549	26.322***	3.577	8.150***	8.927	28.025***

Note: *** $p < 0.01$, ** $p < 0.05$. The variables LTHEXP, LPUHEXP, and LPRHEXP represent the logarithm of per capita health expenditure for total health expenditure (THEXP), private health expenditure (PRHEXP), and public health expenditure (PUHEXP), respectively. LGDPPC stands for GDP per capita, LMRI represents the infant mortality rate, LEB indicates life expectancy at birth, and LPOP65 denotes the proportion of the population aged over 65 years old.

5. DISCUSSION

Our findings suggest that the estimated coefficients of technology progress proxied by the infant mortality rate are negative and statistically significant at 1%. Also, the estimated coefficients of life expectancy at birth are positive and statistically significant at the 5% level. These results are in line with Dreger and Reimers (2005), You and Okunade (2017), and Barkat et al. (2019), who concluded that medical technology is an important driver of rising

healthcare costs. Our findings suggest that medical technology has significantly contributed to improvements in the health status of the population. It means that medical technology brings about improvements in population health, including an increase in the aging population and life expectancy at birth and a decrease in infant mortality. Medical technology decreases infant mortality through a reduction of morbidity and better provision of healthcare. When considering the aging population as a demographic measure, we notice that the elasticities of HCE with respect to the aging population are positive and statistically significant at the 1% level and higher than 1 for all subgroups. However, the elasticities of public health expenditure with respect to the aging population are lower than 1. This means that an increasing number of older people will increase the need for health expenditure, which causes health expenditure in African countries to rise in the long run. Therefore, in the long run, an aging population will progressively have major economic and health implications in African countries. African healthcare systems need to be prepared to appropriately manage this challenge. The estimated short-run coefficients on medical technology, proxied by the infant mortality rate, life expectancy at birth, and the aging population, are statistically insignificant at the conventional 5% level for the whole panel, as well as for the subgroups of countries. This result is similar to those of Okunade et al. (2018) and Llorian and Mann (2022), whose short-run coefficients were statistically insignificant. This may be because changes in medical technology could be very minor in the short run; one may expect changes in technological progress to occur in a long-run context (Barkat et al., 2019; Murthy & Ketenci, 2017). Medical technology change is thus a long-run, not a short-run, phenomenon.

Healthcare appears to be a necessity good rather than a luxury good for the low-income group as well as the middle-income group of sampled countries, whether public or private health expenditure is used as the dependent variable. These results are consistent with previous studies in developing countries, including those in Africa (Barkat et al., 2016; Barkat et al., 2019; Byaro et al., 2018; Gbesemete & Gerdtham, 1992; Kouassi et al., 2018; Murthy & Okunade, 2009; Okunade, 2005). There are two reasons why the response of health expenditure to a change in income is less than 1%. Since poverty rates are high in Africa, an increase in income may lead primarily to an increase in food expenditure even though health and food are not substitutes. People, therefore, increase health expenditure less than proportionally to their increase in income. In poorer countries, people consume healthcare to satisfy health needs so the income elasticity of HCE may be lower than in richer countries. Another potential reason is that health insurance, particularly social health insurance coverage, is not widespread in African countries, meaning that the marginal cost of healthcare utilization remains high, particularly for poor and vulnerable households. This finding contradicts some studies that argue that the income elasticity of healthcare displays the characteristics of a necessity good at individual and household levels, and a luxury good at the national level (Getzen, 2000). The difference between the income elasticity of private HCE and the income elasticity of public HCE we observed may be explained by the fact that demand for private and public health services varies across population groups and levels of development. The greater the government healthcare financing, the greater will be the access of consumers who are unable to pay for healthcare services (Hitiris & Posnett, 1992; Pattnayak & Chadha, 2016). Greater public provision of healthcare services reduces individuals' health expenditures, and greater government control leads to lower healthcare costs, particularly for the poor (Khan & Ul Husnain, 2019; Santerre, Grubaugh, & Stollar, 1991). The fact that the income elasticities of HCE are lower in low-income countries than in middle-income countries may be linked to the fact that an increased level of income is accompanied by positive and strong responsiveness of income elasticity, particularly in low-income countries. HCE reacts to short-run income fluctuations in low-income African countries.

The existence of a bidirectional long-run relationship between each type of HCE and its determinants for all subgroups has important implications for policymakers. For instance, the bidirectional causality between HCE and income indicates that an increase in health expenditure in a country tends to improve population health, which benefits labor productivity and, subsequently, economic growth. The rate of technological progress in the health sector does not increase independently of the historical context but is influenced by several factors, such as the size of the healthcare market, rising incomes, and more generous insurance coverage (Smith et al., 2009).

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

The findings presented in the paper contribute to our understanding of the core drivers of HCE in Africa. We found that HCE (total, public, and private spending), income, medical technology (infant mortality rate, life expectancy at birth), and the aging population have statistically significant long-run economic relationships. We show that beyond income, medical technology and the aging population are also determinants of HCE. The elasticity estimates changed with the two income groups and the HCE component, showing the importance of accounting for income heterogeneity among African economies and the difference between public and private healthcare. Public and private HCE appears to be a necessity good rather than a luxury good for low-income as well as middle-income countries. However, the income elasticities of private health expenditure are higher for low-income countries than for middle-income countries. While medical technology measured by the infant mortality rate reveals that technology is a necessity, medical technology captured by life expectancy at birth suggests that technology is a luxury in low-income countries.

The strength of this paper is the use of the PMG estimator, which allowed us to control for endogeneity issues while allowing the parameter to vary across countries in the short run. It also accounts for the income heterogeneity between two groups of countries, namely low-income and middle-income countries.

Our results have some policy implications. Firstly, focusing policy only on the estimated relationship between total HCE and its determinants is misleading because the estimated effects of the independent variables on HCE vary with the subgroup and the nature of health expenditure. Policymakers should pay attention to these distinctions. The estimated elasticities provided in the paper can be used when projecting HCE, as HCE projections are highly sensitive to assumptions regarding elasticity values. Secondly, HCE is simultaneously determined by income in the sense that they work together and reinforce each other. Medical technology change and HCE are also determined simultaneously. Thus, health policy that consists of increasing HCE, particularly its public component, will not only increase income but also the rate of technological innovation. Therefore, the effect of increasing HCE goes beyond the healthcare system. Given that income and technological innovations in healthcare are important contributors to improvements in population health, the simultaneous determination of income and HCE on the one hand, and technological progress and HCE on the other, will result in the government facing less severe policy dilemmas when trying to increase HCE to improve the population's health.

Our study has a few limitations. A good measure of medical technology in the health sector is not available in the data set. Our measure of medical technology does not explicitly model medical innovations. Private and public health expenditure may be determined by different processes that are not discussed here. The PMG estimator used may suffer from small sample bias, which decreases as T increases. We leave these issues open for future research when more comprehensive data become available.

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APPENDIX 1

Table 1A. Definitions of the variable.

Variables	Definition	Source
THEXP	Current health expenditure per capita, PPP ($ At 2005 prices)	World development indicators World Bank (2021)
PUHEXP	Domestic general government health expenditure per capita, PPP ($ At 2005 prices)	World Bank (2021)
PRHEXP	Domestic private health expenditure per capita, PPP ($ At 2005 prices)	World Bank (2021)
GDPPC	GDP per capita, PPP ($ At 2005 prices)	World Bank (2021)
MRI	Mortality rate, infant (Per 1,000 live births)	World Bank (2021)
LEB	Life expectancy at birth, total (Years)	World Bank (2021)
LPOP65	Population ages 65 and above, total	World Bank (2021)

Table 1B. List of countries.

Countries		
Algeria	**Equatorial Guinea**	**Morocco**
Angola	Eswatini	Mozambique
Benin	Ethiopia	Namibia
Botswana	Gabon	Niger
Burkina Faso	Gambia	Nigeria
Burundi	Ghana	Rwanda
Cabo Verde	Guinea	Senegal
Cameroon	Guinea-Bissau	Sierra Leone
Central African Republic	Kenya	South Africa
Chad	Lesotho	Sudan
Comoros	Liberia	Tanzania
Congo, Dem, Rep,	Madagascar	Togo
Congo, Rep,	Malawi	Tunisia
Cote d'Ivoire	Mali	Uganda
Egypt, Arab Rep,	Mauritania	Zambia

APPENDIX 2. Short-run parameters.

Table 2A. Pooled mean group short run estimation of total health expenditure.

Models	Whole sample	LIC	MIC
(S1)	ARDL1111	ARDL1111	ARDL1111
Ect(-1)	-0.315***	-0.288***	-0.333***
	(0.043)	(0.053)	(0.066)
LGDPPC	0.423**	0.840***	0.100
	(0.202)	(0.257)	(0.289)
LMRI	-1.357	-3.048*	-0.062
	(0.920)	(1.754)	(0.824)
(S2)			
Ect(-1)	-0.340***	-0.293***	-0.413***
	(0.048)	(0.047)	(0.077)
LGDPPC	0.373*	0.570***	0.071
	(0.194)	(0.177)	(0.301)
LLEB	3.288	3.466	4.701
	(2.925)	(4.350)	(4.076)
(S3)			
Ect(-1)	-0.295***	-0.218***	-0.334***
	(0.043)	(0.053)	(0.066)
LGDPPC	0.453***	0.815***	0.197
	(0.174)	(0.196)	(0.271)
LPOP65	0.554	2.717*	-0.590
	(0.968)	(1.494)	(1.283)
(S4)			
Ect(-1)	-0.361***	-0.316***	-0.397***
	(0.047)	(0.056)	(0.075)
LGDPPC	0.436**	0.795***	0.163
	(0.195)	(0.251)	(0.278)
LMRI	-0.781	-1.790	-0.314
	(1.311)	(2.326)	(1.191)
LPOP65	0.730	3.042	-0.859
	(1.157)	(1.939)	(1.196)
N	1,035	460	575

Note: ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

Table 2B. Pooled mean group short run estimation of public health expenditure.

Models	Whole sample	LIC	MIC
(S1)	ARDL1111	ARDL1111	ARDL1111
Ect(-1)	-0.399***	-0.466***	-0.390***
	(0.042)	(0.063)	(0.064)
LGDPPC	0.266	0.882**	-0.324
	(0.270)	(0.397)	(0.364)
LMRI	2.045	5.751	-0.182
	(2.148)	(3.959)	(2.429)
(S2)			
Ect(-1)	-0.414***	-0.422***	-0.415***
	(0.047)	(0.067)	(0.065)
LGDPPC	0.649***	0.762*	-0.011
	(0.242)	(0.427)	(0.291)
LLEB	-4.279	-9.735	5.820
	(5.223)	(8.749)	(6.720)
(S3)			
Ect(-1)	-0.360***	-0.390***	-0.319***
	(0.034)	(0.049)	(0.054)
LGDPPC	0.421	0.963***	-0.163
	(0.256)	(0.324)	(0.354)
LPOP65	0.650	-0.266	0.414

Models	Whole sample	LIC	MIC
	(1.900)	(3.368)	(1.734)
(S4)			
Ect(-1)	-0.465***	-0.511***	-0.473***
	(0.049)	(0.073)	(0.075)
LGDPPC	0.224	0.765**	-0.316
	(0.261)	(0.369)	(0.360)
LMRI	2.871	7.289	0.270
	(2.695)	(5.574)	(3.605)
LPOP65	4.085*	1.354	4.264
	(2.450)	(4.146)	(2.994)
N	1,035	460	575

Note: ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

Table 2C. Pooled mean group short run estimation of private health expenditure.

Models	Whole sample	LIC	MIC
(S1)	ARDL1111	ARDL1111	ARDL1111
Ect(-1)	-0.287***	-0.323***	-0.278***
	(0.040)	(0.072)	(0.051)
LGDPPC	0.218	0.592**	-0.097
	(0.260)	(0.282)	(0.410)
LMRI	0.697	0.047	0.022
	(1.467)	(3.040)	(1.255)
(S2)			
Ect(-1)	-0.274***	-0.264***	-0.284***
	(0.046)	(0.065)	(0.063)
LGDPPC	0.163	0.452**	-0.123
	(0.235)	(0.191)	(0.392)
LLEB	0.301	1.021	-1.916
	(2.839)	(4.769)	(3.716)
(S3)			
Ect(-1)	-0.265***	-0.294***	-0.267***
	(0.043)	(0.069)	(0.056)
LGDPPC	0.281	0.625***	0.074
	(0.232)	(0.193)	(0.378)
LPOP65	1.389	3.345	-1.419
	(1.251)	(2.348)	(1.102)
(S4)			
Ect(-1)	-0.326***	-0.368***	-0.336***
	(0.042)	(0.083)	(0.056)
LGDPPC	0.199	0.561**	0.053
	(0.255)	(0.230)	(0.407)
LMRI	1.225	2.993	-0.382
	(1.633)	(3.682)	(2.105)
LPOP65	1.461	5.669**	-2.576*
	(1.483)	(2.849)	(1.437)
N	1,035	460	575

Note: ***, ** and * indicate 1%, 5% and 10% level of significance, respectively.

Table 2D. Hausmann test between PMG and MG estimators.

Income groups	H-test	Prob>chi2
Whole sample	3.840	0.146
LIC	2.270	0.321
MIC	4.720*	0.094

Note: * indicate 10% level of significance, respectively.