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## Article

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## Article

# Out-of-Pocket Health Expenditure in Sub Saharan Africa: The Role of Government and External Health Expenditures

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**Abstract:** This study aims to analyze the impact of government and external health spending on OOPHE across 30 SSA countries from 1995 to 2021. Using advanced econometric techniques, including the cross-sectionally augmented autoregressive distributed Lags (CS-ARDL) model and the dynamic common correlated effects (DCCE) approach, the study examined both short-term and long-term effects. Findings reveal that in the long term, government health expenditure (GHE) has a more significant impact on reducing OOPHE compared to external health expenditure (EHE). However, in the short term, GHE initially increases OOPHE, while EHE directly reduces it. This suggests that increasing GHE is more effective for long-term progress towards SDG 3. In contrast, EHE can provide immediate relief in the short term. To achieve SDG 3, policymakers should focus on increasing GHE for sustained improvements while leveraging EHE to address short-term challenges. Combining both strategies can optimize progress toward ensuring universal health coverage and well-being for all.

**Keywords:** OOPHE; GHE; EHE; CS-ARDL; DCCE

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## 1. Introduction

Healthcare financing in Sub-Saharan Africa (SSA) remains a critical challenge, as high out-of-pocket health expenditure (OOPHE) exacerbates household poverty and limits access to essential healthcare services. OOPHE accounts for a significant share of total health spending in the region, undermining efforts to achieve SDG 1 (No Poverty) and SDG 3 (Good Health and Well-being). Addressing the financial burden of healthcare is essential for ensuring universal health coverage (UHC) and reducing financial barriers, particularly for low-income populations. This study investigates the impact of government health expenditure (GHE) and external health expenditure (EHE) on OOPHE in SSA, providing insights that can inform policy decisions and improve healthcare financing strategies.

Existing literature has explored the relationship between health spending and OOPHE, but several gaps remain. Studies such as [Frimpong et al. \(2021\)](#) employed the SGMM approach but did not account for cross-sectional dependence (CSD), which is crucial in SSA due to shared economic and institutional characteristics, as well as common regional shocks. Additionally, the dynamic effects of health spending on OOPHE—especially the short-term versus long-term impacts—have not been sufficiently explored. This study seeks to address these gaps by employing advanced econometric techniques, such as the cross-sectionally augmented autoregressive distributed lags (CS-ARDL) model and the dynamic common correlated effects (DCCE) approach.

This study uses the CS-ARDL and DCCE methods to analyze both short-term and long-term dynamics between GHE, EHE, and OOPHE across 30 SSA countries from 1995 to 2021. These techniques account for CSD, slope heterogeneity, and endogeneity, providing a more accurate and comprehensive analysis compared to previous studies. By considering the regional context of SSA—where countries are often exposed to common economic crises, pandemics, and political events—this study offers robust and consistent results.

The findings reveal that in the long run, GHE significantly reduces OOPHE, whereas EHE has a stronger short-term impact, directly reducing OOPHE in both the short and long terms. The impact of GHE on OOPHE is greater in the long term compared to the effect of EHE. These results provide valuable insights for policymakers, international health organizations, and development practitioners, guiding resource allocation and health financing reforms. The study emphasizes the importance of increasing GHE for sustained improvements in healthcare financing while leveraging EHE to address short-term challenges.

This study's use of the CS-ARDL and DCCE models is a notable innovation, as it overcomes limitations in earlier research, such as the failure to account for CSD (Voto & Ngepah, 2024). By focusing on the heterogeneous impact of GHE and EHE on OOPHE across SSA countries with similar economic and institutional characteristics, this research provides a more nuanced understanding of the factors influencing healthcare financing in the region. The findings offer data-driven recommendations for improving healthcare accessibility, reducing reliance on out-of-pocket spending, and fostering sustainable health financing mechanisms.

## 2. Literature Review

### 2.1. Healthcare Financing and OOPHE in SSA

Healthcare financing in Sub-Saharan Africa (SSA) is characterized by a complex interplay of factors, with out-of-pocket health expenditure (OOPHE) being a significant financial burden on households. OOPHE refers to direct payments made by individuals at the point of receiving healthcare services, excluding any prepaid arrangements such as insurance or government subsidies (World Health Organization, 2010). High OOPHE in SSA is a major obstacle to achieving universal health coverage (UHC) and equitable access to healthcare, particularly for vulnerable populations (McIntyre et al., 2006). However, despite the significance of this issue, much of the existing research focuses on descriptive analyses without critically assessing the underlying reasons for the persistence of OOPHE and its long-term effects on health equity.

### 2.2. OOPHE and Government Health Expenditures

Government health expenditure (GHE) plays a crucial role in reducing OOPHE by providing subsidies and expanding health coverage. The welfare state theory suggests that governments have a responsibility to ensure equitable access to healthcare services, with GHE acting as a primary tool to mitigate OOPHE and protect households from financial strain. While GHE can reduce OOPHE and enhance social equity, studies have shown that the proportion of government spending on health in SSA remains low—approximately 2% of GDP compared to the global average of 6% (World Bank, 2018). This low level of investment limits the ability of public health systems in SSA to deliver essential services without significant OOP costs, further exacerbating financial barriers for low-income populations (Lu et al., 2010).

Studies like those by Chuma and Maina (2012) and Tetteh (2014) suggest that increased GHE leads to lower OOPHE and improved healthcare access, particularly in countries like Kenya, Ghana, and Rwanda. However, this research often overlooks critical questions, such

as how variations in the efficiency of government health spending or the presence of fiscal austerity measures affect these outcomes. For example, [McIntyre et al. \(2016\)](#) argue that during economic downturns or periods of fiscal austerity, government health expenditure tends to fluctuate, increasing reliance on OOPHE. The limitations of these studies lie in their inability to address how external factors, such as economic crises or global health priorities, might mitigate or exacerbate the effects of government spending on healthcare.

Recent studies have emphasized the ongoing challenges posed by out-of-pocket health expenditure (OOPHE) in Sub-Saharan Africa (SSA). High OOPHE significantly hinders access to essential healthcare services, especially among low-income households ([Smith et al., 2023](#)). Additionally, [Adeyemo and Olanrewaju \(2023\)](#) highlighted that government health expenditures (GHE) have a more sustainable impact on reducing OOPHE in the long term, while external health expenditure (EHE) offers short-term relief but may not be a reliable solution. Similarly, [Nwachukwu et al. \(2022\)](#) found that increased public health financing was associated with reduced financial barriers to healthcare in SSA, underlining the importance of long-term domestic investments in healthcare infrastructure. These findings suggest that while external aid plays a role, the key to reducing OOPHE in SSA lies in increasing domestic health spending and developing robust health financing systems that are less reliant on volatile external funding ([Adeyemo & Olanrewaju, 2023](#); [Smith et al., 2023](#)).

### 2.3. OOPHE and External Health Expenditures

External health expenditures (EHE), including international aid and donor funding, provide a significant but often unstable source of financing for healthcare in SSA. The dependency theory posits that overreliance on external funding creates instability in healthcare systems, potentially worsening OOPHE if external aid is inconsistent or insufficient. While EHE can help fill financing gaps, it can also create dependency, leading to unpredictable funding streams and making health systems vulnerable to shifts in donor priorities ([Shaw & Griffin, 2014](#)).

However, while these studies are insightful, they fail to critically evaluate the methodological issues surrounding the measurement of EHE, including the reliance on reported data from donor organizations, which may not always accurately reflect the actual impact of external aid on healthcare outcomes. Moreover, they do not address the sustainability of EHE over time. For example, [Lu et al. \(2010\)](#) note that external health funding is often contingent on conditions that can place additional financial burdens on recipient countries. This introduces a gap in the literature regarding the long-term sustainability of EHE as a reliable means of reducing OOPHE.

### 2.4. Balancing Primary, Secondary, and Tertiary Care: Implications for Health Equity

A critical issue that is often overlooked in the literature is the balance between primary, secondary, and tertiary care, particularly in the context of achieving health equity. Primary care, which offers essential services such as preventive care and chronic disease management, is generally more cost-effective compared to secondary and tertiary care. However, an overemphasis on secondary and tertiary care, which tends to be more expensive, could exacerbate OOPHE by creating financial barriers for individuals needing primary care services ([Chuma & Maina, 2012](#)). Studies indicate that shifting resources toward more specialized forms of care without strengthening primary healthcare can disproportionately increase OOPHE for vulnerable populations, driving up overall healthcare costs and widening health disparities ([Ensor & Cooper, 2004](#); [Tetteh, 2014](#)).

While the literature highlights the importance of a balanced healthcare system, few studies critically assess how the allocation of resources between primary, secondary, and tertiary care impacts the financial burden on households, especially in the context of SSA's

specific economic and healthcare challenges. Moreover, there is limited empirical evidence on the long-term effects of such imbalances on health equity, particularly when considering the interaction between public and private financing mechanisms.

### 2.5. Synthesis and Research Gaps

The literature provides valuable insights into the relationship between government and external health expenditures and OOPHE in SSA, with most studies emphasizing that increased GHE and EHE can reduce OOPHE. However, there are several gaps and limitations in the existing research: Much of the literature focuses on descriptive statistics and basic correlations, without a deep dive into methodological issues, such as cross-sectional dependence (CSD) or endogeneity, which may distort the findings. Several studies, including [Frimpong et al. \(2021\)](#), fail to account for the heterogeneity in SSA countries or the impact of economic shocks, which may result in inconsistent or unreliable results. While many studies explore the effects of GHE and EHE on OOPHE, they often fail to address how variations in government efficiency, donor priorities, and economic instability influence these outcomes. Few studies critically examine the long-term sustainability of external health expenditures, particularly in the face of shifting donor priorities or economic crises.

This study fills these gaps by employing advanced econometric techniques, such as the CS-ARDL and DCCE models, to analyze the short-term and long-term effects of GHE and EHE on OOPHE while accounting for cross-sectional dependence and slope heterogeneity. By providing a more robust analysis, this research contributes to a deeper understanding of how different forms of health financing can impact OOPHE and health equity in SSA.

## 3. Methodology and Data

Table 1 provides the source et description of the variables.

**Table 1.** Source and description of the variables.

| Variable               | Description  | Source             |
|------------------------|--|--------------------|
| OOPHE                  | Health expenditures through OOP payments per capita (as a share of THE)  | World-Bank         |
| GHE                    | Government health expenditures of each country as a share of THE (general government). This includes public health services, hospitals, R&D health, etc.   | World-Bank         |
| EHE                    | Current per capita external health expenditures as a share of THE encompass all financial inflows into the national health system from foreign sources. These include direct foreign transfers and government-distributed foreign aid. | World-Bank         |
| GDP per capita         | GDP per capita has been included in our equations 1 and 2 to capture countries' development levels. We have transformed this variable into a natural logarithm in order to reduce its high skewness.                                   | World Bank (WDI)   |
| Old population         | The old population (OLDPOP) is quantified as the % of individuals who are 64 years of age or older.  | World-Bank         |
| Life Expectancy        | Life expectancy at birth reflects the average number of years a newborn is expected to live, assuming that current mortality rates remain constant throughout their lifetime.  | World Bank         |
| Education level        | As measured by the gross secondary school enrollment rate expressed in percentage terms.   | World Bank (WDI)   |
| Educational Inequality | Standard deviation of the level of education   | Author computation |

In this section, we also briefly discuss the dependent and independent variables and justify their inclusion in the empirical models. OOPHE is employed as a dependent variable in this study. The dependent variable, OOPHE, is expected to show a positive relationship, meaning it tends to increase when individuals or households bear more direct costs for health services (World Bank, 2021). Government health expenditure, a regressor, is expected to have a negative relationship, as higher government spending typically reduces the need for individuals to spend out of pocket on health services (Lu et al., 2017). Similarly, EHE is expected to negatively affect out-of-pocket health expenditure, as increased external funding can supplement local resources for health services (World Health Organization, 2015).

Among the control variables, life expectancy is indirectly expected to negatively relate to out-of-pocket health expenditure, as healthier populations may require less healthcare spending (Dieleman et al., 2017). Conversely, educational inequality is expected to have a positive relationship, with higher inequality potentially correlating with increased out-of-pocket health expenditure due to disparities in healthcare access and information (World Bank, 2018). GDP per capita (GDPpc) is also expected to negatively correlate, as wealthier countries often offer more comprehensive health coverage (World Bank, 2019). Old population (OLDPOP) is defined as the percentage of the population aged 64 years and older. Given that health tends to decline with age, we anticipate a positive correlation between OLDPOP and OOPHS (out-of-pocket health spending). The proportion of the population over 64 years old is widely recognized as a standard indicator for assessing the impact of aging on health outcomes (Xu et al., 2011).

### 3.1. Methods

#### Conceptual Framework

Following Frimpong et al. (2021), this study considers an individual with a fixed income  $m$  who allocates spending between quantities of healthcare  $QH$  ( $QH = 1 \dots N$ ) and quantities of other goods and services  $QGS$  ( $QGS = 1 \dots N$ ). These other goods are collectively referred to as “consumption goods”. The goal is to maximize overall well-being under the constraint that total spending cannot exceed total income. The budget constraint is expressed in Equation (1), where  $CH$  represents the cost of healthcare, and  $CCG$  represents the cost of consumption goods. If the individual receives health subsidies  $j$  (where  $j \leq s$ ), this modifies the budget constraint, as shown in Equation (2). The relationship between OOPHE and amount of health subsidies (AHS) is described in Equation (3), where  $F$  represents a function, and  $X$  denotes other factors like income and education that can also influence OOPHE.

$$chQH + ccgQGS \leq m \quad (1)$$

$$(ch - Ahs)QH + ccgQGS \leq m \quad (2)$$

$$OOPHE = F(AHS, X) \quad (3)$$

### 3.2. Empirical Strategy

To investigate out-of-pocket health expenses in Sub-Saharan Africa and the influence of government and external health funding, the health financing and protection theoretical framework is particularly useful. This framework explores how various sources of health financing—such as government funding, international aid, and personal payments—interact and affect access to health care and financial protection (World Health Organization, 2010). It demonstrates how increased government and external financial support can lessen out-of-pocket expenses and enhance equity by making health services more affordable and reducing financial obstacles (Savedoff, 2011). By analyzing these dynamics, the framework sheds light on how well-structured health financing can ease the economic burden on

individuals, particularly in low-income regions, and promote fairer access to health care (Collier, 2007).

The empirical strategy in this research involves several methodological steps. First, the Pesaran (2004) CD test is used to assess CSD among countries, determining whether cross-sectional independence is present. Next, the Pesaran (2015) CD test is employed to evaluate the strength of error dependence, with the null hypothesis suggesting weak dependence. If CSD is identified, the cross-sectionally augmented Im-Pesaran-Shin (CIPS) test by Pesaran (2007) is applied.

The recent empirical literature on panel data emphasizes the need to assess cross-sectional dependence prior to any further analysis. This assessment is crucial to avoid biases in estimated coefficients that could arise from common shocks with varying impacts across countries or from spatial spillover effects among variables in different regions (Eberhardt & Teal, 2011). Thus, it is important to identify cross-sectional dependence, especially when the sample is presumed to consist of similar groups of economies. This applies to our sample, as most countries in both regions share comparable characteristics. Several recent studies using panel data highlight the significance of this consideration for obtaining consistent estimates (Afonso & Jalles, 2013; Menyah et al., 2014).

Therefore, we will first test for cross-sectional dependence before proceeding with any other analyses. To do this, we utilize the CD test developed by Pesaran (2004), which tests the null hypothesis of cross-sectional independence for each variable across countries. Conducting this particular CD test before the panel unit root test is important, as it enables the application of an appropriate test for panel unit roots. If the Pesaran (2004) CD test indicates cross-sectional dependence in the data, we will employ a specific panel unit root test as outlined by Pesaran (2007, Section 4, pp. 275–279). Additionally, if evidence of dependence among variables across countries is found, we will extend our analysis to determine whether this dependence is weak or strong, using the weak cross-sectional dependence test proposed by Pesaran (2015). This test evaluates the null hypothesis that errors are weakly cross-sectionally dependent.

This study will apply the CIPS panel unit root test by Pesaran (2007), which accounts for cross-sectional dependence and structural breaks, to examine the stationarity of variables in the regression model. If all variables are integrated at their levels ( $I(0)$ ), they are deemed stationary, suggesting a potential long-run equilibrium relationship. The unit root test is crucial in preparing for panel cointegration analysis, assuming variables of the same order are integrated. Based on the unit root test results, the study will use the second-generation panel cointegration test, specifically Westerlund's (2007) error-correction-based test, as it addresses cross-sectional dependence, structural breaks, heteroscedasticity, and serial correlation—limitations of first-generation tests like Pedroni's. While Pedroni's test is informative, it does not fully capture these factors, making Westerlund's test more suitable for ensuring robust and reliable results by accounting for parameter heterogeneity, which is often observed in panel data.

Westerlund's (2007) panel cointegration test, used in this study, relies on an error correction equation to assess whether error correction exists for individual panel units or the entire panel. The test includes four statistics: two panel statistics (Pt, Pa), which pool error correction term information across the panel's cross-sectional dimension, and two group mean statistics (Gt, Ga), which do not. The null hypothesis of no panel cointegration is tested, with the decision to reject it based on the significance of the majority of the statistics. This approach is applied to both the full sample and sub-samples to examine long-run equilibrium relationships for two regions.

To investigate causal relationships between GHE, EHE, and OOPHE, the Dumitrescu and Hurlin (2012) heterogeneous pairwise panel causality test is used. This method handles

cross-sectional dependence and stationary time-series, utilizing a bootstrap procedure for robust  $p$ -values. The test determines non-causality by comparing individual Wald statistics across the panel. If causality is confirmed, the CS-ARDL technique is applied to estimate both long- and short-run coefficients while addressing heterogeneity, endogeneity, and cross-sectional dependence. Finally, a robustness check using the DCCE model ensures the validity and empirical support of the results, enhancing the study's credibility.

In this empirical analysis, we employed the dynamic panel model described in Equation (4) based on Equation (3), where OOPHE stands for out-of-pocket health expenditure, GHE represents government health expenditure, and EHE denotes external health expenditure. Other variables include life expectancy, educational inequality, GDP per capita, and the proportion of the old population. To ensure effective interpretation, Equation (1) incorporates the logarithm-form.

$$OOPHE_{it} = \beta_0 + OOPHE_{it-1} + \beta_1 \ln GHE_{it} + \beta_2 \ln EHE_{it} + \beta_3 \ln LifeEX_{it} + \beta_4 \ln EDINEQ_{it} + \beta_5 \ln GDPpc_{it} + \beta_6 \ln Oldpop_{it} + \epsilon_{it} \quad (4)$$

Interpolation and extrapolation techniques are valuable for filling missing data gaps in longitudinal analyses, such as studying the impact of GHE and EHE on OOPHE from 1995 to 2022. These methods ensure data consistency and continuity throughout the entire time span under investigation, crucial for maintaining analytical integrity and robustness (Gelman & Hill, 2007). By filling missing data points within the observed range through interpolation and projecting future values beyond it via extrapolation, this approach optimizes the use of available data and enhances statistical power. It enables capturing the overall trends and patterns of variables like GHE and EHE, essential for understanding their influence on out-of-pocket health expenditures (Shumway & Stoffer, 2017).

Interpolation methods, such as linear or spline techniques, utilize existing data points to estimate values within the known time frame, while extrapolation techniques, like trend extrapolation or time series forecasting, predict future values based on historical trends (Chatfield, 2016), which is important for assessing the long-term effects of GHE and EHE on OOPHE in SSA. Policymakers rely on comprehensive data to assess health expenditure policies effectively over extended periods, and interpolation/extrapolation aids in evaluating their impacts on OOPHE more thoroughly (Bajari et al., 2020). By employing these techniques, this study provides a comprehensive understanding of how GHE and EHE correlate with out-of-pocket health expenditures over an extended period, supporting the formulation of evidence-based policy implications.

### 3.3. CS-ARDL

The CS-ARDL model is a panel data framework designed to study cointegration and long-run relationships in the presence of cross-sectional dependence. It is an extension of the ARDL (autoregressive distributed lag) model, commonly used for single time series but adapted to handle panel data with cross-sectional correlation.

#### Key Features of the CS-ARDL Model

##### 1. Long-run cointegration:

(i) The CS-ARDL model estimates a long-run equilibrium relationship between the variables, just like the traditional ARDL.

(ii) However, it introduces the key feature of accounting for cross-sectional dependence, which is common in economic data (e.g., countries or regions affected by similar global shocks).

(iii) The model captures cross-sectional dependence by including common unobserved factors that affect all cross-sectional units simultaneously.

## 2. Short-run dynamics:

(i) The model includes lagged values of both dependent and independent variables to account for short-run dynamics.

(ii) An error correction term (ECM) is used to capture how the system adjusts over time towards the long-run equilibrium after a shock or deviation.

## 3. Cross-sectional dependence:

(i) One of the main advantages of the CS-ARDL is that it explicitly addresses cross-sectional dependence among the panel units (i.e., correlations between the units' errors or shared external shocks).

(ii) This dependence is modeled using common factors (e.g., global economic conditions) that affect all cross-sections.

In this phase of the analysis, the study applies the final steps of the empirical strategy by utilizing the CS-ARDL and DCCE methodologies to ensure precise parameter estimation. The CS-ARDL technique, developed by Chudik et al. (2016), serves as the primary analytical tool to estimate the long-term elasticities of the specified regressors. This method is specifically designed to address various econometric challenges in panel data analysis, such as endogeneity, cross-sectional dependence (CSD), heterogeneity, omitted variables, and non-stationarity, all of which are relevant to the model used in this study (Chudik et al., 2016). The CS-ARDL model improves upon the traditional ARDL framework by incorporating cross-sectional averages of the covariates, their lags, and the response variable. This adjustment is formalized by adapting Equation (1) into a CS-ARDL specification tailored to the dataset under analysis.

The study employs the CS-ARDL (cross-sectionally augmented autoregressive distributed lags) model and the DCCE (dynamic common correlated effects) method to examine the impact of government and external health expenditures on out-of-pocket health expenditure (OOPHE) across 30 Sub-Saharan African countries. These methods were selected for their ability to address critical challenges in panel data analysis, particularly cross-sectional dependence (CSD) and slope heterogeneity, which are prevalent in Sub-Saharan Africa due to the region's shared economic, political, and institutional characteristics. The CS-ARDL model is particularly advantageous, as it allows for the estimation of both short- and long-term relationships in the presence of CSD—a crucial feature when analyzing countries in a region like SSA, where economic shocks often affect multiple countries simultaneously. This model is also robust to endogeneity, which is a common issue in econometric analyses of public expenditure and health outcomes.

Meanwhile, the DCCE method accounts for unobserved heterogeneity and cross-sectional dependence, thereby enhancing the reliability and consistency of the results. While the CS-ARDL model offers valuable insights into the dynamic relationship between health expenditures and OOPHE over time, the DCCE method provides a deeper understanding of how common factors—such as regional economic integration or shared shocks—affect the results. Both methods, however, have their limitations: the CS-ARDL model may require a large number of time periods to produce reliable estimates, and the DCCE method can be computationally intensive, especially when dealing with large datasets. Nevertheless, these methods were deemed appropriate for this study due to their ability to handle complex panel data structures and offer a more accurate analysis of the relationship between health spending and OOPHE in Sub-Saharan Africa.

$$Y_{it} = C_{yi}^* + \sum_{i=1}^p \phi_i Y_{i,t-1} + \sum_{i=0}^p \beta_i' X_{i,t-1} + \sum_{i=0}^q a_i \bar{Y}_{t-1} + \sum_{i=0}^q b_i' \bar{X}_{t-1} + \epsilon_{it}$$

In our analysis, the dependent variable is denoted as  $Y_{it}$ , and the independent variables are described by  $X_{it}$ . The cross-sectional means  $\bar{X}_t$  and  $\bar{Y}_t$  are used to account for CSD. The CS-ARDL approach requires the following: (i) a dynamic model specification to consider the

weak exogeneity of the regressors and eliminate residual correlations and (ii) the existence of a long-term relationship among the series. To ensure the robustness of our results, we apply the DCCE method developed by [Chudik and Pesaran \(2015\)](#). This technique is designed to address biases and inefficiencies due to CSD and heterogeneous slopes, providing a more reliable alternative to traditional panel data methods like mean group (MG) and pooled mean group (PMG).

The DCCE model accounts for heterogeneous slopes by using a common factor to proxy the variables and incorporates cross-sectional means and lags in the estimation. Its flexibility makes it applicable to various datasets, regardless of size or balance ([Ditzen, 2021](#)). The use of CS-ARDL and DCCE in our study is both theoretically robust and empirically validated. These techniques have been previously applied in diverse research areas beyond healthcare, such as exploring the relationships between economic growth and debt ([Eberhardt & Presbitero, 2015](#)), personal income tax and income inequality ([Voto & Ngepah, 2024](#)), government and energy efficiency ([Chang et al., 2018](#)), and mortality and innovation ([Herzer, 2020](#)). Recently, [Sadiq et al. \(2023\)](#) and [Bozatli and Akca \(2023\)](#) have effectively used these methods in the context of environmental fiscal policy.

## 4. Results

### 4.1. Summary Statistic Results

To analyze the relationship between GHE, EHE, and OOPHE using CS-ARDL, we initially assessed descriptive statistics. According to Table 2, OOPHE exhibits significant variability with a mean of 50.18 and a high standard deviation of 21.24, highlighting diverse spending patterns in healthcare among individuals. In contrast, GHE shows a mean of 31.05 and a standard deviation of 15.46, indicating substantial disparity in public health resource allocation across the sample. This diversity underscores the intricate landscape of health financing in Africa, where disparities in government spending can impact access to essential healthcare services and health outcomes ([Smith et al., 2023](#)).

**Table 2.** Summary statistics.

| Variables | Obs | Mean  | Std. Dev | Min   | Max   |
|-----------|-----|-------|----------|-------|-------|
| OOPHE     | 958 | 50.18 | 21.24    | 2.62  | 79.73 |
| GHE       | 960 | 31.05 | 15.46    | 4.23  | 77.62 |
| EHE       | 960 | 20.42 | 16.72    | 0.12  | 82.35 |
| LifeExp   | 960 | 57.96 | 7.81     | 41.04 | 76.15 |
| GDPPC     | 960 | 54.70 | 7.23     | 14.10 | 74.51 |
| EDUINE    | 960 | 7.21  | 10.27    | 0     | 63.27 |
| OLDPOP    | 960 | 4.12  | 1.24     | 2.07  | 11.31 |

### 4.2. Stationarity Test Results

The [Pesaran \(2007\)](#) CIPS (cross-sectionally augmented IPS) test is a panel unit root test designed to check for unit roots in panel data with cross-sectional dependence. This test extends the Im-Pesaran-Shin (IPS) test by incorporating cross-sectional dependence in the form of common factors. The key idea is to augment the standard unit root tests with the cross-sectional averages of the series.

The CIPS test is based on the following equation:

$$\Delta y_{it} = \mu_i + \lambda_i + \rho y_{i,t-1} + \sum_{j=1}^p \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=1}^N \gamma_j \bar{y}_{t-j} + \epsilon_{it}$$

where

$\Delta y_{it}$  is the series for cross-section  $i$  and time  $t$ ,

$\mu_i$  is the individual-specific intercept,

$\rho$  is the coefficient of the lagged dependent variable (testing for the unit root),  
 $\alpha_{ij}$  are the coefficients of the lagged differences for the individual time series,  
 $\bar{y}_{t-j}$  is the cross-sectional average of the series at time  $t - j$ ,  
 $\epsilon_{it}$  is the error term,  
 $\lambda_i$  is a time-specific effect.

The importance of the CSD test lies in its capacity to evaluate the appropriateness of first-generation tests, such as those by [Levin et al. \(2002\)](#) and [Im et al. \(2003\)](#), or the cross-sectionally Augmented Im-Pesaran-Shin (CIPS) test developed by [Pesaran \(2007\)](#), for this research. Due to the existence of CSD, we employ second-generation stationarity tests to ensure that our findings in Table 3 are robust and not misleading. The findings show that the test statistics for the series fall below the critical values at the 1% significance level for first differences, confirming their stationarity. The CIPS test rejects the  $H_0$  of non-stationarity for the series in first differences, demonstrating that all series are integrated of order one (I(1)).

**Table 3.** [Pesaran \(2007\)](#) CIPS panel unit root t (test for cross-sectional dependence and structural break).

| SSA      |       |                |       |       |           |          |                |       |       |          |
|----------|-------|----------------|-------|-------|-----------|----------|----------------|-------|-------|----------|
| At Level |       |                |       |       |           | First D. |                |       |       |          |
| Var      | Stat  | Critical Value |       |       | Decision  | Stat     | Critical Value |       |       | Decision |
|          |       | 10%            | 5%    | 1%    |           |          | 10%            | 5%    | 1%    |          |
| OOP      | −2.13 | −2.71          | −2.38 | −2.24 | Fail to R | −5.71    | −3.24          | −3.48 | −3.78 | RejetHo  |
| GHE      | −2.21 | −2.71          | −2.38 | −2.24 | Fail to R | −5.83    | −3.24          | −3.48 | −3.78 | RejetHo  |
| EHE      | −2.18 | −2.71          | −2.38 | −2.24 | Fail to R | −5.95    | −3.24          | −3.48 | −3.78 | RejetHo  |
| LifeExp  | −2.22 | −2.71          | −2.38 | −2.24 | Fail to R | −5.79    | −3.24          | −3.48 | −3.78 | RejetHo  |
| GDPpc    | −2.17 | −2.71          | −2.38 | −2.24 | Fail to R | −5.65    | −3.24          | −3.48 | −3.78 | RejetHo  |
| Inst     | −2.15 | −2.71          | −2.38 | −2.24 | Fail to R | −5.84    | −3.24          | −3.48 | −3.78 | RejetHo  |
| ICT      | −2.12 | −2.71          | −2.38 | −2.24 | Fail to R | −5.68    | −3.24          | −3.48 | −3.78 | RejetHo  |
| EducIn   | −2.16 | −2.71          | −2.38 | −2.24 | Fail to R | −5.76    | −3.24          | −3.48 | −3.78 | RejetHo  |
| Oldpop   | −2.20 | −2.71          | −2.38 | −2.24 | Fail to R | −5.78    | −3.24          | −3.48 | −3.78 | RejetHo  |

Note: Fail to R is fail to reject  $H_0$  while Rejet Ho is reject  $H_0$ : The null hypothesis is  $H_0$ : homogeneous-non-stationarity. To reject this  $H_0$  of panel non-stationarity, the computed CIPS statistic must exceed the specified critical value. The decision to reject is made at a 1% significance level.

#### 4.3. Panel Cointegration Results

The [Westerlund \(2007\)](#) panel cointegration test is used to test for cointegration in panel data, accounting for possible cross-sectional dependence. It provides tests for the null hypothesis of no cointegration and allows for heterogeneity in the panel. Westerlund offers multiple test statistics based on residuals from the long-run relationship between the variables. The model used for testing cointegration is as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}$$

where

$y_{it}$  and  $x_{it}$  are the two variables for cross-section  $i$  and time  $t$ ,  
 $\alpha_i$  represents individual-specific effects (fixed effects),  
 $\beta_i$  is the coefficient for the long-run relationship between  $y_{it}$  and  $x_{it}$ ,  
 $u_{it}$  is the residual, which should be tested for stationarity (if the residuals are stationary, the series are cointegrated).

This study utilizes the [Westerlund \(2007\)](#) panel cointegration test, accounting for CSD and heterogeneous slopes, to assess cointegration among variables. Table 4 results reject the  $H_0$  of no panel cointegration. Specifically, two out of four test statistics ( $G_t$ ,  $P_t$ ) are

statistically significant at the 1% level, suggesting long-run cointegration between income disparity and the regressors. Therefore, CS ARDL estimation is necessary to assess the long-term association among cointegrated variables.

**Table 4.** The [Westerlund \(2007\)](#) panel cointegration test (with CD and structural breaks).

| SSA   |        |                 |
|-------|--------|-----------------|
|       | Value  | <i>p</i> -Value |
| $G_t$ | −4.086 | 0.000 ***       |
| $G_a$ | −5.384 | 1.000           |
| $p_t$ | −15.98 | 0.000 ***       |
| $p_a$ | −4.123 | 0.017 *         |

Note: \*\*\*, and \* denotes the rejection of the null hypothesis of no cointegration at the 10% and 1% levels of significance, respectively. Null hypothesis: No cointegration.

#### 4.4. CSD Results

The findings from Table 5 demonstrate that there is CSD among our series across countries in SSA, as shown by *p*-values below the 5% significance level, rejecting the  $H_0$  of independence. This robust CSD in the errors is further affirmed by rejecting the  $H_0$  of weak dependence at the 1% significance level.

**Table 5.** Panel results for CSD test panel results for weak dependence.

| Variables | SSA                   | SSA                   |
|-----------|-----------------------|-----------------------|
| OOPHE     | 18.245 **<br>(0.012)  | 92.384 ***<br>(0.000) |
| GHE       | 38.425 ***<br>(0.005) | 86.789 ***<br>(0.000) |
| EHE       | 42.357<br>(0.248)     | 98.486 ***<br>(0.000) |
| LifeEXP   | 10.279 ***<br>(0.007) | 28.678 ***<br>(0.000) |
| GDPpc     | 19.862 ***<br>(0.000) | 85.695 ***<br>(0.007) |
| EDUCINEQ  | 79.538 ***<br>(0.000) | 92.358 ***<br>(0.004) |
| OLDPOP    | 58.301 ***<br>(0.000) | 58.769 ***<br>(0.000) |

Note: \*\*\* describes the rejection of  $H_0$ : existence of cross-sectional-independence at 1% significance, and \*\* describes the rejection of  $H_0$ : errors are weakly CSD at 1% significance.

## 5. Basic Results

To analyze the relationship between GHE, EHE, and OOPHE using CS-ARDL, we initially assessed the correlation matrix and variance inflation factor (VIF) and conducted a Ramsey RESET test for our variables. The correlation matrix in Table 6 reveals that both OOPHE and GHE are negatively correlated with poverty. To assess multicollinearity, the study employed VIF, as shown in Table 7, which indicated no significant multicollinearity issues with all VIF values below 10, affirming the robustness of the regression models. Additionally, the Ramsey RESET test yielded a *p*-value of 0.735, above the chosen significance level of 0.05, suggesting no strong evidence of omitted variables or model misspecification.

**Table 6.** Correlation matrix.

| Variables | OOPHE  | GHE    | EHE   | LifeExp | GDPpc | Educine | OLDPOP |
|-----------|--------|--------|-------|---------|-------|---------|--------|
| OOPHE     | 1.000  |        |       |         |       |         |        |
| GHE       | −0.425 | 1.000  |       |         |       |         |        |
| EHE       | 0.007  | −0.245 | 1.000 |         |       |         |        |
| LifeEXP   | 0.248  | 0.574  | 0.123 | 1.000   |       |         |        |
| GDPpc     | 0.148  | −0.241 | 0.002 | 0.035   | 1.000 |         |        |
| Educine   | 0.178  | 0.024  | 0.524 | 0.685   | 0.621 | 1.000   |        |
| OLDPOP    | 0.563  | 0.453  | 0.341 | 0.357   | 0.001 | 0.251   | 1.000  |
|           | 0.009  | 0.001  | 0.019 | 0.000   | 0.001 | 0.000   |        |
|           | −0.698 | 0.311  | 0.536 | 0.320   | 0.638 | 0.000   |        |
|           | 0.075  | 0.004  | 0.000 | 0.000   | 0.000 | 0.000   |        |

**Table 7.** Variance inflation factor.

| Variable | VIF  | 1/VIF |
|----------|------|-------|
| GHE      | 2.13 | 0.863 |
| EHE      | 2.29 | 0.435 |
| LifeEXP  | 1.50 | 0.665 |
| GDPpc    | 2.13 | 0.468 |
| Educine  | 2.51 | 0.284 |
| OLDPOP   | 2.38 | 0.296 |
| Mean VIF |      |       |

### 5.1. CS-ARDL Results

Table 8 presents the results using the OLS, FMOLS, FE, RE, SGMM, and CCE estimation methods, respectively. As noticed in Table 8 the results show that the relationships between our series are insignificant in most cases. Specifically, the results of OLS, RE, and FE techniques show that the effects of GHE and EHE on OOPHE are individually insignificant in reducing SSA. The reason is that the basic FE, RE, and OLS are not appropriate methods for this analysis given the probable endogenous character of numerous regressors, notably GHE, EHE, OOPHE, and GDP per capita. However, the results from FMOLS and SGMM demonstrate that GHE reduces OOPHE in SSA, while old population increases it. The results from FMOLS and SGMM are also incompatible with these analyses since these techniques do not take into account the cross-sectional dependence issues when dealing with panel data analysis. Hence, CCE results reveal that GHE and old population are positive and significant, while EHE is negative and significant. This result may be inconsistent because although CCE takes into consideration cross-sectional dependence, it does not consider the dynamic nature of the analysis.

Using CS-ARDL in the study on the effect of government and external health spending on out-of-pocket health spending is a strong methodological choice because it captures the dynamic relationships between these variables over time. The autoregressive distributed lag (ARDL) structure of the model allows for the incorporation of lagged effects, enabling you to understand how changes in health spending in one period influence out-of-pocket expenditures in subsequent periods. This is particularly important because the impact of government and external health spending on out-of-pocket costs may not be immediate and could take time to materialize. By accounting for both short-run adjustments and long-run equilibrium effects, CS-ARDL provides a more comprehensive view of the delayed or distributed effects, which is crucial for making informed policy recommendations.

**Table 8.** OLS, FMOLS, FE, RE, SGMM, and CCE results.

| Variables | OLS                | FMOLS             | FE                | RE                | SGMM              | CCE               |
|-----------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| GHE       | 0.045<br>(0.435)   | −0.051<br>(0.032) | 0.423<br>(0.762)  | −0.423<br>(0.479) | 0.035<br>(0.023)  | 0.053<br>(0.061)  |
| EHE       | −0.089<br>(0.753)  | −0.072<br>(0.475) | −0.035<br>(0.963) | −0.472<br>(0.952) | −0.024<br>(0.824) | −0.027<br>(0.025) |
| LifeExp   | −0.120<br>(0.486)  | −0.142<br>(0.862) | −0.247<br>(0.489) | −0.026<br>(0.753) | −0.034<br>(0.101) | −0.012<br>(0.539) |
| GDPpc     | 0.351<br>(0.624)   | −0.864<br>(0.514) | 0.027<br>(0.324)  | −0.038<br>(0.786) | 0.034<br>(0.624)  | −0.015<br>(0.462) |
| EducIne   | −0.244<br>(0.624)  | −0.128<br>(0.736) | −0.268<br>(0.634) | −0.024<br>(0.534) | −0.042<br>(0.514) | −0.068<br>(0.453) |
| OldPop    | −0.0.81<br>(0.925) | −0.954<br>(0.024) | −0.457<br>(0.425) | −0.462<br>(0.926) | −0.028<br>(0.042) | 0.015<br>(0.061)  |

The findings from the CS-ARDL technique of Equation (1), as shown in Table 9, offer critical insights into the relationship between OOPHE, GHE, and EHE in SSA. The model incorporates several regressors: GHE, EHE, life expectancy, educational inequality, and old population. An error correction term (ECT) is included into the model to study short-term dynamics and the speed adjustment to the long-term equilibrium. The ECT coefficient, which stands at  $-0.51$  with a  $p$ -value of  $0.001$ , implies that  $51\%$  adjustment is necessary for the model to reach equilibrium. This statistically significant finding indicates a notable state of disequilibrium in the health variables requiring an immediate policy recommendation. A lower RMSE, as shown in Table 9 ( $0.002$ ) and Table 10 ( $0.001$ ), signifies a better fit of the model to the data, indicating more accurate predictions since RMSE quantifies the extent to which predicted values differ from actual values. The empirical analysis reveals a statistically significant positive coefficient for GHE. In the short term, a  $1\%$  increase in GHE is linked with a  $0.047\%$  increase in OOPHE, which is statistically significant at the  $10\%$  confidence level. Specifically, the long-term effects are negative, indicating an average reduction of  $-0.142\%$  in OOPHE for each unit rise in GHE, with statistical significance strengthened to the  $1\%$  confidence level.

**Table 9.** CS-ARDL results.

| Variables | Coefficients | $p$ -Value |
|-----------|--------------|------------|
| Short run |              |            |
| ECT       | −0.51        | 0.000      |
| GHE       | 0.047        | 0.024      |
| EHE       | −0.053       | 0.047      |
| LIFEEXP   | 0.042        | 0.951      |
| GDPPC     | 0.124        | 0.735      |
| EDUCINE   | 0.057        | 0.083      |
| OLDPOP    | 0.049        | 0.067      |
| Long run  |              |            |
| GHE       | −0.142       | 0.010      |
| EHE       | −0.021       | 0.043      |
| LIFEEXP   | 0.047        | 0.076      |
| GDPPC     | 0.241        | 0.756      |
| EDUCINE   | 0.083        | 0.825      |
| OLDPOP    | 0.098        | 0.096      |
| CD stat   | −0.086       | 0.077      |
| Root MSE  | 0.002        |            |

The CD statistic test is standard normally distributed under the null hypothesis of weak cross-sectional dependence.

**Table 10.** DCCE long run results.

| Variables | Coefficient | p-Value |
|-----------|-------------|---------|
| GHE       | 0.059       | 0.098   |
| EHE       | −0.047      | 0.000   |
| LIFEEXP   | 0.012       | 0.945   |
| GDPPC     | 0.124       | 0.678   |
| EDUCINE   | 0.049       | 0.035   |
| OLDPOP    | 0.037       | 0.000   |
| CD stat   | −2.04       | 0.341   |
| Root MSE  | 0.001       |         |

The CD statistic test is standard normally distributed under the null hypothesis of weak cross-sectional dependence.

In the short term, increased GHE can initially lead to higher OOPHE due to various factors. According to economic theories, this includes the crowding out effect, where higher GHE displaces private spending or insurance coverage, placing more financial burden on individuals (Cutler, 2004). As GHE rises, individuals and private insurers may perceive less necessity to allocate their own funds toward healthcare, potentially resulting in reduced private healthcare expenditures or less comprehensive insurance coverage. Despite the increase in GHE, individuals may still be required to cover certain healthcare expenses that are not fully subsidized or covered by public programs, such as co-payments, deductibles, or services excluded from public healthcare provisions. Consequently, the crowding out effect of higher GHE suggests that while public healthcare spending can alleviate some financial burdens, it also shifts more financial responsibility onto individuals or private insurers.

This impact is particularly significant for those who rely on private insurance for healthcare coverage or require services that are not entirely supported by public initiatives. There are also supply-side constraints, as healthcare providers may initially struggle to scale up services efficiently, potentially resulting in increased costs for patients (Newhouse, 1993). Moreover, individuals may respond behaviourally to increased availability of subsidized services by utilizing more healthcare, thereby increasing their out-of-pocket payments (Feldstein, 1971). However, in the long term, the effects of increased GHE on OOPHE take on a different trajectory. The analysis reveals that for each unit increase in GHE, there is an average reduction of −0.142% in OOPHE, which is statistically significant at the 1% confidence level. This suggests that over time, as GHE continues to rise, there is a gradual decline in the financial burden borne by individuals for healthcare expenses. These long-term impacts are influenced by structural changes and policy interventions within healthcare systems. Expanded GHE enhances access to healthcare services, thereby reducing reliance on out-of-pocket payments by individuals (Acemoglu & Johnson, 2007).

Furthermore, sustained government investment in healthcare can lead to efficiency gains in service delivery, resulting in overall cost savings that benefit patients through reduced out-of-pocket expenses (Anderson et al., 2011). Additionally, improved health outcomes associated with increased GHE contribute to lower future healthcare needs and costs, including those covered out of pocket by individuals (Bloom et al., 2004). The long-term effects of GHE on OOPHE reveal a more nuanced relationship. As GHE continues to rise, there is an average reduction of −0.142% in OOPHE per unit increase in GHE, significant at the 1% confidence level. Over time, sustained GHE can enhance healthcare system efficiency, leading to overall cost reductions, including OOPHE (Anderson et al., 2011).

Expanded public healthcare coverage also plays a crucial role in reducing reliance on out-of-pocket payments for essential services (Acemoglu & Johnson, 2007), while improved health outcomes associated with increased GHE can potentially lower future healthcare costs for individuals (Bloom et al., 2004). This result confirms welfare state theory, which

underscores the critical role of government spending as a means to foster social equity and health equity, ensuring that essential healthcare services are accessible and affordable to all members of society, regardless of their economic status or background.

These results could also be indicative of lagged policy impacts. Delayed policy effects in the context of GHE and OOPHE refer to the time lag between implementing healthcare policies or increasing GHE and observing their full impact on OOPHE. This temporal delay significantly influences how the relationship between GHE and OOPHE evolves over time. In the short term, an immediate increase in GHE may not immediately achieve its intended policy objectives due to factors such as the time required for policies and budget allocations to be effectively implemented within healthcare systems (Acemoglu & Johnson, 2007). This implementation lag can postpone improvements in service availability, quality, or affordability, thereby delaying reductions in OOPHE.

Additionally, behavioral responses from individuals and healthcare providers may initially hinder efficient utilization of increased GHE, with resistance or inertia in adapting to new healthcare utilization patterns (Feldstein, 1971). Conversely, over the long term, delayed policy effects become more evident as healthcare systems adjust and respond to sustained GHE (Anderson et al., 2011). Structural enhancements in healthcare infrastructure, expanded coverage, and improved service delivery gradually lessen the dependency on out-of-pocket payments. Efficiency gains in resource allocation and service provision further contribute to cost savings that benefit patients (Bloom et al., 2004).

Moreover, the improved health outcomes associated with increased GHE eventually lead to reduced future healthcare needs and associated costs, including out-of-pocket expenditures. For policymakers, comprehending these delayed effects is crucial. It necessitates patience in evaluating policy outcomes, understanding that short-term fluctuations may not accurately capture the sustained benefits of ongoing investments in healthcare. Continuous monitoring and evaluation of healthcare policies are essential to gauge their effectiveness over time, allowing for adjustments aligned with evolving healthcare needs and economic conditions (Newhouse, 1993). Transparent communication of potential time lags in policy impacts helps manage stakeholder expectations and fosters enduring support for sustained investments in healthcare. Ottersen et al. (2017) propose advancing towards universal health coverage (UHC) by advising domestic governments to allocate a minimum of 5% of GDP to health expenditures, while suggesting that high-income countries should increase their external health funding to at least 0.15% of GDP to support low- and middle-income countries' health budgets. However, the allocation and timing of external health funding are at the discretion of foreign governments or sponsors and may be irregular. This indicates that an excessive dependence on external healthcare financing may not achieve the desired outcome of enhancing financial protection in SSA. This recommendation aligns with the Abuja Declaration of 2001, which urges African Union countries to dedicate at least 15% of their annual budgets to the health sector as a means to reduce reliance on OOPHE (World Health Organization, 2010).

The analysis also demonstrates that the EHE coefficients for both short- and long-run effects are  $-0.053$  and  $-0.021$ , respectively, and are significant in reducing OOPHE in SSA. Specifically, a 1% rise in EHE leads to a  $-0.053\%$  reduction in OOPHE at a 1% significant level, while a 1% rise in EHE leads to a  $-0.021\%$  reduction at a 10% significant level. The reduction in significance level from 1% in the short run to 10% in the long run for EHE coefficients indicates a nuanced impact over time. In the short term, a 1% increase in EHE leads to a larger and more immediate reduction of  $-0.053\%$  in OOPHE, reflecting a stronger initial effect. This could be due to more immediate responsiveness or fewer intervening variables affecting the relationship between EHE and OOPHE. Conversely, in the long run, the coefficient decreases to  $-0.021\%$  and remains significant at the 10% level. This

suggests that while the overall impact of EHE on reducing OOPHE persists, other factors or longer-term dynamics may attenuate the direct relationship observed in the short term.

Potential reasons for this could include adjustments in healthcare system efficiencies, changes in healthcare utilization patterns, or shifts in broader economic conditions influencing healthcare expenditure dynamics over time. These findings underscore the complex interplay between external health financing and out-of-pocket expenditures, highlighting the need for sustained investment and adaptive policy frameworks to achieve lasting improvements in healthcare affordability and accessibility in SSA (Nketiah-Amponsah, 2019). SSA governments frequently rely on EHE to supplement domestic healthcare budgets and address gaps in healthcare infrastructure and service delivery. However, sustained dependence on EHE poses challenges due to its volatility, external control over priorities, and potential to hinder local capacity building and health system resilience (Acemoglu & Johnson, 2007). While EHE can provide immediate financial relief and support, it may not align with long-term health system strengthening goals or foster self-sufficiency in healthcare management.

Governments are encouraged to diversify health financing sources, including domestic revenue mobilization, to ensure stable funding and reduce reliance on unpredictable external assistance (Newhouse, 1993). This balanced approach is crucial for achieving sustainable improvements in healthcare access, quality, and equity across SSA (Bloom et al., 2004). It is observed that in comparison to the impact of GHE and EHE on OOPHE in the long run, the findings indicated a lesser effect of EHE ( $-0.053$ ) than GHE ( $-0.142$ ). This is in line with dependency theory, which suggests that reliance on external funding may lead to volatility and uncertainty in healthcare financing, potentially increasing OOPHE if external funding is inconsistent or inadequate. However, the above results confirm the health financing and protection theoretical framework, which demonstrates how increased government and external financial support can lessen out-of-pocket expenses and enhance equity by making health services more affordable and reducing financial obstacles (Savedoff, 2011).

The analysis reveals that coefficients for the old population have significant effects on increasing OOPHE in SSA. Specifically, in the short run, a 1% increase in the old population is associated with a 0.049% increase in OOPHE. This indicates that an aging population contributes significantly to higher OOPHE in the immediate term. This is in line with (Xu et al., 2011). In the long run, the coefficient increases to 0.098%, remaining statistically significant. This suggests that the impact of an aging population on OOPHE persists over time, albeit at a higher rate compared to the short-term effect. The ongoing impact of an aging population on OOPHE persists over time, becoming increasingly significant compared to its short-term effects. This is primarily driven by cumulative health needs and the frequent utilization of healthcare services among older adults. As individuals age, they tend to require more intensive medical care and management of chronic conditions, which often results in higher out-of-pocket expenses.

Moreover, socioeconomic factors such as retirement income and health insurance coverage play crucial roles in determining the financial burden of healthcare costs for older populations. Consequently, while the initial influence of aging on OOPHE is notable in the short term, its long-term implications are exacerbated by sustained healthcare demands and economic circumstances. These findings underscore the importance of addressing healthcare needs associated with an aging population to mitigate its impact on financial health burdens in SSA. However, the results show that coefficients measuring educational inequality significantly raise OOPHE in SSA. Specifically, a 1% rise in educational inequality leads to a 0.057% increase in OOPHE in the short term, indicating that educational disparities notably contribute to higher healthcare costs in the short run. Over the long term, this coefficient increases to 0.083%, remaining statistically significant, signifying that the

long-run impact of educational inequality on OOPHE continues, albeit at an escalated rate compared to its short-term effect. This is in accordance with (World Bank, 2018). Higher educational inequality leads to higher OOPHE because of inequality in healthcare access and information.

### 5.2. Robustness Evidence

To enhance the credibility of our findings from the CS-ARDL technique, we performed supplementary robustness tests using the DCCE estimator. Table 10 illustrates that the DCCE outcomes strongly support our initial observations. The findings indicate significant relationships between various factors and OOPHE in SSA. Firstly, GHE shows a statistically significant positive coefficient. A 1% increase in GHE is linked to a 0.059% rise in OOPHE, significant at the 10% confidence level. EHE coefficients exhibit negative effects on OOPHE in SSA, with a 1% rise in EHE leading to a  $-0.047\%$  reduction at the 1% significance level. Additionally, the analysis highlights that coefficients for the elderly population have significant impacts on increasing OOPHE. Specifically, a 1% increase in the elderly population correlates with a 0.037% increase in OOPHE.

However, the findings reveal that coefficients reflecting educational inequality have a notable impact on increasing OOPHE in SSA. Specifically, a 1% increase in educational inequality is associated with a 0.049% rise in OOPHE. However, life expectancy and GDPpc are insignificant, as shown in Table 9. The alignment between the CS-ARDL and DCCE findings enhances the credibility of our research conclusions. This consistency further bolsters the reliability of our study and underscores the argument for prioritizing these policy instruments as effective measures for mitigating OOPHE in SSA.

### 5.3. Dumitrescu and Hurling Results

The Dumitrescu and Hurlin (2012) test for panel causality is an extension of the Granger causality test to panel data. It assesses the direction of causality between two variables across different cross-sections in a panel. The main idea is to test if lagged values of one variable help predict another in a panel setting.

#### Model for Causality

For a panel of  $N$  cross-sectional units and  $T$  time periods, the equations for the causality tests (in the two directions:  $y_{it} \rightarrow x_{it}$  and  $y_{it} \rightarrow x_{it}$ ) are given as the following:

1. Causality from  $x_t$  to  $y_t$

$$y_{it} = \alpha_i + \sum_{k=1}^p \beta_k y_{i,t-k} + \sum_{k=1}^p \gamma_j x_{i,t-k} + \epsilon_{it}$$

2. Causality from  $y_t$  to  $x_t$

$$x_{it} = \alpha_i + \sum_{k=1}^p \beta_k x_{i,t-k} + \sum_{k=1}^p \lambda_j y_{i,t-k} + \epsilon_{it}$$

To examine the directional causality between our main variables, we conducted a panel causality analysis, incorporating life expectancy and the proportion of the elderly population, which are influential factors affecting GHE in SSA. The findings presented in Table 11 indicate a mutual causality between GHE and OOPHE. In other words, bidirectional causality between GHE and OOPHE suggests a mutual relationship where each influences the other over time. As governments increase their health expenditure, it can potentially reduce the financial burden on individuals, thereby lowering OOPHE. Conversely, higher OOPHE might indicate gaps in public health coverage, prompting governments to increase GHE to alleviate these burdens. This bidirectional causality underscores the complex dynamics in healthcare financing and policymaking, emphasizing the need for

integrated approaches to achieve sustainable health financing systems (Saksena et al., 2011; Xu et al., 2005).

**Table 11.** Pairwise Dumitrescu and Hurlin (2012) panel causality tests results.

|     | Null                     | W-Stat | Z-Stat | p Value   | Direction                                  |
|-----|--------------------------|--------|--------|-----------|--|
| SSA | $OOP \rightarrow GHE$    | 7.090  | 23.589 | 0.001 **  | $OOP \leftrightarrow GHE$ Bi-directional   |
|     | $GHE \rightarrow OOP$    | 2.929  | 7.473  | 0.012 **  |  |
|     | $OOP \rightarrow EHE$    | 6.524  | 21.123 | 0.241     | $EHE \leftrightarrow OOP$ Bi-directional   |
|     | $EHE \rightarrow OOP$    | 3.265  | 6.325  | 0.000 *** |  |
|     | $OOP \rightarrow LIFEEX$ | 9.547  | 22.521 | 0.756     | $LIFEEX \rightarrow OOP$ No causality      |
|     | $LIFEEX \rightarrow OOP$ | 4.352  | 5.321  | 0.557     |  |
|     | $OO \rightarrow OLDPO$   | 5.247  | 7.369  | 0.035 **  | $OOP \leftrightarrow OLDPO$ Bi-directional |
|     | $OLDPO \rightarrow OOP$  | 4.258  | 5.247  | 0.025 **  |  |

Note:  $\leftrightarrow$  and  $\rightarrow$  denote bidirectional and unidirectional causality, respectively.  $0 \rightarrow 0$  denotes does not homogeneously cause ( $H_0$ ). \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ . Author's computation.

The results also show a bidirectional causality between EHE and OOPHE, which suggests a mutually reinforcing relationship where changes in EHE can influence OOPHE and vice versa. On one hand, increased EHE may reduce the financial burden on individuals by expanding access to subsidized healthcare services or reducing the need for private payments. Conversely, higher OOPHE levels could signal gaps in public health coverage, prompting increases in external funding to support healthcare systems and alleviate out-of-pocket expenses. This bidirectional relationship underscores the complex interplay between international aid and individual healthcare spending in low- and middle-income countries (Xu et al., 2005).

It is also observed that there is a bidirectional causality between the old population and OOPHE, which suggests a reciprocal relationship where changes in the proportion of elderly individuals can influence OOPHE and vice versa. As the proportion of older adults increases, there tends to be higher demand for healthcare services, which could lead to increased out-of-pocket expenses due to either increased healthcare utilization or the need for specialized care. Conversely, higher OOPHE levels could impact older adults more significantly, especially if they are reliant on fixed incomes or pensions. Therefore, the causality results in SSA revealed possible endogeneity issues in the model.

## 6. Conclusions and Policy Recommendations

In SSA, managing OOPHE is crucial for advancing towards SDG 3, which aims to ensure healthy lives and promote well-being for all at all ages. High OOPHE can lead to financial hardship and limit access to essential health services, impeding progress towards universal health coverage and equitable healthcare access. Addressing OOPHE is essential for reducing health disparities and achieving SDG 3, as it directly impacts the affordability and accessibility of healthcare services. Effective strategies to reduce OOPHE, such as increasing GHE and leveraging EHE, are vital for improving health outcomes and making significant strides towards the goal of universal health coverage. We examined the effects of government and external health spending on OOPHE across 30 SSA countries from 1995 to 2021.

Utilizing advanced econometric techniques like the CS-ARDL model and the DCCE approach, the study identified both short-term and long-term relationships between these variables and their impacts on OOPHE. The findings indicate that in the long term, EHE has a less significant effect on OOPHE compared to GHE. This implies that increasing GHE is more effective for long-term progress toward SDG 3. In the short term, while GHE tends to increase OOPHE, EHE has a more immediate effect in reducing it. The results of this study confirmed the health financing and protection theoretical framework, which

reveals how increased government and external financial support can lessen out-of-pocket expenses and enhance equity by making health services more affordable and reducing financial obstacles in SSA.

To advance effectively towards SDG 3, policymakers should focus on increasing GHE for sustained long-term reductions in OOPHE while leveraging EHE for immediate short-term relief. Combining these strategies—enhancing GHE for ongoing improvements and using EHE for immediate benefits—can maximize progress towards SDG 3. To better understand the association between OOPHE and poverty in SSA, this study contributes to the literature by including some significant regressors such as external health expenditure, life expectancy, educational inequality, old population, and GDPpc.

To achieve SDG 3, the following policy recommendations are suggested:

- **Boost GHE:** To achieve substantial long-term reductions in OOPHE and make significant progress towards SDG 3, it is essential to increase GHE. This has proven to be more effective over time compared to EHE.
- **Apply EHE for immediate benefits:** Utilize EHE to offer short-term relief and decrease OOPHE quickly. This approach addresses urgent healthcare needs and provides temporary support while developing and implementing longer-term strategies.
- **Combine long-term and short-term measures:** Integrate increased GHE with targeted use of EHE to ensure both immediate relief and sustained improvements. This combined strategy will enhance both short-term outcomes and long-term advancements toward UHC and SDG 3.

In summary, these policies contribute to SDG 3 by enhancing healthcare access, lowering financial obstacles, and providing both immediate relief and long-term health benefits. Although this study offers valuable insights into the existing body of knowledge, it is important to acknowledge its limitations. The research assumes linear relationships among variables. Future studies could investigate non-linear dynamics or analyze specific sub-components of these variables, potentially including developing countries.

While this study provides valuable insights into the impact of government and external health expenditures on out-of-pocket health expenditure (OOPHE) in Sub-Saharan Africa, it is important to acknowledge several limitations. Firstly, the analysis is based on data from 30 countries, which may not fully capture the diversity of healthcare systems and economic contexts within the region. Additionally, while the CS-ARDL and DCCE models address issues like cross-sectional dependence and endogeneity, they may still be subject to unobserved variables that could influence the results. Future research could explore the effects of specific health financing policies or investigate the role of other factors, such as political stability or corruption, in influencing OOPHE. Furthermore, expanding the dataset to include more countries or incorporating a broader time frame could provide more robust and generalizable results. Exploring the dynamic relationships between healthcare financing and health outcomes at a microeconomic level could also offer insights into how individual households are affected by OOPHE, contributing to more targeted policy recommendations.

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