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Health expenditures and Income with Nonstationary Panel Data: Evidence from ECOWAS Member Countries

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Abstract

Using non-stationary panel data techniques and controlling for cross-section dependencies and heterogeneities, the relationship between income and health care expenditure is revisited for the ECOWAS regional bloc in this paper. Our results confirm the existence of long run relationship between health care spending and the per capita Gross Domestic Product (GDP). In addition, country-level analyses show some common features, especially for non-observable factors. The income elasticity of health care expenditure derived from panel data estimation technique confirms the popular demand by citizens and the international community, for more investment on health care services in the ECOWAS sub-region.

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1. Introduction

Acknowledging the key role played by public funding of health care to ensure sustainable and equitable coverage, in 2001, African Union heads of state pledged to allocate at least 15 percent of annual expenditure to health under the Abuja Declaration[1]. As a result, the World Health Organization (WHO) (2016) noted that the average level of per capita public spending on health rose from about US$70 in the early 2000s to more than US$160 in 2014 (Parity Purchasing Power, PPP). In addition, health care expenditure as a share of gross domestic product (GDP) in most countries of the Economic Community of West African States (ECOWAS) sub-regional bloc almost doubled between 1995 and 2012. At an average of 5.8 to 7.3 percent, many countries in the sub-region devoted higher share of gross domestic product (GDP) to health care than the African average of 3 percent over the same period (WHO *op cit*). Surprisingly, countries with relatively low income in the sub-region—Sierra Leone, Liberia, Guinea and Togo—continue to spend even more on average, than the relatively prosperous ones like Cape Verde and Nigeria.

In light of this continuous growth in health spending in the sub-region, the debate continues in the development community on the efficiency of health-oriented policies of governments. The Ebola epidemic of 2014/2015 and the seemingly unmanageable cases of malaria and other infectious diseases reveal major weaknesses in health care management systems of the region. It is therefore being argued that observed appreciable increases in health care expenditure over the years might as well be attributed to numerous programs implemented and encouraged by the Word Bank, International Monetary Fund (IMF), the African Development Bank (AfDB) and other international development partners as against the direct commitment of respective governments.

This paper revisits the relationship between income and health expenditure in the ECOWAS sub-region using heterogeneous panel data from 15 member countries covering the period 1995 to 2012[2]. The income elasticity of health is also investigated with a particular focus on the stationarity properties and possible cointegration between the two variables; controlling for cross-section dependencies and heterogeneity.

The remainder of the paper is organised as follows: Section 2 discusses some stylised facts and examines earlier literature on the relationship between health care spending and income. The methodology employed for our analysis is exhaustively described in Section 3. Our empirical results are reported and extensively discussed in Section 4. Section 5 concludes the paper.

2. Health Expenditure and Income: Some Stylized Facts and Earlier Literature

Beginning with the seminal works of Kleiman (1974) and Newhouse (1977), the relationship between health care spending and income as widely studied by a number of researchers have produced divergent results, just as numerous empirical analyses on the income elasticity of

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[1] See http://www.who.int/healthsystems/publications/abuja_report_aug_2011.pdf?ua=1

[2] The 15 ECOWAS member countries are: Benin, Burkina-Faso, Cape Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Togo, Sierra- Leone.

health spending have not led to a consensus of opinion[3]. While some studies (Hitiris 1997; Clemente *et al* 2004; Mehrara *et al* 2010; and Liu *et al;* 2011; etc.) found elasticity greater than 1, others, such as Culyer (1988), Blomqvist and Carter (1997), Di Matteo (2003), Sen (2005), Baltagi and Moscone (2010), Farag *et al* (2012), Hitiris and Posnett (1992), Murthy and Ukpolo (1994), and Las Penas *et al* (2013) found less than or near-unit elasticity. The differences in econometric methods used, variables selected for analysis, as well as nature of data employed seem to account for the divergence in results of these earlier studies. In this regard, worth mentioning is the contribution of Getzen (2000), who used a multilevel decision model and highlighted the fact that whereas at the individual level, higher estimates of elasticity are obtained—health care expenditure is a necessity or non-discretionary—macro level data tend to yield lower estimates. The implications of these are that whilst lower elasticity estimates lead to prescription of market-oriented policies such as private insurance, higher estimates imply more government intervention in funding health care.

Incidentally, rather few papers had specifically examined the link between health care spending and income in Africa. One of the first was the study by Gbesemete and Gerdtham (1992). Based on a cross-section of 30 African countries—including 11 from ECOWAS—Gbesemete and Gerdtham (*ibid*) confirmed the view that health care spending in Africa is a necessity; shedding further light on a question that had been limited to the Organization for Economic Cooperation and Development (OECD) countries. By separating health care spending into private and public in 28 Sub-Saharan African countries that included 10 from ECOWAS, Jaunky and Khadaroo (2008) arrived at a conclusion somewhat close to the findings of Getzen (2000). They posited that as long as health remains a human capital component to be preserved and developed (*aka* Grossman 1972), the income elasticity of public health expenditure would remain greater than unity. More recently, using semi-parametric techniques and panel data on 42 African countries that also included 12 ECOWAS member States, Lv and Zhu (2014) found that health care is an income-inelastic 'good'; elasticity is not constant but vary with income level, a result that is somewhat consistent with the findings of Gbesemete and Gerdtham (1992).

This paper builds on existing literature by focusing on ECOWAS member countries only. Since cross-section dependencies are very likely among countries of an economic union—albeit becoming an economic union is still in work-in-progress for ECOWAS member States—the resulting correlations as well as issues of heterogeneity are considered in this paper using second generation non stationary panel data techniques.

3. Econometric Methodology

Strauss and Yigit (2003) highlighted a number of weaknesses associated with first generation non stationary panel data techniques, especially when evidence support the presence of cross-section dependence. Baltagi (2013) also stressed the need to include issues of cross-section dependencies in order to increase the power of the unit root and cointegration tests. Furthermore, just as are numerous papers in medical journals, Revelli (2006), Moscone and Knapp (2005); Moscone *et al.*, (2007), Baltagi and Moscone (2010), contributed to the debate on same issue by emphasizing the need to consider geographical or spatial correlations. ECOWAS member countries are likely to exhibit such spatial linkages as their populations

[3] Baltagi and Moscone (2010) and Las Penas *et al.* (2013) provide detailed literature survey on the discrepancies observed in empirical results, albeit in OECD countries.

are culturally very close, with similar dietary and lifestyle habits. This motivates the need for the kind of econometric technique conceptualized and the analysis undertaken in this paper.

To start with, we consider the following linear heterogeneous panel regression model,

$$y_{it} = \alpha_i + \lambda_t + \beta_i' x_{it} + \varepsilon_{it}, \; i = 1, \cdots, N \text{ and } t = 1, \cdots, T \tag{1}$$

where y_{it} is total health care expenditure of country i in year t (also denoted by $Thexp_{it}$), x_{it} is a k-vector of regressors including GDP per capita ($GDPpc_{it}$) and total public spending on health as a percentage of GDP ($Phexp_{it}$). All the variables are expressed in natural logarithm terms. α_i is a country-specific intercept, λ_t is a time dummy, and ε_{it} is the error term.

We next consider a multifactor error structure model to account for cross-section dependence in (1). That is,

$$\varepsilon_{it} = \gamma_i' f_t + \nu_{it} \tag{2}$$

where f_t is the $m \times 1$ vector of unobserved common effects and ν_{it} is an idiosyncratic error term. The regressors in (1) are allowed to be correlated with the unobserved effects f_t. As a result, they also serve as the channel through which common factors can impact health expenditure.

The estimation and testing approach to (1) and with multifactor errors (2) are based on the Common Correlated Effects (CCE) method developed by Pesaran (2006). Our initial model therefore becomes,

$$y_{it} = \alpha_i + \lambda_t + \beta_i' x_{it} + g_i' \bar{z}_t + \nu_{it}, \; i = 1, \cdots, N \text{ and } t = 1, \cdots, T \tag{3}$$

where $\bar{z}_t = \left(\bar{y}_t, \bar{x}_t'\right)'$ with $\bar{y}_t$ and $\bar{x}_t$ being the cross-section averages of the dependent variable and covariates respectively. Similarly, as in Pesaran (2006), the CCE Pooled (CCEP) estimator for the average of the slope coefficients is computed. Heterogeneity is captured by the individual specific fixed effects α_i, the time dummies λ_t, and the loadings g_i. For the sake of comparison, the fixed effects (FE) estimator with period dummies is also computed.

To test for unit root, we used the p^{th} order augmented Dickey Fuller regression method (Baltagi, 2013). That is,

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{i,j} \Delta q_{i,t-j} + \varepsilon_{it} \tag{4}$$

where q_{it} is the regressand and $x_{j,it}$ the j^{th} regressor. ε_{it} are errors that we assume to have a single factor structure, where the idiosyncratic component may follow a spatial autoregressive process as in Anselin (1988). To test for unit root, the null hypothesis is,

$$H_0: \; b_i = 0, \quad i = 1, \cdots, N \tag{5}$$

against the alternative that,

$$H_1:\begin{cases}\rho_1 < 0, \; for \; i = 1, \cdots, N_1 \\ \rho_1 = 0, \; for \; i = N_1 + 1, \cdots, N\end{cases} \tag{6}$$

where N_1 is such that $\frac{N_1}{N}$ is non-zero and tends towards a fixed constant as N tends to infinity (see also Baltagi and Moscone, 2010; and Breitung and Pesaran, 2007). The familiar CIPS statistics proposed by Pesaran (2007) for testing (5) against (6) through the simple average of the t-ratios of the ordinary least squares estimates of b_i is also computed. That is:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N}\tilde{t}_i \tag{7}$$

where $\tilde{t}_i$ is the ordinary least squares t-ratio of b_i in the following Dickey Fuller regression, augmented with the cross-section averages $\bar{q}_{t-1}$ and $\Delta\bar{q}_{t-j}$, for $j = 0, \cdots, p$,

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{i,j}\Delta q_{i,t-j} + g_i'\bar{z}_t + \varepsilon_{it} \tag{8}$$

where $\bar{z}_t = \left(\bar{q}_{t-1}, \Delta\bar{q}_t, \Delta\bar{q}_{t-1}, \cdots, \Delta\bar{q}_{t-p}\right)'$. The critical values for the CIPS tests are showed in Table II (a)–(c) of Pesaran (2007).

Although the CIPS, by implication, tests the unit root hypothesis when a factor structure is considered, Monte Carlo experiments have established how robust it remains in the presence of other sources of cross-section dependence, such as the spatial autoregressive process (see Baltagi and Pesaran 2007). For additional robustness check, we also undertake the panel unit root test proposed by Im *et al.* (IPS) (2003), and Breitung (2000), which do not account for cross-section dependence in the data.

After the unit root test, we next check for the existence or otherwise of long-rung relationship between health expenditure and income; that is, cointegration tests that involve computing the residual-based DF and ADF as in Kao (1999). An associated assumption of this test is that of a homogenous panel, with identical cointegration vectors among countries. To overcome this seemingly unrealistic assumption for countries in the ECOWAS sub-region, we undertake the Pedroni (2000, 2004) tests. These tests consider a null hypothesis of no cointegration in a panel data model that allows for heterogeneity. Furthermore, we undertake the four tests suggested by Westerlund (2007). The first two of the four tests are based on group mean statistics and are given by $G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{a_i}{SE\left(a_i\right)}$ and, $G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{Ta_i}{a_i\left(1\right)}$. The last two statistics are: $P_\tau = \frac{a}{SE\left(a_i\right)}$ and $Pa = Ta$

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An important question that arises when dealing with nonstationary panel data has to do with the treatment of cross-section dependency. Acknowledging this constitutes the bridge between the first and second generation tests in assessing unit root and cointegration in panel data (Baltagi, 2013). In this regard, it becomes important to check for the presence of cross-section dependence in the dataset.

A statistic that tends to capture the total amount of cross-section dependence in data is the average pairwise correlation coefficient, that is,

$$\bar{\rho} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{9}$$

where ρ_{ij} is given by,

$$\rho_{ij} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2 \right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2 \right)^{1/2}} \tag{10}$$

And e_{it}s are regression residuals from (1) or (4) (see also Baltagi, 2013).

Finally, we undertake another cross-section dependence diagnostic test, based on the above pairwise correlation coefficients, namely the CD_{LM} test (see Frees, 1995),

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\rho_{ij}^2 - 1 \right) \tag{11}$$

Under the null hypothesis of no cross-section dependence, the CD_{LM} tends to a N(0, 1) distribution with $T \rightarrow \infty$ and $N \rightarrow \infty$.

4. Data and Empirical Results

The empirical analysis is based on panel data for 15 ECOWAS member countries for the period 1995 to 2012 (T=18), obtained from the World Development Indicators online (World Bank 2015). The variables are as described in table I; all variables expressed in natural logarithms.

Table I: Definition of variables

Variable	Description	N	T	NT
$Thexp_{it}$	Total health care expenditures per capita	15	18	270
$Phexp_{it}$	Public health spending as a percentage of total government spending	15	18	270
$GDPpc_{it}$	GDP per capita in terms of PPP	15	18	270

The results of Pesaran (2004) and Breusch and Pagan (1980) tests for cross-section dependence are as shown in tables II and III. The results, in levels, indicate the presence of cross section correlation between pairs of countries for almost all variables. The Moran I statistics, also in levels, suggest the presence of geographical concentration of health care spending and its determinants. These tests show that pairs of countries in our dataset are correlated to each other, and for almost all variables; an indication of the geographical/spatial pattern.

In first differences, however, the hypothesis of cross-section independence of the variables can hardly be rejected. That is, ECOWAS countries share pairwise correlations based on some common factors that are eliminated by the differentiation procedure. Conley and Ligon (2002) who found similar dependences in OECD, argue that this dependence is a function of the '*political and social distance*' between countries. The political instability experienced by several ECOWAS member countries over the period covered in this paper may have created negative shocks on the health sector, especially from 1999 to 2002 as suggested by a quick graphical inspection of health expenditure and income. Countries such as Cote d'Ivoire, Guinea Bissau, Guinea, Liberia, and Nigeria—to a lower extent—were characterised by violent political and military crises during the said period.

In sum and based on above results, the two sources of correlation detected are accounted for when the time series properties of the variables are examined in estimating the health care spending equation. Failure to do so may lead to misleading inference, particularly if the source of cross-section dependence is correlated with the regressors (Andrews 2005).

Table II: Cross-section dependence (in levels and first differences)

Variables	Coefficient ρ	Statistic CD_{LM}	Moran I
$Thexp_{it}$	0.683	27.110[b]	102.42
$Phexp_{it}$	0.075	2.990[b]	58.47
$GDPpc_{it}$	0.627	15.720[b]	172.88
$\Delta Thexp_{it}$	0.031	1.210	0.29
$\Delta Phexp_{it}$	0.230	0.880	0.02
$\Delta GDPpc_{it}$	-0.002	- 0.080	0.24

Note: *Rejection of the null hypothesis at the 5% significance level.

Table III: Cross-section dependence based on Breusch and Pagan (1980)

	$Thexp_{it}$	$Phexp_{it}$	$GDPpc_{it}$	$\Delta Thexp_{it}$	$\Delta Phexp_{it}$	$\Delta GDPpc_{it}$
			With intercept only			
CD_{LM}	147.1[a]	123.9	128.6	112.6	118.6	130.1[a]
Moran I	-0.408	-0.557	-0.393	0.620	-0.015	0.231
$\bar{\rho}$	-0.043	-0.005	-0.008	0.038	-0.024	0.011
			With intercept and trend			
CD_{LM}	166.7[a]	124.4	183.2[a]	122c	123.8	132.9[a]
Moran I	-0.551	-0.159	-0.545	0.507	-0.133	-0.148
$\bar{\rho}$	-0.057	-0.015	-0.019	-0.014	-0.033	-0.061

Notes: *Rejection of the null hypothesis at the 5% significance level.

Table IV presents results of the panel unit root tests which do not account for cross-country dependence. Panel A of the table reports on the Im, Pesaran and Shin (2003) W_{t-bar} statistic for the logarithm of our variables when the ADF regression has an intercept only.

Interestingly, all the variables considered are stationary in first differences. Panel B on the other hand shows the Im, Pesaran and Shin (2003) statistic for the logarithm of the variables when the ADF regression has an intercept and a linear time trend. In this second case, all the variables are stationary in first differences. The same conclusion applies when we undertake the Breitung panel unit root test as shown in Table V.

Table V: IPS Unit Root Tests

	Number of lags			
	0	1	2	3
	Panel A: Intercept only			
$Thexp_{it}$	1.444	1.825	1.013	2.208
$\Delta Thexp_{it}$	-13.198[a]	-6.361[a]	-3.688[a]	-2.239[a]
$Phexp_{it}$	-1.952[b]	-1.604[c]	-2.365[a]	-1.205
$\Delta Phexp_{it}$	-13.282[a]	-7.755[a]	-4.022[a]	-2.292[b]
$GDPpc_{it}$	0.869	0.122	-0.515	0.592
$\Delta GDPpc_{it}$	-10.333[a]	-4.526[a]	-3.101[a]	-1.214
	Panel B: Intercept and trend			
$Thexp_{it}$	-1.619[c]	-0.244	-1.316	-0.061
$\Delta Thexp_{it}$	-12.043[a]	-5.040[a]	-2.745[a]	-1.517[c]
$Phexp_{it}$	-0.570	-0.251	-1.174	0.284
$\Delta Phexp_{it}$	-11.115[a]	-6.091[a]	-2.365[a]	-1.491c
$GDPpc_{it}$	1.406	1.392	-0.515	1.744
$\Delta GDPpc_{it}$	-8.694[a]	-3.444[a]	-3.101[a]	-0.460

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table VI: Breitung Unit Root Tests

	Number of lags			
	0	1	2	3
	Panel A: Intercept only			
$Thexp_{it}$	3.654	3.094	2.442	1.064
$\Delta Thexp_{it}$	-10.151[a]	-4.797[a]	-4.326[a]	-1.809[b]
$Phexp_{it}$	-2.559[a]	-2.154[b]	-1.622[c]	-2.570[a]
$\Delta Phexp_{it}$	-11.508[a]	-6.318[a]	-4.311[a]	-1.783[b]
$GDPpc_{it}$	5.192	2.581	1.764	1.086
$\Delta GDPpc_{it}$	-7.835[a]	-5.204[a]	-2.004[b]	0.805
	Panel B: Intercept and trend			
$Thexp_{it}$	-2.219[b]	-1.059	0.395	-0.175
$\Delta Thexp_{it}$	-7.638[a]	-4.681[a]	-2.897[a]	-1.837[b]
$Phexp_{it}$	-2.593[a]	-1.347[c]	-0.149	-2.593[a]
$\Delta Phexp_{it}$	-10.011[a]	-6.113[a]	-3.749[a]	-2.013[b]
$GDPpc_{it}$	1.832	1.343	2.046	1.293
$\Delta GDPpc_{it}$	-4.906[a]	-2.156[b]	0.222	0.530

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table VI shows the CADF and CIPS statistics for the logarithm of our variables. These results are for lag of orders $p = 0;1;2;3$. As can be gleaned from the table, in levels, most of the variables are non-stationary with an intercept only, and when an intercept and a linear trend are included. However, in most cases, they are stationary when the same tests are applied to the first differences, particularly when the intercept and trend assumption prevail. Given the sizeable amount of cross-country dependence detected by tests reported in tables II and III, the CADF and CIPS unit root tests give more reliable inference than those that do not account for cross-section dependence. We can thus conclude that the variables are non-stationary.

Table VI: CIPS Unit Root Tests

	Number of lag			
	0	1	2	3
	Panel A: Intercept			
$Thexp_{it}$	-2.457[b]	-2.284[b]	-2.284[a]	-2.627[a]
$\Delta Thexp_{it}$	-2.833[b]	-4.555[a]	-4.555[a]	-4.864[a]
$Phexp_{it}$	-1.536	-2.313[b]	-2.613[a]	-2.421[b]
$\Delta Phexp_{it}$	-3.973[a]	-4.495[a]	-4.475[a]	-4.540[a]
$GDPpc_{it}$	-4.084[a]	-1.537	-1.423	-1.537
$\Delta GDPpc_{it}$	-3.147[a]	-3.601[a]	-3.601[a]	-3.601[a]
	Panel B:Intercept and Trend			
$Thexp_{it}$	-2.492	-2.397[b]	-2.397	-3.060[a]
$\Delta Thexp_{it}$	-2.960*	-4.696[a]	-4.696[a]	-4.679[a]
$Phexp_{it}$	-1.993	-2.251	-2.332	-2.332
$\Delta Phexp_{it}$	-4.182*	-4.511[a]	-4.558[a]	-4.590[a]
$GDPpc_{it}$	-4.071*	-1.863	-1.810	-1.863
$\Delta GDPpc_{it}$	-3.676*	-3.744[a]	-3.744[a]	-4.047[a]

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

In order to check the sensitivity of our panel unit root tests, we run the tests again, eliminating one country at a time from the sample. Tables VII and VIII highlight the CADF and CIPS statistics for the variables. The results show that by eliminating a country from the sample, the results of the CADF and CIPS tests are similar to those reported in tables IV and V. The variable that exhibits the most sensitivity is income.

Table VII: Sensitivity analysis: CIPS Panel Unit Root Tests – Panel A: Intercept

Country	$Thexp_{it}$				$Phexp_{it}$				$GDPpc_{it}$			
	Number of lags				Number of lags				Number of lags			
	0	1	2	3	0	1	2	3	0	1	2	3
Benin	-2.082	-2.191[c]	-2.191[c]	-2.553[a]	-2.031	-2.271[b]	-2.592[a]	-2.378[a]	-1.496	-1.521	-1.395	-1.521
Burkina-Faso	-2.249	-2.324[b]	-2.324[b]	-2.687[a]	-2.116	-2.304[b]	-2.620[a]	-2.381[a]	-1.527	-1.496	-1.376	-1.496
Cape Verde	-2.258	-2.339[b]	2.339[b]	-2.705[a]	-2.090	-2.341	-2.448[a]	-2.448[a]	-1.634	-1.611	-1.633	-1.611
Cote d'Ivoire	-2.333	-2.384[b]	-2.384[b]	-2.742[a]	-2.047	-2.269	-2.362b	-2.362[b]	-1.473	-1.521	-1.408	-1.521
Gambia	-2.064	-2.162[c]	-2.162[c]	-2.530[a]	-2.142	-2.367[b]	-2.685[a]	-2.510[a]	-1.412	-1.431	-1.277	-1.431
Ghana	-2.105	-2.191[c]	-2.191[c]	-2.554[a]	-2.105	-2.301[b]	-2.403[b]	-2.403[b]	-1.777	-1.746	-1.712	-1.746
Guinea	-2.183	-2.246[b]	-2.246[b]	-2.610[a]	-2.064	-2.315[b]	-2.416[b]	-2.359[b]	-1.531	-1.544	-1.427	-1.544
Guinea-Bissau	-2.220	-2.308[b]	-2.308[b]	-2.308[b]	-1.971	-2.255[a]	-2.540[a]	-2.540[a]	-1.543	-1.532	-1.643	-1.532
Liberia	-2.459	-2.679[a]	-2.679[a]	-3.215[a]	-2.256	-2.544[a]	-2.544[a]	-2.482[a]	-1.52	-1.526	-1.406	-1.805
Mali	-2.054	-2.113[c]	-2.113[c]	-2.475[a]	-2.063	-2.285[b]	-2.605[a]	-2.372[b]	-1.561	-1.585	-1.460	-1.585
Niger	-2.267*	-2.267[a]	-2.267[a]	-2.630[a]	-2.191	-2.279[b]	-2.681[a]	-2.603[a]	-1.465	-1.496	-1.399	-1.496
Nigeria	-2.029	-2.084	-2.084	-2.084	-2.032	-2.259[b]	-2.341[b]	-2.341[b]	-1.562	-1.521	-1.362	-1.521
Senegal	-2.223	-2.323	-2.323[b]	-2.323[b]	-2.166	-2.301	-2.700[a]	-2.620[a]	-1.531	-1.537	-1.423	-1.537
Sierra-Leone	-2.148	-2.236[b]	-2.236[b]	-2.602[a]	-2.030	-2.230[b]	-2.338[b]	-2.338[b]	-1.552	-1.506	-1.343	-1.448
Togo	-2.228	-2.303[c]	-2.303[b]	-2.663[a]	-2.082	-2.374[b]	-2.783[a]	-2.538[a]	-1.445	-1.464	-1.369	-1.464

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table VIII: Sensitivity Analysis: CIPS Panel Unit Root Tests – Panel B: Intercept and Trend

Country	$Thexp_{it}$				$Phexp_{it}$				$GDPpc_{it}$			
	Number of lags				Number of lags				Number of lags			
	0	1	2	3	0	1	2	3	0	1	2	3
Benin	-2.212	-2.305	-2.305	-2.615	-1.934	-2.189	-2.267	-2.189	-1.462	-1.833	-1.777	-1.833
Burkina-Faso	-2.449	-2.508	-2.508	-3.214[a]	-2.009	-2.209	-2.565	-2.276[b]	-1.315	-1.752	-1.697	-1.752
Cape Verde	-2.354	-2.438	-2.438	-3.153[a]	-1.931	-2.281[b]	-2.281	-2.281[b]	-1.743	-1.902	-1.969	-1.902
Cote d'Ivoire	-2.554	-2.630	-2.630	-3.007[a]	-1.894	-2.258	-2.258	-2.258	-1.464	-2.032	-1.971	-2.032
Gambia	-2.239	-2.330	-2.330	-2.637	-2.032	-2.321	-2.411	-2.321	-1.322	-1.732	-1.670	-1.732
Ghana	-2.260	-2.327	-2.327	-2.627	-1.870	-2.167	-2.167	-2.167	-1.672	-2.149	-2.033	-2.027
Guinea	-2.316	-2.369	-2.369	-3.073[a]	-1.861	-2.283	-2.283	-2.283c	-1.429	-1.866	-1.812	-1.866
Guinea-Bissau	-2.388	-2.466	-2.466	-2.739	-1.839	-2.227	-2.529	-2.529	-1.270	-1.864	-1.953	-1.864
Liberia	-2.644	-2.887[b]	-2.887[b]	-3.512[a]	-2.279	-2.599	-2.599	-2.896	-1.711	-1.867	-2.055	-2.030
Mali	-2.218	-2.262	-2.262	-2.562	-1.805	-2.189	-2.534	-2.253	-1.517	-1.926	-1.869	-1.926
Niger	-2.384	-2.384	2.384	-3.088[a]	-2.013	-2.156	-2.561	-2.511	-1.418	-1.958	-1.900	-1.958
Nigeria	-2.234	-2.296	-2.298	-2.619	-1.931	-2.225	-2.225	-2.225	-1.274	1.840	-1.777	-1.840
Senegal	-2.329	-2.432	-2.432	-2.766	-1.948	-2.225	-2.584	-2.312	-1.477	-1.888	-1.831	-1.888
Sierra-Leone	-2.225	-2.316	-2.316	-3.025[a]	-1.939	-2.188	-2.188	-2.188	-1.291	-1.900	-1.680	-1.908
Togo	-2.387	-2.462	-2.462	-2.845[b]	-1.898	-2.282	-2.369	-2.282[b]	-1.585	-2.055	-1.994	-1.995

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

The results of Pedroni (2000, 2004) tests, with and without a linear trend, are shown in table IX. The panel-adf statistics, which is theoretically the most appropriate when the time dimension is not too large $(T = 18 < 20)$ reveals that there is no cointegrating relationship between health expenditure and income, regardless of the assumptions imposed. However when only an intercept is included, three tests statistics (*panel-rho, t and group-t*) reject the null hypothesis. With a linear trend, only two out of the seven test statistics (*panel-t and panel group-t*) find a cointegrating relationship.

Table IX: Pedroni (2000, 2004) Cointegration Tests

	With Intercept only	With Intercept and Trend
Intra Dimension (Common AR coefficient)		
panel – v statistics	-0.151	-2.794[b]
panel – rho statistics	-5.507[a]	-2.913[b]
panel – t statistics	-10.660[a]	-13.410[a]
panel –adf statistics	0.238	-3.573[a]
Between Dimension (Individual AR coefficient)		
group – rho statistics	-3.567	-1.087
group- t statistics	-12.290[a]	-14.760[a]
group–adf statistics	-0.782	-3.359[a]

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table X shows the results of the Westerlund cointegration tests that enable us to account, not only for the time-series dimension but also the cross-sectional dimension. In presence of only an intercept, two statistics $(P_t \text{ and } P_a)$ reject the presence of long-run relationship, while the group statistics $(G_t \text{ and } G_a)$ show otherwise. In the presence of an intercept and trend, which is the most realistic given on our dataset, all the statistics reveal the existence of a long-run relationship between health care expenditure and income in the ECOWAS sub-region.

Table X: Westerlund (2007) Cointegration Tests

	$Thexp_{it}$ and $GDPpc_{it}$	$Thexp_{it}$ and $Phexp_{it}$
	Panel A: Intercept	
Statistics	Coefficient	Coefficient
G_t	-3.360[a]	-0.809
G_a	-12.556[a]	-3.643
P_t	-4.654	-6.319
P_a	-5.329	-6.563
	Panel B: Intercept and Trend	
G_t	-4.142[a]	-2.993[a]
G_a	-16.354[a]	-15.803[b]
P_t	-17.796[a]	-13.714[a]
P_a	-20.524[a]	-50.522[a]

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table XI shows results of the FE, Spatial MLE, and CCEP estimation when income is the only variable included in the regression (Panel A), as well as when public expenditure is added (Panel B). The FE estimates in (column (I) Panels A, B) shows that estimated income elasticity is greater than one, suggesting the luxury nature of health care. Furthermore, public health expenditure is significant in the second regression (Panel B), thus confirming the specific nature of health care in ECOWAS countries. For the MLE that takes into account spatial correlation (column IV of Panels A, B), estimates of income elasticity are different from the FE non-spatial counterpart. Similarly, the estimates of the other control variables are significantly different. Interestingly, controlling for the period effects, the estimated spatial coefficients are positive. These may be an indication of the indirect effects of unobservable neighboring variables, such as environmental risks that are difficult to measure.

The CCEP results (columns II and III Panels A, B) give the estimates of income elasticity. These results corroborate the hypothesis that health care is a necessity under CCE (pooled) and a luxury for CCE (MG). Given the sizeable amount of correlation across countries detected in the exploratory data analysis, there are strong indications that the CCE (pooled approach), which accounts for the effect of unobservable common factors, is more appropriate and realistic in estimating (1). Table XI also shows the CD_{LM} statistics and the Moran's I applied to the residuals of the CCE, spatial MLE, and FE regressions. The results indicate the presence of a general form of cross section dependence.

Table XII (XIIa and XIIb) show results of the CIPS panel unit roots tests on the residuals from the estimated equations showed in table XI. The CCEP residuals from the first and second regression are stationary for $p = 0,1,2$; suggesting the existence of a long-run relationship between health expenditure and income, whether we control for public expenditure and dependency rates or not. In contrast, for the FE regressions, we do not reject the unit root hypothesis in the residuals, for $p = 0,1,2,3$, whether we control for public expenditure or not. Hence, there is a marked difference between the CCEP and FE approaches.

Finally, results of the error correction models related to the CCEP estimation are shown in table XIII. The results also reveal a cointegration relation between the variables. The coefficient of $\left(h_{i,t-1} - \beta' x_{i,t-1}\right)$ measures the speed of adjustment of health care spending to a deviation from long-run equilibrium relation between the variable and its determinants. As expected, this coefficient is negative and significant in both regressions. It is important to note though that unlike the case of OECD countries as reported in reviewed literature, short run changes in per capita income and public expenditure have significant effects on health expenditure in ECOWAS sub-region. This is typical to most developing countries.

Table XI: Estimation Results - The Determinants of Health Expenditure

	(I) CCE Fixed Effects		(II) CCE pooled		(III) CCE MG		(IV) Spatial MLE	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Panel A								
$GDPpc_{it}$	1.511	0.000	0.962	0.000	1.386	0.016	0.779	0.000
δ	-	-	-	-	0.339	-0.089	0.042	0.000
CD Statistics								
CD_{LM}	30.026		10.181		5.661		95.227	
CD_{ρ}	10.677		-2.360		1.420		38.472	
Moran I	0.846		0.698		1.360		7.987	
Panel B								
$GDPpc_{it}$	1.342	0.000	0.736	0.000	1.056	0.049	0.779	0.000
$Phexp_{it}$	0.428	0.000	0.234	0.000	0.291	0.234	-0.036	0.514
Intercept	0.000	0.392	0.000	0.392	0.000	0.392	-3.432	0.001
F-test for $\varepsilon_i = 0$			-	-	0.217	0.227		
CD_{LM}	27.899		7.477		2.840		103.195	
CD_{ρ}	9.803		-2.030		-0.115		39.973	
Moran I	1.135		0.565		0.360		12.271	

Table XIIa: CIPS Panel Unit Root Test on the Residuals (with intercept only)

	Number of lags			
	0	1	2	3
	Regression I (without control variables)			
$\hat{u}_{it}$ (FE)	-1.521	-1.340	-1.365	-1.163
$\hat{u}_{it}$ (*Spatial MLE)*	-2.474[b]	-2.304[b]	-2.164[b]	-2.510[b]
$\hat{u}_{it}$ (*CCE MG)*	-3.099[b]	-2.533[b]	-2.444[b]	-2.268[b]
$\hat{u}_{it}$ (*CCE Pooled)*	-2.756[b]	-2.320[b]	-2.362[b]	-2.141[b]
	Regression II (with control variables)			
$\hat{u}_{it}$ (FE)	-1.833	-1.546	-1.467	-1.344
$\hat{u}_{it}$ (*Spatial MLE)*	-2.509[b]	-2.336[b]	-2.184[b]	-2.572[b]
$\hat{u}_{it}$ (*CCE MG)*	-3.463[b]	-2.709[b]	-2.490[b]	-2.184[b]
$\hat{u}_{it}$ (*CCE Pooled)*	-3.217[b]	-2.498[b]	-2.302[b]	-1.951[b]

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table XIIb: CIPS Panel Unit Root Test on the Residuals (with intercept and trend)

	Number of lags			
	0	1	2	3
Regression I (without control variables)				
$\hat{u}_{it}$ (FE)	-2.496[b]	-2.213[b]	-2.072[b]	-2.215[b]
$\hat{u}_{it}$ (*Spatial MLE*)	-3.455[b]	-3.052[b]	-3.533[b]	-3.473[b]
$\hat{u}_{it}$ (*CCE MG*)	-2.989[b]	-2.435[b]	-2.347[b]	-2.186[b]
$\hat{u}_{it}$ (*CCE Pooled*)	-2.673[b]	-2.258[b]	-2.656[b]	-2.198[b]
Regression II (with control variables)				
$\hat{u}_{it}$ (FE)	-2.809[b]	-2.519[b]	-2.358[b]	-2.551[b]
$\hat{u}_{it}$ (*Spatial MLE*)	-3.476[b]	-3.101[b]	-3.588[b]	-3.514[b]
$\hat{u}_{it}$ (*CCE MG*)	-3.361[b]	-2.616[b]	-2.370[b]	-2.077[b]
$\hat{u}_{it}$ (*CCE Pooled*)	-3.156[b]	-2.533[b]	-2.810[b]	-2.275[b]

Notes: [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% respectively.

Table XIII: CCEP Estimation of Error Correction Model

	Regression (I) (without control variables)		Regression (II) (with control variables)	
	Coefficient	P-value	Coefficient	P-value
$h_{i,t-1} - \hat{\beta}' \mathrm{x}_{i,t-1}$	-0.685	0.000	-0.696	0.000
$\Delta h_{i,t-1}$	-0.513	0.000	-0.413	0.000
$\Delta GDPpc_{it}$	1.106	0.000	0.994	0.000
$\Delta Phexp_{it}$	-	-	0.311	0.000
CD Statistics				
Rho	0.031		-0.009	
CD_{ρ}	1.344		-0.413	
CD_{LM}	3.038		1.071	
Moran I	0.041		0.046	
Moran standardized	0.170		0.364	

Notes: Regression (I) does not have control variables; whereas regression (II) does.

5. Conclusions

In this paper, we revisit the estimation of income elasticity of health expenditure using nonstationary panel data techniques for 15 ECOWAS countries over the period 1995 to 2012. Accounting for cross-section dependence and heterogeneity, the several tests undertaken reveal that there is a strong long-run relationship between health care expenditure and income in the ECOWAS sub-regional bloc. The income elasticity is particularly significant; ranging between 0.736 and 0.962 and confirming that health is a necessity. This suggests that health care is a necessity and there is need for governmental intervention, either through regulation or by directly investing in the provision of services and medical supplies—medications, personnel and hardware.

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