Health expenditure and Real disposable Income in the ECCAS: A Causal Study using spatial panel approach

DO ANGO, Simplicio and AMBA OYON, Claude Marius

Department of Economics, University Omar Bongo-Libreville, Gabon, Department of Economics, University of Yaoundé II, Cameroon

2016

Health Expenditure and Real Disposable Income in ECCAS

A Causal Study Using a Spatial Panel Approach[+]

Do Ango Simplicio

Corresponding Author: Department of Economics, University Omar Bongo-Libreville, Email: doangos@yahoo.fr

Marius C. O. Amba

Department of Economics, University of Yaoundé II, Email: mariusamba@gmail.com

Abstract:

This paper examines the long-run economic relationship between health care expenditure and income in Economic Community of Central African States observed over the period 1995-2014. Particularly we study the non-stationarity and cointegration properties between health care spending and income, ultimately measuring income elasticity of health care. This is done in a panel data framework controlling for both cross-section dependence and unobserved heterogeneity. Specifically, in our regression equations we assume that the error is the sum of a multifactor structure and a spatial autoregressive process, which capture global shocks and local spill overs in health expenditure. Our findings reveal that the majority of the countries presents an income elasticity lower than one, confirming that health care is a necessity good.

Keywords: Health expenditure, income elasticity, cross section dependence, panels, ECCAS.

JEL code: C31, C33, H51

[+] The authors want to thank anonymous referee for their helpful comments.

1. Introduction

Population health status in African countries in general is still considerably low and weak than in most other parts of the World. Low life expectancy at birth, high infant and maternal mortality rates, malaria and tuberculosis, HIV/AIDS and recently ‘Ebola fever’ are some of the unique devastating images of the population health in African countries. According to World Bank (2014), in 2012, a new infant born in Sub-Saharan Africa has expected 56 life-years to live, but if the same infant were born in high-income countries of the World during the same period, he would have expected 79 years to live.

Health has become as important as any other economic and social concerns, such as unemployment, low wages and a high cost of living. As Bloom et al. (2004) noted ‘the most basic human capabilities that is leading a long life, being knowledgeable, and enjoying a decent standard of living’ (e.g., see UNDP, 1990) can be represented by health, education, and income. These are considered as the three pillars of human development. Furthermore, health is consistently ranked number one in the things people desire in life.

Across the globe there are great variations on the amount countries spend on health. In high income countries per capita health expenditure is over 3000 USD on average, while in resource poor countries it is only 30 USD per capita. There are also wide variations in health expenditure with respect to economic development. Some countries spend more than 12% of GDP on health, while others spend less than 3%, on health (e.g., see Xu et al., 2011). Health care expenditure in the Africa regions vary considerably over time and across countries.

Health financing is essential for the advancement of health status in any economy. At the macroeconomic level, the level and growth of health care expenditure has been attributed to the income level of such country. The performance of the health sector is therefore assumed to reflect the size of the income elasticity of health care.

There are therefore some important questions related to health status African countries need to address: Is it important to finance the health system? Is it a necessity or a luxury? How should the health system be financed? Is it by revenue or income? Or by creating a new tax? What are the important factors explaining differences across countries in the level and growth of health care expenditure?

To investigate the above important questions, we need to examine stochastic properties of two most important variables in the health system: the income and health expenditure variables. Pursuing the analysis, their long run behaviour will be analysed as well.

This paper demarcates from traditional analyses as: (i) it will be conducted in the context of panel data analysis; (ii) we control for heterogeneity which may exist between Economic Community of Central African States (ECCAS, hereafter); (iii) we control as well for spatial correlation which may exist between geographic units.

The remainder of the paper proceeds as follows: Section 2 is related to previous studies. Section 3 describes the data and variables used. The econometric methodology used is explained in section 4. Empirical results are reported in Section 5. And section 6 concludes the paper.

2. Literature Review

Many studies have focused on the above issues with some policy implications for the financing and distribution of health care resources. The discussion is still open on whether health care is a luxury or a necessity good, depending on whether income elasticity of expenditure is above or below unity (e.g., see Parkin et al., 1987; Gerdtham et al., 1992; Hansen and King, 1996; Blomqvist and Carter, 1997; Di Matteo and Di Matteo, 1998, Freeman, 2003). Conversely, supporters of health care being a luxury good argued that it is a commodity much like any other and is best left to market forces (e.g., see Culyer, 1988).

Since the seminal papers by Kleiman (1974) and Newhouse (1977) income has been identified as the most important factor explaining differences across countries in the level and growth of health care expenditure. The relationship between health status and economic growth has received generous enquiries in the literature. Outcomes from several studies seem to suggest that there is a positive association between health status and economic development. The wide acceptance of this nexus prompted the prominence of health outcome in the Millennium Development Goals (MDGs). In fact three of the goals are health specific while the others can also be regarded as health enhancing. However, the mechanisms of this relationship are fraught with disagreements. While high health expenditure is viewed as a channel of developing the health status of a nation, the results differ across countries and regions. Thus, the financing of health care expenditure becomes more important in many resource constraint countries. The opportunity costs of spending on health is very high and thus the need for a justification on the increase or otherwise of health spending in such countries. Incidentally, Africa is arguably the most underdeveloped region in the world with its attendant problems. Therefore, provision of adequate funding for health care either by the household or the government remains difficult. Some authors have argued that this might be the reasons for the bad health outcomes in the region (e.g., see Bichaka and Gutema, 2008; Kaseje, 2006; Jaunky and Khadaroo, 2006).

Moreover, regarding the relationship between expenditure and income, one main issue is whether the stationarity assumption holds for both time series variables. It is well known that the violation of this assumption leads to spurious estimates under the OLS (e.g., see Engle and Granger, 1987). Certainly, if the two series are both integrated, the absolute value of their correlation coefficient will be nonzero, whether or not an economic relationship between them exists. Non-stationarity in the two series introduces the issue of determining whether there is a long-run equilibrium between health expenditure and income. If both time series variables are integrated and there exists a linear combination of these variables that is itself stationary, we can conclude that the two variables are cointegrated. In this situation, the stationary linear combination represents the cointegrating or long-run relationship, which can be specified in levels with short-run dynamics modelled via an error correction process. It follows that integration and cointegration between spending and income represent fundamental properties when specifying and interpreting a time-series model for health expenditure.

Several studies investigate the non-stationarity in health expenditure and income and their long-run relationship in a panel data framework for the developed and OECD countries (e.g., see McCoskey and Selden, 1998; Gerdtham and Lothgren, 2000; Okunade and Karakus, 2001; Jewell et al., 2003; Carrion-i-Silvestre, 2005; Dregerand Reimers, 2005; Wang and Rettenmaier, 2006, Chou, 2007, Baltagi and Moscone 2010, Wang 2011). Very little literature has been done for African countries, this may be due to the paucity of data. Previous studies such as Gbesemete and Gerdtham (1992) estimate the impact of per capita income on per capita health expenditure with 1984 data from 30 African countries and conclude that income elasticity of health expenditure is very close to unity while Vasudeva (2004) reports that health care income elasticity is greater than unity. Using African data, Jaunky and Khadaroo (2008) explore the income elasticity of health care expenditure for 28 African countries in a panel dimension over the decade 1991–2000. Also Okunade (2005) reports large variations in both per-capita GDP and per capita health expenditure shares of national incomes among countries and within regions in Africa. Olaniyan et al. (2013) examine the long-run economic relationship between health care expenditure and GDP for 32 sub-Saharan African countries observed over the period 1995-2009. Using panel unit roots and cointegration techniques, they found that there is a long run relationship between health care expenditure and GDP in the countries. Also, the results suggest that health care is a necessity rather than a luxury with income elasticity value of 0.46 and further shows that the demographic factors are significant in explaining health variations across Sub-Sahara Africa countries. Lv and Zhu (2014) consider a semi-parametric panel data analysis for the study of the relationship between per capita health care expenditure and per capita GDP for 42 African countries over the period 1995–2009. They found that the income elasticity is not constant but varies with income level, and health care is a necessity rather than a luxury for African countries.

Another important point of our argument concerns the cross section dependence in health expenditure. Fundamentally, the presence of cross section dependence in the data is an important characteristic of health expenditure. The assumption of zero correlation on the shocks affecting individual population units in a given cross section is very strong and is not likely taking into account in empirical studies of health expenditure. Two sources of interdependence are identified among observational units. The first is observed when the behaviour of agents are similar in front of external forces and unanticipated events such as technological advances, health shocks, the implementation of new health policies and sociological structural changes (e.g., see Andrews, 2005). On the other hand, these shocks are often unobservable to the econometrician and perturb the health system as a whole, simultaneously affecting the behaviour of agents (e.g., recipients, providers, etc.), ultimately impacting on health costs. A particular characteristic of these shocks is that they induce a correlation between pairs of statistical units that does not depend on how close they are in the geographical space. Therefore, we will refer to this type of correlation as long-range or global interdependence. Lastly, we note that some of the unexpected events that affect health spending directly might also impact indirectly by hitting the fundamentals of health expenditure, such as disposable income.

Another source of interdependence, namely spatial correlation, is related to location and distance among units, with respect to the geographical, economic or social space in which they are embedded (e.g., see Anselin, 2001). Spatial correlation might be engendered by cross State borders movements of health services beneficiaries (e.g., see Centers for Medicare and Medicaid Services, 2007). Actually, it is plausible that individuals move to regions whose revenues and expenditure pattern best match their preferences (e.g., see Tiebout, 1956; Baicker, 2005). Other reasons why we should expect spatial dependence in health spending have been suggested by a recent strand of literature in public economics and health economics, which focuses on strategic interaction among jurisdictions in deciding resources allocation (e.g., see Revelli, 2006, Moscone et al., 2007a, 2007b; Moscone and Knapp, 2005; Costa-i-Font and Moscone, 2007; Moscone and Tosetti, 2010).

This study examines the long-run economic relationship between health care expenditure and income in the African countries, ultimately assessing whether health care is a luxury or a necessity. Furthermore, several empirical studies pointed to the possible non-stationarity of health care spending and income, which in turn cast doubt on prior inference on income elasticity obtained from spurious regressions. Using a panel of 38 African countries followed over the period 1995-2012, we examine the non-stationarity and cointegration properties between health care spending and income. In our regression equations, we assume that the error term is a linear combination of few common time-specific effects with heterogeneous loadings and a spatial process. Therefore, we analyse the extent to which spending is driven by income, unobservable common shocks and spatial spill overs, determining the speed of adjustment of health expenditure to deviations from the long-run equilibrium relation.

3. Data and Variables

The data used are annual and are obtained from World Development Indicator 2015 for the period 1995 to 2014, and for 09 ECCAS. The principal variables used h and y are respectively health expenditure per capita and real gross domestic product per capita. Figure 1 (see appendix) plots the evolution of health care expenditure in ECCAS and some countries.

We gathered data for the following variables that have been identified by the literature as having a role in determining health care expenditure: public expenditure on health care computed as government expenditure over total health care expenditure; the dependency rates for old and young people, defined as the population aged 65 and over divided by the population aged 15–64, and the population aged 0–14 divided by the population aged 15–64, respectively. All variables are expressed in natural logarithm. As shown in Table 1, the sample of 09 countries and 20 years is still balanced when public expenditure on health care and the age structure are added to the regression. And, in table 2, the Jarque-Bera test clearly shows that at five percent level, all the variables follow a normal distribution.

Table 1: Description of variables

Variable	Description	N	T
h	Health expenditure per capita (current US$)	9	20
y	GDP per capita (constant 2005 US$)	9	20
Publ	% Government expenditure	9	20
Old	Dependency rate, Old people	9	20
Young	Dependency rate, Young people	9	20

Table 2: Descriptive Statistics

	GDP per Cap	Health	Public H	Old	Young
Mean	6.874	4.532	1.944	1.846	4.438
Median	6.815	4.404	1.940	1.804	4.421
Maximum	9.580	7.478	2.928	2.432	4.637
Minimum	4.947	1.782	0.162	1.533	4.171
Std. Dev.	1.355	1.177	0.480	0.217	0.126
Skewness	0.375	0.359	-0.691	0.963	-0.080
Kurtosis	2.052	2.449	4.023	3.661	1.866
Jarque-Bera	10.966	6.143	22.174	31.123	9.844
Probability	0.004	0.046	0.000	0.000	0.007
Sum	1237.35	815.80	349.94	332.21	798.76

Sum Sq. Dev.	328.56	248.02	41.20	8.45	2.85
Observations	180	180	180	180	180

4. Econometric Methodology

4.1. The Common Correlated Effect Estimators

The usual cross common effect used the following simple linear heterogeneous panel (e.g. see Tosetti and Moscone, 2007):

$$y_{it} = \alpha_i + \beta_i x_{it} + \eta_{it} \qquad i = 1,\ldots,N; t = 1,\ldots,T \tag{1}$$

where y_{it} and x_{it} respectively represent the dependent variable and the explanatory variable for the i*th* country at time *t*, α_i is the country intercept while β_i is the specific country coefficient; η_{it} is the error term. Since we deal for cross section dependence arising from global shocks, equation (1) assumes that the errors have the following multifactor structure

$$\eta_{it} = \gamma_i' f_t + \upsilon_{it} \tag{2}$$

in which f_t is the $m \times 1$ vector of unobserved common effects and υ_{it} is a country-specific error. The coefficients γ_{ij} for $i = 1,\ldots,N; j = 1,\ldots,m$, are called factor loadings, and represent the sensitivities of statistical units (country), to movements in the factors f_t. Hence, according to this specification, each country can respond, with a different intensity, to unanticipated events, or perturbations.

We incorporate cross section dependence arising from spatial spill overs by assuming that υ_{it} it follows a spatial autoregressive process (Cliff and Ord, 1981)

$$\upsilon_{it} = \rho \bar{\upsilon}_{it} + \varepsilon_{it} \tag{3}$$

In model (1), we allow x_{it} to be correlated with the unobserved effects f_t, and assume that

$$x_{it} = c_i + \lambda_i' f_t + \nu_{it} \tag{4}$$

where λ_i' is a $m \times 1$ vector of factor loadings, and ν_{it} is an error term assumed to be distributed independently of the common factors f_t and of ε_{it}. Therefore, common factors can impact on health expenditure not only directly via the factor structure (2), but also indirectly by hitting income via equation (4).

To sum up, model (1)-(4) represents the relationship between health spending and income, taking into account the sources of cross section dependence described in Section 2, namely global shocks and spatial spill overs.

Our estimation and testing strategy is based on the Common Correlated Effects (CCE) approach advanced by Pesaran (2006) and its augmented form developed by Eberhardt & Teal (2010). According to the method of Pesaran, the unobservable effects f_t can be well approximated by the cross section averages of the dependent and explanatory variables. Hence, the slope parameters β_i can be consistently estimated applying standard panel techniques to the following equation:

$$y_{it} = \alpha_i + \beta_i x_{it} + g_i' \bar{z}_t + \eta_{it} \tag{4}$$

with $\bar{z}_t = \left(\bar{y}_t, \bar{x}_t\right)$

Pesaran (2006) suggests the following CCE estimator for the *i*th slope coefficient

$$\hat{\beta}_{CCE,i} = \left(x_i'\bar{M}x_i\right)^{-1}\left(x_i'\bar{M}y_i\right) \tag{5}$$

with $\bar{M} = I_T - \bar{H}\left(\bar{H}'\bar{H}\right)^{-}\bar{H}'$, $\bar{H} = \left(\tau, \bar{z}_t\right)$ and $\tau = \left(1, \cdots, 1\right)'$. Further, he proposes the following two estimators for the mean of the slope coefficients

$$\hat{\beta}_{MG} = N^{-}\sum\nolimits_i \hat{\beta}_{CCE,i} \tag{6}$$

and $$\hat{\beta}_P = \left(\sum\nolimits_i x_i'\bar{M}x_i\right)^{-1}\left(\sum\nolimits_i x_i'\bar{M}y_i\right) \tag{7}$$

The first, known as CCE Mean Group estimator, is a simple average of the individual CCE estimators in (5). The second is the CCE Pooled estimator, which gains efficiency from pooling observations (See Pesaran, 2006 for more details). The 'Augmented Mean Group' estimator (Eberhardt & Teal, 2010), is a two-step procedure conceptually similar to the Pesaran (2006) CCE estimator in the Mean Group version. We can summarize these steps in two lines:

(i) $$\Delta y_{it} = b'\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \Rightarrow \hat{c}_t \equiv \hat{u}_t^{\bullet} \tag{8}$$

(ii) $$y_{it} = a_i + b'x_{it} + c_i t + d_i \hat{u}_t^{\bullet} + e_{it} \Rightarrow \hat{\beta}_{AMG} = N^{-1}\sum\nolimits_i \hat{b}_i \tag{9}$$

We further considered a misspecified structure that ignores the presence of common factors and/or spatial correlations, i.e. the fixed effects estimator:

$$\hat{\beta}_{FE} = \left(\sum\nolimits_i x_i' M_\tau x_i\right)^{-1}\left(\sum\nolimits_i x_i' M_\tau y_i\right) \tag{10}$$

Where, $M_\tau = I_T - \tau\left(\tau'\tau\right)^{-1}\tau$. Before concluding, it's important to note that model (1)-(4) is able to capture some discontinuities in the relationship between spending and income by the means of the factor structure. However, we remark that it does not allow for the presence of structural breaks in the slope coefficients.

The next section explains how the CCE approach can be adopted when testing for unit roots, controlling for cross section dependence. Again, the idea is to use cross section averages of dependent and explanatory variables as proxies for the unobserved common factors, in the context of a Dickey Fuller regression.

4.2. Panel Unit Root Tests

Consider the p^{th} order augmented Dickey Fuller regression

$$\Delta q_{it} = a_i + b_i q_{it-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{it-3} + \mu_{it} \qquad \text{if } p > 0 \tag{8a}$$

$$\Delta q_{it} = a_i + b_i q_{it-1} + c_i t + \mu_{it} \qquad \text{if } p = 0 \tag{8b}$$

where q_{it} is either the logarithm of health spending, the logarithm of real disposable income, or regression residuals from equation (1). μ_{it} are errors that we assume to have a single factor structure, where the idiosyncratic component follows a spatial autoregressive process as in (3). When testing for unit roots, the null hypothesis is

$$H_0 : b_i = 0,\ i = 1, \ldots, N; \tag{9}$$

against the alternative that (Breitung and Pesaran, 2007)

$$H_1 : b_i \prec 0,\ i = 1, \ldots, N_1; b_i = 0,\ i = N_1 + 1, \ldots, N \tag{10}$$

where N_1 is such that $N_1 N^{-1}$ is nonzero and tends to a fixed constant as N goes to infinity. Following the same rational as in Section 3.1, we consider the following Dickey Fuller (CADF) regression augmented with the cross section averages:

$$\Delta q_{it} = a_i + b_i q_{it-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{it-3} + g_i' \overline{z}_t + e_{it} \quad \text{if } p > 0 \tag{11a}$$

$$\Delta q_{it} = a_i + b_i q_{it-1} + c_i t + g_i' \overline{z}_t + e_{it} \qquad \text{if } p = 0 \tag{11b}$$

where $\overline{z}_t = \left(\overline{q}_{t-1}, \Delta\overline{q}_t, \Delta\overline{q}_{t-1}, \cdots, \Delta\overline{q}_{t-p}\right)'$ for $p > 0$ and $\overline{z}_t = \left(\overline{q}_{t-1}, \Delta\overline{q}_t\right)'$ when $p = 0$. Pesaran (2007) proposes to test (9) against (10) by computing the simple average of the *t*-ratios of the OLS estimates of b_i in equation (11), namely,

$$CIPS = N^{-} \sum_{i=1}^{N} \tilde{t}_i \tag{12}$$

where $\tilde{t}_i$ is the OLS *t*-ratio of b_i. The critical values for the $CIPS$ tests are given in Tables 2(a)-2(c) in Pesaran (2007).

We remark that the CIPS unit roots test requires that the errors μ_{it} in (8) have a single factor structure. However, controlling for only one global shock might not be enough to capture the whole, long-range, contemporaneous correlation present in the data. In our empirical investigation we provide some statistics of cross section dependence after having controlled for such common factor to see whether significant correlation is left in the residuals. As a robustness check, we also calculate the panel unit roots test proposed by Im, Pesaran and Shin (2003) (IPS) and Breitung (2000), which do not account for cross-section dependence in the data. The IPS statistic is given by (9) where $\tilde{t}$ is based on (8) rather than (11), (i.e., the original model not augmented with the cross-section averages, see Baltagi (2008, p.278)). The Breitung (2000) statistic is a modification of the augmented Dickey Fuller statistic from (6) that has more power than IPS if individual specific trends are included, see Baltagi (2008, p.280).

4.3. Cross Section Dependence Tests

Now, we briefly review some statistics of cross section dependence used in this empirical work. A statistic which captures the overall amount of cross section dependence in the data, at a descriptive level, is the following average pairwise correlation coefficient

$$\bar{\rho} = 2\left[N(N-1)\right]^{-}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij} \tag{13}$$

where ρ_{ij} is given by

$$\rho_{ij} = \left(\sum_{t=1}^{T} q_{it}^{2}\sum_{t=1}^{T} q_{jt}^{2}\right)^{-1/2}\sum_{t=1}^{T} q_{it}q_{jt} \tag{14}$$

and q_{it} is either the logarithm of health expenditure or the logarithm of real disposable income, expressed in first differences, or regression residuals from equations (1), and (8).

We also consider two diagnostic tests for cross section dependence, based on the above pairwise correlation coefficients. The CD_P test, recently advanced by Pesaran (2004), is

$$CD_{P} = \sqrt{2T\left[N(N-1)\right]^{-1}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij} \tag{15}$$

and the CD_{LM} test based on the Lagrange Multiplier statistic (Frees, 1995) is

$$CD_{LM} = \left[N(N-1)\right]^{-1/2}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\rho_{it}^{2}-1\right) \tag{16}$$

Under the null hypothesis of no cross section dependence, the CD_P tends to a $N(0,1)$ for N and T going to infinity in any order, and the CD_{LM} tends to a $N(0,1)$ with $T \to \infty$ and then $N \to \infty$. We note that, while the CD_P is based on the pair-wise correlation coefficients, the CD_{LM} uses their squares. In practice, the CD_P test might give misleading results when the cross correlations cover negative as well as positive values. Though the CD_{LM} does not suffer from this problem, we note that it is likely to exhibit some size distortions for N large and T small (Frees, 1995).

In our work, we also test for spatial correlation, after having controlled for long-range dependence represented by the common factors structure. In particular, we compute the following Moran's I test statistic (Kelejian and Prucha, 2001)

$$I = T^{-1} \sum_t s_t^{-2} \left(\sum_i \sum_j \omega_{ij} \right)^{-1} \sum_i \sum_j \omega_{ij} \hat{e}_{it} \hat{e}_{jt} \tag{17}$$

where $s_t^2 = N^{-1} \sum_i \left(\hat{e}_{it} - \bar{\hat{e}}_{\bullet t} \right)^2$, and ω_{ij} is the generic *(i; j)*th element of a $N \times N$ nonnegative matrix, *W*, known as spatial weights matrix, which provides information on the neighborhood linkages among countries. In this study, we define neighbourliness via a contiguity criterion, and assign $\omega_{ij} = 1$ when country *i* and *j* share a common border or vertex, and $\omega_{ij} = 0$ otherwise; $\hat{e}_{it}$, for $i = 1, \ldots, N$, are the estimated regression residuals in (11).

The Moran's *I* is asymptotically normally distributed as *N* goes to infinity, for fixed *T*. Spatial statistics such as the Moran's *I* differ from the CD statistics (15)-(16) since they exploit information on the spatial ordering of data, giving more importance to country that are close to each other. As such, the Moran's *I* should be interpreted as a measure of local cross section dependence.

4.4. Cointegration Analysis and Error Correction Model

The possibility of cointegration between two variables x and y is explored using a two-stages procedure, along the lines suggested by Pesaran et al. (2006), Chang (2005), and Bai and Kao (2006). In a first step we estimate the CCE Mean Group (CCE Pooled) estimator and compute the residuals

$$\hat{u}_{it} = y_{it} - \hat{\beta} x_{it} - \hat{\alpha}_i \tag{18}$$

while in the second stage we run the CIPS panel unit root tests to assess whether $\hat{u}_{it}$ is stationary. If results lead to a rejection of a unit root in $\hat{u}_{it}$, we can conclude that x and y are cointegrated. One advantage of this procedure is that we take into account contemporaneous correlation in both steps, rather than only in one step as in Wang and Rettenmeir (2006). To check the robustness of our results, we also consider Pedroni and Johansen-Fisher cointegration tests.

After having established the existence of a cointegration relationship, we now turn to the estimation of the following error correction model

$$\Delta y_{it} = \hat{\alpha}_i + \theta_i \left(y_{i,t-1} - \hat{\beta} x_{i,t-1} \right) + \vartheta_i \Delta y_{it-1} + \delta_i \Delta x_{it} + u_{it} \tag{19}$$

where in the parenthesis we have the previous periodic cointegrating relation.

5. Empirical Finding and Comments

We first make a preliminary exploratory data analysis and after, our empirical study is structured as follows: we check whether our variables are nonstationary; we then estimate the income elasticity controlling for a set of regressors and for unobserved common factors; finally, we test whether our variables form a cointegrating set and therefore if they are linked in the long-run.

Table 3 shows cross section dependence tests for the first differences of health expenditure and real disposable income (both in log) across the 09 Central African countries. The results reveal a tiny correlation between real GDP per capita (08%) and Health expenditure per capita (07%) among country. Figure 2 (see appendix) plots a static comparative of health and income in central African countries for three years (1995, 2005 and 2014); as we see all the points are centered around a straight line; it seems that it exist a long-run relationship between our principal variables.

Table 3: Cross Section Dependence in First Difference

Variables	**Rho**	**CD(p)**	**CD(lm)**
Health	0.083	2.238	2.845
GDP per capita	0.076	2.034	1.856

Table 4 reports the results of some first generation panel unit root tests. These tests do not account for cross-country dependence. The first two columns report the Im, Pesaran and Shin (2003) W_{tbar} statistic and the two lasts, the Levin Lin and Chu (2002) t statistic for the logarithm of our principal variables; for both, we use two approaches: (i) intercept only and (ii) intercept and trend; and the inclusion of lags allows us to control for possible serial correlation in the data. As we can see, health expenditure and real disposable income do not reject the null hypothesis of unit root. This means that for first generation tests they are non-stationary.

Table 4: Some First Generation Tests

	IPS W-stat		LLC t-stat	
		Health		
Model	Intercept	Intercept and Trend	Intercept	Intercept and Trend

Lag	Coef	P-value	Coef	P-value	Coef	P-value	Coef	P-value
1	0.70	0.75	1.73	0.96	-1.03	0.15	0.55	0.71
2	0.96	0.83	2.80	0.99	-0.40	0.34	3.18	0.99
				GDP				
Model	Intercept		Intercept and Trend		Intercept		Intercept and Trend	
1	0.26	0.60	0.09	0.54	-0.39	0.35	-2.42	0.01
2	1.04	0.85	1.30	0.90	1.16	0.88	0.26	0.60

Table 5 shows the CIPS statistics for the logarithm of our variables. We report these results for lag orders p=0; 1; 2. As we can see from the table, all the variables are non-stationary when adding an intercept only, and when including an intercept and a linear trend.

Table 5: CIPS Panel Unit Root Test

	Health			
Model	Intercept only		Intercept and Trend	
Lag	**Coef**	**P-value**	**Coef**	**P-value**
0	-0.71	0.24	0.23	0.59
1	1.96	0.97	2.63	0.99
2	2.18	0.98	3.29	0.99
	GDP			
0	1.26	0.89	1.52	0.93
1	-1.03	0.15	-0.14	0.44
2	1.57	0.94	2.66	0.99

In order to check the sensitivity of our panel unit root results, we run these tests again but now removing one country at a time from the sample. Table 6 (see appendix) reports the CIPS statistics for the variables health care expenditure and income in all cases. By and large, these results show that if we drop any country from the analysis, the results of the CIPS tests are similar to those reported in Table 5. The variable that exhibits the most sensitivity is health care expenditure.

Turning to the relationship between health care expenditure and real disposable income in ECCAS, the results of the estimation of the income elasticity for each of our 09 countries are summarized in Table 7. We obtain elasticity above unity for Burundi, Congo and Gabon this mean that health care is a luxury good in these countries. While for the other countries in our sample, we get elasticity lower than one; confirming that health care is, overall, a necessity good.

Table 7: CCE Estimated Coefficient by country

	GDP		Cross Section Average Regressors			
Country	**Slope**	**Std Error**	**Health**	**Std Error**	**GDP**	**Std Error**
Angola	0.178	0.432	1.131 [b]	0.580	0.600	0.917
Burundi	2.008	1.703	-0.127	0.722	2.480 [c]	1.500
Cameroon	0.459	0.797	-0.094	0.237	1.144 [b]	0.482
Central Af R	0.605 [a]	0.130	-0.445 [b]	0.200	1.403 [a]	0.349
Chad	-0.103	0.522	0.212	0.578	0.551	0.895
Congo D	0.776	0.618	2.053 [b]	0.904	-2.221	1.615
Congo	2.812 [a]	1.174	1.764 [a]	0.720	-2.998 [a]	1.026
Eq Guinea	0.421 [a]	0.174	1.980 [a]	0.717	-0.017	1.981
Gabon	1.022 [a]	0.333	1.159 [a]	0.230	-1.506 [a]	0.480
ECCAS	0.909 [a]	0.311	0.848 [a]	0.326	-0.063	0.604

a, b and c respectively indicate significance of the coefficient at 1%, 5% and 10%

Table 8 shows results from Fixed Effect, CCE Mean Group, CCE Augmented Mean Group and CCE Pooled estimation when income is the only variable included in the regression (Panel A), as well as when public expenditure and dependency rates are added (Panel B). If we focus on the FE estimates (Panels A, B), the income elasticity is smaller than one, suggesting the necessity nature of health care. The variables public expenditure has a significant and positive influence on health care expenditure for the regression reported in panel B; however, the variable dependency rate for young people has a significant and negative influence on health in central African countries. For the CCE MG accounting for spatial correlation (Panels A, B), the parameter estimates for the income elasticity are close to their FE non-spatial counterpart. However, the estimates of the other control variables are different, with the young people variable becoming positive but not significant. In the CCE AMG, we remark that the income elasticity is upper than one when we added control variables. The CCEP estimates (column Panels A, B) give the lowest estimates of the income elasticity, especially when we control for non-income variables. These results corroborate the hypothesis that health care is a necessity good. Given the sizeable amount of correlation across countries detected in our exploratory data analysis, we believe that the CCEP approach, incorporating the effect of unobservable common factors, is more appropriate for estimating Eq. (1). Table 6 also reports the statistics CD_{LM}, and Moran's I applied to the residuals of the CCE and FE regressions. These indicate the presence of a general form of cross-section dependence in the FE and CCE Pooled regressions.

Table 8: Determinants of Health Expenditure in ECCAS

Panel A								
	Fixed Effect		**CCE MG**		**CCE AMG**		**CCE Pooled**	
Variable	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**	**Coef**	**Std Error**
GDP	0.968 [a]	0.060	0.909 [a]	0.311	0.985 [b]	0.380	0.810 [a]	0.024
Cte	-2.121 [a]	0.414	-5.029 [b]	2.628	-3.043	2.559	-1.033 [a]	0.166
CD Statistics								
Rho	0.247		-0.091		-0.090		0.103	

CD(p)	6.639		-2.438		-2.409		2.761	
CD(lm)	16.974		1.830		2.945		12.562	
Moran's I	0.441		0.002		-0.041		-0.050	
Panel B								
Variable	**Coef**	**Std. Error**	**Coef**	**Std. Error**	**Coef**	**Std. Error**	**Coef**	**Std. Error**
GDP	0.939 [a]	0.071	0.219	0.264	1.320 [a]	0.345	0.866 [a]	0.026
Publ	0.380 [a]	0.039	0.365 [a]	0.073	0.373 [a]	0.068	0.390 [a]	0.062
Young	-1.588 [b]	0.762	2.892	7.341	5.939	4.836	-0.304	0.312
Old	-0.486	0.621	3.111	5.838	-3.237	3.946	-0.702 [a]	0.161
Cte	5.284 [a]	2.171	82.088	51.723	-26.430	16.423	0.468	1.662
CD Statistics								
Rho	0.009		-0.061		-0.065		-0.014	
CD(p)	0.251		-1.626		-1.734		-0.369	
CD(lm)	2.418		1.493		2.049		21.321	
Moran's I	-0.047		0.018		-0.002		-0.170	

The possibility of cointegration between two variables health and income is explored using the procedure described above. For comparative purposes, we also implement this two stages procedure using the fixed effects estimator in the first step, which ignores cross section dependence. Table 9a shows the unit root test on residuals from CCE and FE estimations with an intercept only. Looking the results, we note that CCE Mean Group reject the unit root hypothesis in the residuals, at lags 0, 1 and 2 (only for the second regression); The CCE Augmented Mean Group residuals from the first and second regression are stationary at lag 0 and 1 (only for the second regression); In contrast, for the FE and Pooled regressions, we do not reject the unit root hypothesis in the residuals, for p=0, 1, 2 whether we control for public expenditure and dependency rates, or not. These findings clearly show that health spending and income are cointegrated since his combination yield a stationary process; hence, it exist a long relationship between health care expenditure and disposable income ECCAS.

Table 9a: CIPS Unit Root Test on Residuals

	Regression I			Regression II		
Lag	**0**	**1**	**2**	**0**	**1**	**2**
Fixed Effect	-1.42	1.58	1.77	-2.31 [b]	0.271	0.15
CCE MG	-4.74 [b]	-3.06 [b]	-1.38	-10.01 [b]	-4.76 [b]	-3.48 [b]
CCE AMG	-5.38 [b]	-1.80	-1.04	-8.70 [b]	-3.50 [b]	-1.29
CCE Pooled	-1.36	1.86	2.11	-2.07	0.62	0.20

Notes: [b] indicates statistical significance at 5 percent. Critical values are taken from Pesaran (2007). The 5% critical value is -2.11 for the intercept only case.

In addition, because of the high possibility of spatial correlation, spatial cointegration between health and income is investigated using Pedroni and Johansen-Fisher cointegration tests. As we can see in table 9b, Pedroni residual (PP and ADF) and Johansen Fisher panel cointegration tests reject the null hypothesis of no cointegration between health and real disposable income.

Table 9b: Some Cointegration Tests

Pedroni Residual cointegration Test					
Alternative hypothesis: Common AR Coefficients. (Within-dimension)					
		Unweight		Weighted	
		Statistic	Prob.	Statistic	Prob.
Panel	PP-Statistic	-1.716 [b]	0.043	-1.325 [c]	0.093
Panel	ADF-Statistic	-2.023 [b]	0.022	-1.533 [c]	0.063
Alternative hypothesis individual AR coefficients. (between-dimension)					
		Statistic	Prob.		
Group	PP-Statistic	-1.326 [c]	0.093		

Group	ADF-Statistic	-1.578 [c]	0.057	
		Johansen Fisher Panel Cointegration Test		
Nber of CE	From Trace	Prob.	From Eigen-V	Prob.
None	84.12 [a]	0.000	68.37 [a]	0.000
At most 1	34.69 [a]	0.010	34.69 [a]	0.010

[a], [b] and [c] indicate statistical significance at 1, 5 and 10 percent respectively All these used model with intercept and trend

Results of the error correction model are show on Table 10. For all the estimation method the coefficient of the error correction term has the expected negative and significant sign (for CCE MG and CCE AMG). Indeed, we respectively get -0.28 for FE, -0.63 for CCE mean group, -0.58 for CCE augmented mean group and -0.27 CCE Pooled. We can explain the weak value of fixed effect error correction term by the fact that it doesn't take account of cross effect.

Table 10: Error Correction Models

	Fixed Effect		**CCE MG**		**CCE AMG**		**CCE Pooled**	
	Coef	std Error	Coef	std Error	Coef	std Error	Coef	std Error
Ecm	-0.280	0.181	-0.630 [c]	0.340	-0.583 [c]	0.320	-0.274	0.188
health	-0.412 [a]	0.150	-0.472 [a]	0.160	-0.507 [a]	0.179	-0.410 [a]	0.152
gdp	0.883 [c]	0.515	0.612	0.517	0.509	0.527	0.843	0.516
cte	0.039 [a]	0.019	0.047 [a]	0.020	0.053 [a]	0.019	0.008	0.021
				CD statistic				
Rho			0.180		0.144		0.105	
CD(p)			4.839		3.854		2.804	
CD(lm)			5.214		3.572		3.095	

Conclusion

This paper investigated the long-run economic relationship between health care expenditure and income in the Economic Community of Central Africa States. Using a panel of 09 Central African countries followed over 20 years, we have studied the non-stationarity and cointegration properties of health care expenditure and real disposable income, ultimately measuring income elasticity of health care.

Our investigation indicates that health care expenditure and real disposable income are non-stationary in level and that they are linked in the long-run. Further, our results show that, as many studies, health care expenditure is a necessity good rather than a luxury in Central African countries.

As for non-income determinants, our analysis indicates a role for the public health in explaining health expenditure variations. It would be interesting to use this approach to analyze health spending for African regions, to see if the same conclusions hold.

References

Andrews, D (2005) 'Cross Section Regression with Common Shocks', Econometrica, 73, 1551-1585.

Anselin, L (2001) Spatial Econometrics. In Baltagi, B (ed.), A Companion to Theoretical Econometrics. Blackwell, Oxford.

Baltagi, BH and Moscone, F (2010) 'Health Care Expenditure and Income in the OECD Reconsidered: Evidence From Panel Data', Economic Modelling, 27(4), 804-811.

Bai, J and Ng, S (2004) 'A Panic Attack on Unit Roots and Cointegration', Econometrica,72, 1127-1177.

Baicker, K (2005) 'The Spill over Effects of State Spending', Journal of Public Economics, 89, 529-544.

Bichaka, F and Paulos, G (2008) ‘A Health Production Function for Sub-Saharan Africa (SSA), A Working Paper Series.

Bloom, D, Canning, D and Sevilla, J (2004) ‘The Effect of Health on Economic Growth: A Production Function Approach’, World Development, 32(1), 1–13.

Blomqvist, G and Carter, RAL (1997) ‘Is Health Care Really a Luxury?’, Journal of Health Economics, 16(2), 207-229.

Carrion-i-Silvestre, JL (2005) ‘Health Care Expenditure and GDP: Are they Broken Stationary?’, Journal of Health Economics, 24(5), 839-854,

Centers for Medicare and Medicaid Services (2007) State Health Expenditure Accounts: State of Provider, 1980-2004. Definition and Methodology. www.cms.hhs.gov.

Costa-i-Font, J and Moscone, F (2007) Inter-territorial Interactions of Regional Health Expenditure in Spain, Mimeo, London School of Economics and Political Science.

Culyer, AJ (1988) Health Care Expenditures in Canada: Myth and Reality; Past and Future, Canadian, Tax Paper 82, Canadian Tax Foundation, Toronto.

Di Matteo, L and Di Matteo, R (1998) ‘Evidence on the Determinants of Canadian Provincial Government Health Expenditures: 1965-1991’, Journal of Health Economics, 17(2), 211-228.

Dregen, C and Reimers, H-E (2005) Health Care Expenditures in OECD Countries: A Panel Unit Root and Cointegration Analysis, IZA Discussion Paper 1469.

Engle, RF and Granger, CWJ (1987) ‘Co-Integration and Error Correction: Representation, Estimation and Testing’, Econometrica, 55, 251-276.

Freeman, DG (2003) ‘Is Health Care a Necessity or a Luxury? Pooled Estimates of Income Elasticity from US State-Level Data’, Applied Economics, 35, 495-502

Gbesemete, KP and Gerdtham, U-G (1992) ‘Determinants of Health Care Expenditure in Africa: A Cross-Sectional Study’, World Development, 20(2), 303–308.

Gerdtham, UG, Sogaard, J, Andersson, F and Jonsson, B (1992) ‘An Econometric Analysis of Health Care Expenditure: A Cross-Section Study of the OECD Countries’, Journal of Health Economics, 11(1), 63-84.

Gerdtham, UG and Lothgren, M (2000) ‘On Stationarity and Cointegration of International Health Expenditure and GDP’, Journal of Health Economics, 19(4), 461-475.

Hansen, P and King, A (1996) ‘The Determinants of Health Care Expenditure: A Cointegration Approach’, Journal of Health Economics, 15(1), 127-137.

Jaunky VC and Khadaroo AJ (2008) ‘Health Care Expenditure and GDP: An African Perspective’, Applied Econometrics and International Development, 8(1), 131–146.

Jewell, T, ,Lee, J, Tieslau, M, and Strazicich, MC (2003) ‘Stationarity of Heath Expenditures and GDP: Evidence from Panel Unit Root Tests with Heterogeneous Structural Breaks’, Journal of Health Economics, 22(2), 313-323.

Kaseje, D (2006) ‘Health Care in Africa: Challenges, Opportunities and Energy model for improvement’, Wilson International Center for Scholars.

Khadaroo,V and Jaunky, A (2008) ‘Health Care Expenditure and GDP: An African Perspective’, Applied Econometrics and International Development, 8(1), 131–146.

Kleiman, E (1974) The Determinants of National Outlay on Heath. Macmillan, London.

Lv, Z and Zhu, H (2014) ‘Health Care Expenditure and GDP in African Countries: Evidence from Semiparametric Estimation with Panel Data’, The Scientific World Journal ID 905747.

McCoskey, SK and Selden, TM (1998) ‘Health Care Expenditure and GDP: Panel Data Unit Root Test Results’, Journal of Health Economics, 17(3), 369-376.

Moscone, F and Knapp, M (2005) ‘Exploring the Spatial Pattern of Mental Health Expenditure’, The Journal of Mental Health Policy and Economics, 8, 205-217.

Moscone F and Tosetti F (2010) ‘Health Expenditure and Income in the United States’, Health Economics, 19(12), 1385-1403.

Moscone, F, Knapp, M, and Tosetti, E (2007a). ‘Mental health Expenditure in England: A Spatial Panel Approach’, Journal of Health Economics, 26(4), 842-864.

Moscone, F, Tosetti, E, and Knapp, M (2007b) ‘SUR Model with Spatial Effects: an Application to Mental Health Expenditure’, Health Economics Letters, 11(2), 3-9.

Murthy, VN, Okunade, AA (2009) ‘The Core Determinants of Health Expenditure in the African context: Some Econometric Evidence for Policy’, Health Policy, 91(1), 57-62.

Newhouse, JP (1977) ‘Medical Care Expenditure: A Cross-National Survey’, Journal of Human Resources, 12, 115-125.

Okunade, AA and Karakus, MC (2001) ‘Unit Root and Cointegration Tests: Time-Series versus Panel Estimates for International Health Expenditure Models’, Applied Economics, 33, 1131-1137.

Okunade, AA (2005) 'Analysis and Implications of the Determinants of Healthcare Expenditure in African Countries', Health Care Management Science, 8, 267–276.

Olaniyan,O, Onisanwa ID, and Oyinlola, A (2013) Health Care Expenditures and GDP in Sub-Saharan African Countries: Evidence from Panel Data. Conference on Economic Development in Africa, St Catherine's College, Oxford, 17-19 March 2013.

Parkin, D, McGuire, A and Yule, B (1987) 'Aggregate Health Care Expenditures and National Incomes: Is Health Care A Luxury Good?', Journal of Health Economics, 6(2), 109-127.

Pesaran, MH (2006) 'Estimation and Inference in Large Heterogenous Panels with Multifactor Error Structure', Econometrica, 74, 967-1012.

Pesaran, MH (2007) 'A Simple Panel Unit Root Test in the Presence of Cross Section Dependence', Journal of Applied Econometrics, 22, 265-312.

Pesaran, MH, Smith VL and Yamagata T (2013) 'Panel unit root tests in the presence of a Multifactor error', Journal of Econometrics, 175(2), 94-115.

Revelli, F (2006) 'Performance Rating and Yardstick Competition in Social Service Provision', Journal of Public Economics, 90, 459-475.

Samadi, A, and Homaie Rad E (2013) 'Determinants of Healthcare Expenditure in Economic Cooperation Organization (ECO) Countries: Evidence from Panel Cointegration Tests', International Journal of Health Policy and Management, 11, 63-68.

Tiebout, C (1956) 'A Pure Theory of Local Expenditure', Journal of Political Economy, 64, 416-424.

Vasudeva, MN (2004) 'Health Care Expenditures in Africa: An Econometric

Analysis', Atlantic Economic Journal, 32(4), 358-358.

Wang, KM (2011) 'Health Care Expenditure and Economic Growth: Quantile Panel-Type Analysis', Economic Modelling, 28, 1536–1549.

Westerlund, J (2007) 'Testing for error correction in panel data', Oxford Bulletin of Economics and Statistics, 69, 709–48.

Xu, K and Saksena, P and Holly, A (2011) The Determinants of Health Expenditure: A Country-Level Panel Data Analysis. The Results for Development Institute, Working Paper.

Appendix

Table 6: Sensitivity Analysis on CIPS Unit Root Test

	Health				GDP			
Model	Intercept only		Intercept and Trend		Intercept only		Intercept and Trend	
Country	Z-stat	P-value	Z-stat	P-value	Z-stat	P-value	Z-stat	P-value
	-1.23	0.11	0.33	0.63	2.38	0.99	1.98	0.98
Angola	-1.45	0.07	0.64	0.74	0.34	0.63	0.93	0.82
	-0.11	0.46	2.65	1.00	2.49	0.99	3.22	1.00
	-1.67	0.05	-0.43	0.33	1.86	0.97	1.83	0.97
Burundi	-1.48	0.07	0.93	0.82	-1.26	0.10	-0.42	0.34
	-0.90	0.19	1.46	0.93	1.31	0.91	2.14	0.98
	-1.21	0.11	0.20	0.58	0.28	0.61	0.92	0.82
Cameroon	-1.55	0.06	0.22	0.59	-1.29	0.10	-0.42	0.34
	-0.10	0.46	2.54	1.00	1.24	0.89	2.43	0.99
Central	-1.16	0.12	0.37	0.64	0.42	0.66	1.71	0.96
Africa	-1.78	0.04	0.52	0.70	-1.54	0.06	-1.06	0.15
Republic	-0.93	0.18	2.08	0.98	1.01	0.84	1.73	0.96
Chad	-1.29	0.10	0.09	0.54	2.21	0.99	1.92	0.97

	-1.90	0.03	0.11	0.54	0.11	0.54	0.74	0.77
	-0.99	0.16	1.56	0.94	2.63	1.00	2.98	0.99
Congo Democratic	-2.23	0.01	-1.27	0.10	1.54	0.94	1.56	0.94
	-2.58	0.01	-1.28	0.10	-0.39	0.35	0.77	0.78
	-0.37	0.36	1.23	0.89	1.92	0.97	3.31	1.00
Congo Republic	-2.76	0.00	-1.81	0.04	1.37	0.92	1.87	0.97
	-2.41	0.01	-0.80	0.21	-0.82	0.21	0.36	0.64
	-1.04	0.15	0.97	0.84	1.69	0.95	2.75	1.00
Equatorial Guinea	-1.47	0.07	-0.18	0.43	1.08	0.86	2.25	0.99
	-2.24	0.01	-0.58	0.28	1.50	0.93	2.66	1.00
	-0.66	0.26	1.95	0.97	1.58	0.94	2.72	1.00
Gabon	-1.57	0.06	-0.20	0.42	1.12	0.87	1.15	0.87
	-1.62	0.05	0.41	0.66	-1.16	0.12	-0.69	0.24
	-0.54	0.30	2.15	0.98	1.86	0.97	2.42	0.99

The first, second and third column respectively represent CIPS Panel Unit Root tests at lag 0, 1 and 2.

Figure 1: Health Expenditure Evolution in ECCAS and some countries

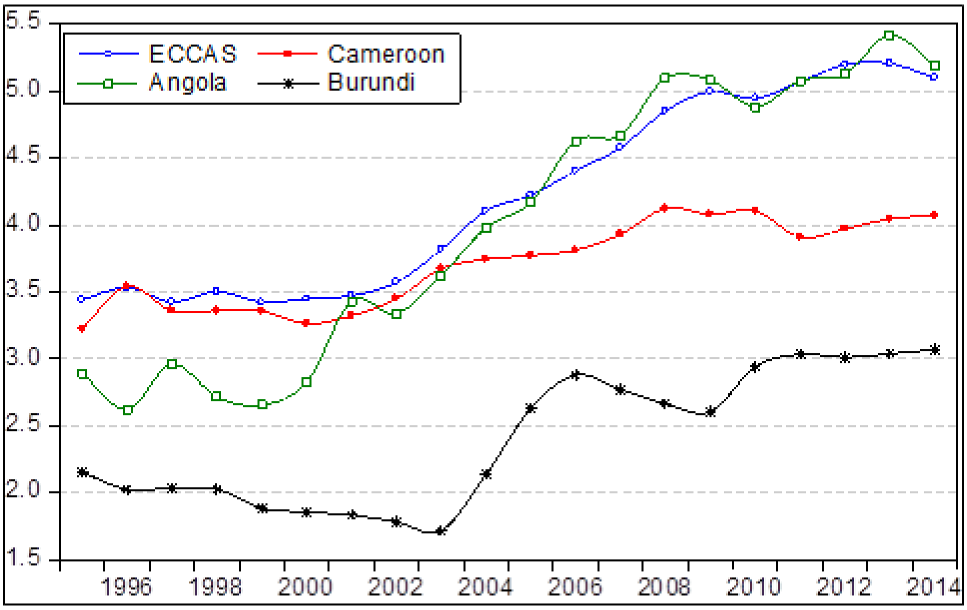

Figure 2: Static Comparative of ECCAS