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RESEARCH ARTICLE

Health expenditure and growth dynamics in the SADC region: evidence from non-stationary panel data with cross section dependence and unobserved heterogeneity

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Abstract This paper investigates the long run relationship between health care expenditure and economic growth, using panel data for 14 Southern African Development Community (SADC) member countries over the period 1995–2012. The non-stationarity and cointegration properties between health expenditure per capita and GDP per capita were examined, controlling for cross section dependence and heterogeneity between countries. Our results suggest that health expenditure and GDP per capita are non-stationary and cointegrated. These findings seem to confirm the notion that health expenditure is non-discretionary—health is a necessary good—in the SADC region. The estimated income elasticity is below unity but higher than what was obtained for the OECD regional grouping. The policy implication of our result is that adequate health care service provision should be a key objective of governmental intervention in the SADC region.

Keywords Health expenditure · Economic growth · non-stationary panels · Cross section dependence · Unobserved heterogeneity · Income elasticity

JEL Classification C31 · C33 · H51

Introduction and motivation

Despite spirited efforts by governments in the Southern African Development Community (SADC) sub regional grouping to contain growing costs of health care provision, aggregate health expenditure in the region has been rising. Data from the World Development Indicators

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(World Bank 2015) indicate that between 1995 and 2013, health expenditure as a percentage of gross domestic product (GDP) in SADC averaged around 6.4%. GDP per capita averaged around US$4,426.10, with an average growth rate of 4.1% over same period. Although the trend of health expenditure does not appear to move in same direction with economic growth, this may not be sufficient to conclude the absence of long-run relationship between the two variables in SADC.

A number of studies have examined the relationships (long and short run) between health care spending and economic growth; many others have also estimated the responsiveness of health care spending to gross domestic product (GDP)—income-elasticity of health care spending (Moscone and Tosetti 2010; Gerdtham and Löthgren 2000, 2002; Erdoğan and Arica 2010; Freeman 2003; Dreger and Reimers 2005; Baltagi and Moscone 2010; Hansen and King 1996). Many find that the elasticity is greater than one (Gerdtham and Löthgren 2002; Freeman 2003; Newhouse 1977), indicating that health is a luxury good, but some find that the elasticity is one or less (Hitiris and Posnett 1992; Baltagi and Moscone 2010; Blomqvist and Carter 1997). Studies that use macro-level data (Newhouse 1977; Di-Matteo 2003; Blomqvist and Carter 1992; Freeman 2003; Roberts 1999) tend to arrive at higher estimates. Correctly estimating the income elasticity is important because some government policies depend on whether health is a luxury or necessity. For example, if health care is a luxury—income elasticity greater than unity—then health care services should rather be left to the dictates of market forces. Studies that use individual-level data tend to find smaller elasticities (Moscone and Tosetti 2010). One possible reason is that insurance diminishes the relationship between income and expenditure at the individual level.

Using heterogeneous panel data model with cross sectionally correlated errors, this paper investigates the relationship between health care expenditure and GDP. To avoid the pitfalls of earlier studies of this nature, we control for cross section dependence and unobserved heterogeneity in panel data by using an approximate multifactor structure. We also include other non-income determinants that affect health care expenditure in order to check the robustness of our results.

The remainder of the paper is as follows: in "Related literature review" section we briefly review existing literature. "Econometric methodology" section lays out the econometric method employed. A description of data and preliminary analyses are presented in "Data and preliminary analysis" section, while econometrics results are reported and discussed in "Econometric results" section. "Final remarks" section concludes the paper.

Related literature review

Interests in examining the underlying reasons for rapid increases in aggregate health expenditure, even during periods of economic recession kindled since Newhouse's (1977) seminal paper. Literature on the non-stationarity of health expenditure and economic growth data as well as their short and long run relationships has therefore grown considerably over the years (Freeman 2003; Hansen and King 1996; Gerdtham and Löthgren 2000, 2002; Dreger and Reimers 2005; Erdoğan and Arica 2010; Baltagi and Moscone 2010). While many of these researchers suggest that income or per capita GDP is the main determinant of health expenditure, others identified some non-income determinants such as age structure of the population, proportion of the population aged below 15, proportion of the population aged 65 and above, urbanization, the share of health expenditures in total public expenditure, medical technology, and so on (Tang 2010; Baltagi and Moscone 2010; Hitiris and Posnett 1992). Moreover, given the difficulty in finding an appropriate proxy for medical care technology, researchers who explored technological progress as a determinant of health expenditure differ widely in approach. Whereas Dreger and Reimers (2005) used life expectancy and infant mortality as proxy for technological progress, Weil (1995); Baker and Wheeler (2000) used research and development on health care and surgical procedures. Table 1 summarises the determinants of health care used by various authors.

The nature and type of econometric techniques employed have also impacted the results obtained by different researchers. Those that used the ordinary least squares multiple regression technique (Bakare and Sanmi 2005; etc.) found a long run relationship between health care expenditure and economic growth whilst McCoskey and Selden (1998) used the IPS test by Im et al. (2003) and rejected the hypothesis of unit root for both variables in all countries in their sample. Others such as Hansen and King (1996) found no cointegrating relationship between the two variables, whereas Roberts (1999) opined that the cointegration relationship between health care expenditure and economic growth is inconclusive (see Table 2). More recently, empirical evidence seems to reveal that results derived using panel data might be sensitive to the inclusion of time trend in the ADF equation. In this regard, Jewell et al. (2003) highlighted the importance of controlling for cross sectional dependence. Some studies have also emphasized the importance of controlling for structural breaks and employing the bootstrap procedure. Carrion-i-Silvestre (2005) found that the two variables are stationary after controlling for structural breaks, whereas Wang and Rettenmaier (2006) failed to reject the null hypothesis and concluded that spending and income have a unit root, but are not cointegrated. Moreover, an important limitation of the bootstrap procedure is that it suffers from size distortions in cases where N is small relative to T.

In this paper, we investigate both the heterogeneity and cross section dependence characteristics as they are likely to be present in our dataset.

Econometric methodology

Specification

The empirical model used derives from the linear heterogeneous panel framework as follows:

$$h_{it} = \alpha_i + \beta_i' y_{it} + u_{it} \quad i = 1, \ldots, N; t = 1, \ldots, T \tag{1}$$

where h_{it} indicates real per capita health care expenditure in the ith country at time t, y_{it} is a $k \times 1$ set of regressors, which include GDP per capita, health related environmental factors (e.g., measles), age structure and others; $\alpha_i$is a country specific intercept; and u_{it} is the error term. Only variables in monetary terms—real GDP per capita and health expenditure per capita—are expressed in natural logarithms. Following Moscone and Tosetti (2010) and Baltagi and Moscone (2010), we also use the cross-section dependence model conceptualized in what follows. We begin with the assumption that the errors have a multifactor structure, i.e.

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

where f_t is the $m \times 1$vector of unobserved common effects and υ_{it} is the country-specific error assumed to be independently distributed across i and t with the following moment restrictions $E(\upsilon_{it}) = 0$, $E\left(\upsilon_{it}^2\right) = \sigma_i^2$ and $E\left(\upsilon_{it}^4\right) < \infty$. Cross section dependence arising from spatial spillovers is incorporated by assuming that υ_{it}follows a spatial autoregressive

Table 1 Synthesis literature on variables used by different studies as non income determinants of health expenditure

References	Countries	Period	Model	Variables							
				LE	Income	Election	Price	Employment	Age old	Age young	GE
Hartwig (2006)	OECD	1990–2003	OLS	+	−		+	+			
Moscone and Tosetti (2010)	49 US states	1980–2004	Heterogeneity panel		+						
Narayan et al. (2010)	5 Asian countries	2007	DOLS		+						
Tang (2010)	Malaysia	1967–2007	VECM		+		−		+		
Baltagi and Moscone (2010)	20 OECD	1971–2004	CCE		+				−	+	+
Bilgel and Tran (2013)	Canada (10 provinces)	1975–2002	GMM and GIV		+						+
Fedeli (2015)	Italy	1982–2009	ECM		+	+					

Table 2 Synthesis of literature on cointegration between health expenditure and economic growth

References	Period	Country	Method	Findings
Hansen and King (1996)	1960–1987	20 OECD Countries	Engle– Granger	There is no cointegration between HE and GDP
Roberts (1999)	1960–1993	10 EC Countries		Cointegration relationships between HE and GDP are not conclusive
Dreger and Reimers (2005)	1975–2001	21 OECD Countries		There is a long run relationship between GDP and HCE
Kiymaz et al. (2006)	1984–1989	Turkey	Johansen	There is a positive long run relationship between health care expenditure, GDP per capita and population growth
Moscone and Tosetti (2010)	1980–2004	49 US States	CCE Mean Group & CIPS	There is a long run relationship between income and HCE
Esteve et al. (2007)	1960–2001	Spanish	Stock–Watson–Shin cointegration tests	There is a strong evidence of deterministic cointegration between HE and GDP
De Mello-Sampayo and De Sousa-Vale (2014)	1989–2009	OECD Countries	Pedroni	Cointegration exists between age dependency (y), age dependency (o), infant mortality, per capita income
Khadaroo and Jaunky (2008)	1991–2000	20 African countries	Pedroni, panel ADF Test	Health expenditure and GDP are cointegrated
Erdoğan and Arica (2010)	1970–2007	18 OECD Countries	Pedroni, Kao, Johansen, Fisher panel	There exists a long run relationship between health expenditures and GDP per capita
Narayan et al. (2010)	1974–2007	5 Asian countries	Residual LM test	There exists a long run relationship between per capita income, health, investment, exports education and imports
Sulku and Caner (2011)	1984–2006	Turkey	Johansen multivariate	There is a long run relationship between per capita GDP, health expenditure and population growth
Tang (2010)	1967–2007	Malaysia	Johansen–Juselius cointegration	Health and its determinants are cointegrated (income, health care price, proportion of population aged more than 65yrs old)
Mehrara and Musai (2011)	1995–2005	Middle East and North Africa countries	Pedroni	There is a long run relationship between GDP and health expenditure

process (Cliff and Ord 1981; Moscone and Tosetti 2010; Baltagi and Moscone 2010); that is,

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

where ρ is a scalar parameter, and

$$\overline{\upsilon}_{it} = \sum_{j=1}^{N} \omega_{ij}\upsilon_{jt}$$

(see Anselin 1988). ω_{ij} is the (i, j)th element of the spatial weights matrix W, which provides information on neighborhood linkages among countries in SADC. In the empirical analysis, the weight ω_{ij} takes on the value 1 when countries i and j share a common border or vertex, and 0 otherwise. Hence, in Eq. (3) the error term, υ_{it}, associated with the ith country at time t depends on the average of errors in its adjacent countries at the same time t. In Eq. (1), we allow y_{it} to be correlated with the unobserved effects f_t. We also impose the assumption,

$$y_{it} = c_i + \lambda_i' f_t + \nu_{it};\, i = 1, \ldots, N;\, t = 1, \ldots, T \tag{4}$$

where λ_t 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 affect health care expenditure not only directly through the factor structure as in Eq. (2), but also indirectly by impacting income via Eq. (4).

Our estimation and testing strategy rely on the Common Correlated Effects (CCE) approach developed by Pesaran (2006). Based on this method, the unobservable effects f_t are approximated by the cross section averages of the dependent and explanatory variables. From Eqs. (1), (2) and (4), we rewrite real health care expenditure as,

$$h_{it} = \alpha_i + \beta_i' c_i + \left(\beta_i'\lambda_i' + \gamma_i'\right) f_t + \beta_i'\nu_{it} + \upsilon_{it}. \tag{5}$$

With this, we also rewrite Eqs. (1)–(4) more compactly as,

$$z_{it} = \begin{pmatrix} h_{it} \\ y_{it} \end{pmatrix} = \begin{pmatrix} \alpha_i + \beta_i' c_i \\ c_i \end{pmatrix} + \begin{pmatrix} \beta_i'\lambda_i' + \gamma_i' \\ \lambda_i' \end{pmatrix} f_t + \begin{pmatrix} \beta_i'\nu_{it} + \upsilon_{it} \\ \nu_{it} \end{pmatrix} \tag{6a}$$

$$z_{it} = \begin{pmatrix} 1 & \beta_i' \\ 0 & I_k \end{pmatrix}\begin{pmatrix} \alpha_i \\ c_i \end{pmatrix} + \begin{pmatrix} I_m & \beta_i' \\ 0 & I_k \end{pmatrix}\begin{pmatrix} \gamma_i' \\ \lambda_i' \end{pmatrix} f_t + \begin{pmatrix} 1 & \beta_i' \\ 0 & I_k \end{pmatrix}\begin{pmatrix} \upsilon_{it} \\ \nu_{it} \end{pmatrix} \tag{6b}$$

$$z_{it} = \Gamma_i^1 \tilde{b}_i + \Gamma_i^m \tilde{C}_i' f_t + \Gamma_i^1 \tilde{\zeta}_{it} \tag{7}$$

where $\tilde{b}_i = \begin{pmatrix} \alpha_i \\ c_i \end{pmatrix}$, $\tilde{C}_i' = \begin{pmatrix} \gamma_i' \\ \lambda_i' \end{pmatrix}$, $\tilde{\zeta}_{it} = \begin{pmatrix} \upsilon_{it} \\ \nu_{it} \end{pmatrix}$, $\Gamma_i^j = \begin{pmatrix} I_j & \beta_i' \\ 0 & I_k \end{pmatrix}$, $j = 1, 2, \ldots, m$ is a block triangular matrix affecting the multifactor structure. Hence,

$$z_{it} = b_i + C_i' f_t + \zeta_{it} \tag{8}$$

with,

$$b_i = \Gamma_i^1 \tilde{b}_i,\, C_i = \Gamma_i^m \tilde{C}_i \text{ and } \zeta_{it} = \Gamma_i^1 \tilde{\zeta}_{it}$$

Considering the simple cross section average of (8),

$$\overline{z}_t = \overline{b} + \overline{C}' f_t + \overline{\zeta}_t \tag{9}$$

and

$$\bar{z}_t = \frac{1}{N}\sum_{i=1}^{N} z_{it}, \bar{\zeta}_t = \frac{1}{N}\sum_{i=1}^{N} \zeta_{it}, \bar{b} = \frac{1}{N}\sum_{i=1}^{N} b_i \text{ and } \bar{C} = \frac{1}{N}\sum_{i=1}^{N} C_i.$$

And assuming that $\bar{C}$ is a full rank matrix, we re-write (9) as,

$$f_t = \left(\overline{CC}'\right)^{-1} \bar{C}\left(\bar{z}_t - \bar{b} - \bar{\zeta}_t\right) \tag{10}$$

Under the condition that the spatial weights matrix, W, has bounded absolute row and column sums, it is possible to show that,

$$\bar{\zeta}_t \xrightarrow{q.m} 0, \text{ as } N \to \infty \tag{11}$$

(see Pesaran and Tosetti 2007).

It follows that the cross section averages, $\bar{z}_t$, can be used to approximate the common factors. Hence, the slope parameters β_i can be consistently estimated applying standard panel techniques to the following equation,

$$h_{it} = \alpha_i + \beta_i' y_{it} + g_i' \bar{z}_t + e_{it} \tag{12}$$

where $\bar{z}_t = \left(\bar{h}_t, \bar{y}_t'\right)'$. Once the slope parameters are estimated and since $\bar{z}_t$ is consistent for f_t, the spatial coefficient ρ in (3) can be obtained by applying the maximum likelihood method to the residuals $\hat{e}_{it}$ from Eq. (12) (see Anselin 1988). Pesaran (2006) suggests the following CCE estimator for the ith slope coefficient,

$$\underset{CCE,i}{\overset{\wedge}{\beta}} = \left(y_i'\overline{M}y_i\right)^{-1} y_i'\overline{M}h_i \tag{13}$$

with $M = I_T - \overline{H}\left(\overline{H}'\overline{H}\right)^{-1}\overline{H}'$ and $\overline{H} = \left(\tau, \ \overline{Z}\right)$ with $\tau = (1, \ldots, 1)'$ and $\overline{Z}$ being the $T \times 2$ matrix of the observations on $\bar{z}_t$, $t = 1, \ldots, T$. Further, Pesaran (2006) proposes the following two estimators for the mean of the slope coefficients,

$$\widehat{\beta}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \widehat{\beta}_{CCE,i} \tag{14}$$

and

$$\widehat{\beta}_P = \left(\sum_{i=1}^{N} y_i'\overline{M}y_i\right)^{-1} \sum_{i=1}^{N} y_i'\overline{M}h_i \tag{15}$$

Equation (10), known as the CCE mean group estimator, is a simple average of the individual CCE estimators in Eqs. (9), (12) is the CCE pooled estimator, which gains efficiency from pooling observations. Their variances are provided in Pesaran (2006). Monte Carlo studies in Pesaran (2006) and in Pesaran and Tosetti (2007) further showed that these estimators perform well with small sample, allows for common factors and an idiosyncratic component, υ_{it}, to be serially correlated so long as it is stationary, and the number of factors m may not be that important as long as it is a finite fixed number (see Kapetanios et al 2006).

Equations (1)–(4) capture discontinuities in the relationship between health care spending and income by means of the factor structure. However, it does not allow for the presence of structural breaks in the slope coefficients, β_i. The likelihood of structural breaks in the relation between health expenditure and income is assumed marginal in our analysis given the relatively short time span.

Unit roots tests

We adopt the CCE approach to test for unit roots, controlling for cross sectional dependence. Cross section averages of health expenditure and disposable income are used as proxies for unobserved common factors, in the context of a Dickey Fuller regression. From Eq. (15), the pth order augmented Dickey Fuller regression model is re-stated as follows:

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{i,t-j} + u_{it} \tag{16}$$

where q_{it} in this case is either the logarithm of health care expenditure per capita, the logarithm of GDP per capita, or regression residuals from Eq. (1). u_{it} are errors; we assume that they have a single factor structure, where the idiosyncratic component follows a spatial autoregressive process as in Eq. (4). The unit root test hypothesis is,

$$H_0 : b_i = 0,\ i = 1, \ldots, N \tag{17}$$

$$H_1 : b_i < 0,\ i = 1, \ldots, N_{1;}\ b_i = 0,\ i = N_1 + 1, \ldots, N \tag{18}$$

where N_1 is such that N_1/N is nonzero and tends to a fixed constant as N goes to infinity. In addition, Pesaran (2007) proposed a simpler method, the cross sectionally augmented Dickey-Fuller (CADF) test that deals with the issue of cross sectional dependence that arises due to the common factor. This method is based on the usual ADF regression, augmented with the lagged cross sectional mean and its first difference $\bar{q}_{t-1}$ and $\Delta\bar{q}_{t-j}$, for $j = 0, \ldots, p$. The CADF test is specified as,

$$\Delta q_{it} = a_i + b_i q_{i,t-1} + c_i t + \sum_{j=1}^{p} d_{ij} \Delta q_{i,t-j} + g_i' \bar{z}_t + e_{it} \tag{19}$$

where $\bar{z}_t = \left(\overline{q}_{t-1}, \Delta\overline{q}_t, \Delta\overline{q}_{t-1}, \ldots, \Delta\overline{q}_{t-p}\right)'$. Pesaran (2007) proposes to test (17) against (18) by computing the simple average of the t-ratios of the OLS estimates of b_i in Eq. (18), i.e.

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} \widetilde{t}_i \tag{20}$$

where $\widetilde{t}_i$ is the OLS t-ratio of b_i. The CADF and the CIPS test have reasonable size and power for small samples of N and T.

Cross section dependence tests

The CIPS test requires that u_{it} follows a single factor structure. Hence cross section dependence test for the data becomes one of the necessary steps. Further, since using only one global shock might not be enough to correct for correlation in the data, we also use the following average pairwise correlation coefficient,

$$\bar{\rho}_{AVPC} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{21}$$

where ρ_{ij} is given by,

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

Two diagnostic tests for cross section dependence, based on the above pairwise correlation coefficients were undertaken. The CD_Ptest, proposed by Pesaran (2004) defined as,

$$CD_P = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{22}$$

and the CD_{LM} test that derives from the Lagrange Multiplier statistic (Frees 1995). That is,

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\rho_{ij}^2 - 1\right) \tag{23}$$

Under the null hypothesis of no cross section dependence, the $CD_P \to N(0, 1)$ for $N, T \to \infty$ in any order; and $CD_{LM} \to N(0, 1)$ with $N, T \to \infty$. While the CD_P is based on the pairwise correlation coefficients, the CD_{LM} uses their squares. This implies a possibility of the CD_P test yielding misleading results when the cross correlations coefficient have values that range from negative to positive. On the other hand, the CD_{LM} is likely to exhibit some size distortions for large N and small T (Frees 1995).

We also tested for spatial correlation, controlling for long-range dependence represented by the common factors structure. That is, we compute the following Moran's I test statistic (see Kelejian and Prucha 2001),

$$I = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{t=1}^{N} \sum_{j=1}^{N} \omega_{ij} \widehat{e}_{it} \widehat{e}_{ij}}{s_t^2 \sum_{t=1}^{N} \sum_{j=1}^{N} \omega_{ij}} \tag{24}$$

where $s_t^2 = \frac{1}{N} \sum_{i=1}^{N} (\widehat{e}_{it} - \overline{e}_t)^2$ and ω_{ij}; $i, j = 1, \ldots, N$are spatial weights. This statistic is asymptotically normally distributed and tends to infinity for fixed T. Moran's I explores information on the spatial ordering of the data and takes into account the proximity of countries; a measure of local cross section dependence (Baltagi and Moscone 2010). Furthermore, since the Moran's I test is parametric, we complement it with the Mantel test which is semi-parametric (see Sokal and Rohlf 1995; Grullot and Rousset 2013).

Data and preliminary analysis

The data

The empirical analysis is based on panel data for 14 SADC member countries for the period 1995 to 2012, obtained from the World Development Indicators (World Bank 2015). UNCTAD's online database and individual country's national statistics database were also consulted. The definition of variables and their expected signs are in Table 3.

Preliminary analysis

The spatial distribution and concentration of health expenditure and GDP per capita were first investigated. Table 4 shows the cross section dependence of the logarithm of the two

Table 3 Definition of variables

Variable	Variable description	Expected sign
Environmental factors	Immunization for measles	+
Age dependency for old and for young	People younger than 15 and above 65	+
Growth dynamics	Real GDP per capita	+
Urbanization	The number of people in urban areas as a percentage of the total population. This variable measures the pressure of population on health facilities	+/−

Table 4 Cross section dependence in the first differences

	$\bar{\rho}$	CD_P	CD_{LM}
Real GDP per capita	0.332	13.435	17.890
Health expenditure per capita	0.308	12.448	12.029

The variables are in the first difference of their logarithm

variables computed using Eqs. (22) and (23). As could be gleaned from the table, we observe the presence of cross section correlation between pairs of countries. These results suggest that correlation amongst pairs of countries are considered in the health care spending equation to avoid spurious results. Similar results were found by Baltagi and Moscone (2010) and Dreger and Reimers (2005).

Table 5 shows results of the average pairwise correlation coefficient tests of spatial correlation between and within the 14 SADC member countries. Comparing off-diagonal values in Table 5 indicates that correlation within countries appears larger than between countries. For example, South Africa is more correlated on average with Lesotho, Botswana, Mozambique, Mauritius and Swaziland, than with Angola or Madagascar, both for health spending and income. Similar results were obtained by Baltagi and Moscone (2010) and Dreger and Reimers (2005).

Econometric results

In Table 6 we present results of the cross-sectional augmented IPS test (CIPS) for the logarithm of GDP and health expenditure for lag of orders $p = 0, 1, 2, 3$. The inclusion of lags allows us to control for possible serial correlation in the data. The logarithms of the two variables are non-stationary with intercept, as well as with intercept and linear trend in the CADF regression (especially for small lags which turn out to be more appropriate). The non-stationary nature of health care expenditure may be explained by increases in disposable income as well as changes in medical technology and treatment over time. This result is consistent with those of earlier studies (Blomqvist and Carter 1997; Gerdtham and Löthgren 2000; Freeman 2003; De Mello-Sampayo and De Sousa-Vale 2014).

Table 7 shows results of the cross section dependence statistics on residuals from the CADF regressions, before and after controlling for common factors. In case (A) in the table, the cross section dependence test was based on the residuals $(\widehat{u}_{it})$ while in case (B), the residuals

Table 5 Average pairwise correlation matrix

	Ang	Bots	Leso	Mdg	Moz	Mus	Malw	Nam	Swaz	Seych	Tanz	S. Afric.	C. DRep.	Zamb
Real GDP per capita														
Angola	1													
Botswana	0.372	1												
Lesotho	0.288	0.878	1											
Madagascar	0.416	0.177	0.105	1										
Mozambique	0.363	0.859	0.956	0.018	1									
Mauritius	0.714	0.628	0.554	0.539	0.539	1								
Malawi	0.519	0.054	0.001	0.118	−0.007	0.219	1							
Namibia	0.621	0.255	0.286	0.417	0.274	0.606	0.296	1						
Swaziland	0.246	0.822	0.953	−0.028	0.970	0.457	−0.038	0.171	1					
Seychelles	0.313	0.515	0.472	−0.326	0.498	0.349	0.055	0.304	0.467	1				
Tanzania	0.264	0.142	−0.174	0.318	−0.099	0.320	0.239	0.312	−0.228	0.064	1			
South Africa	0.269	0.875	0.979	0.025	0.975	0.472	0.010	0.189	0.973	0.452	−0.180	1		
Congo D. Rep.	0.495	0.191	0.122	−0.036	0.210	0.286	0.038	0.091	0.160	0.062	−0.148	0.166	1	
Zambia	0.643	0.560	0.542	0.217	0.556	0.543	0.200	0.283	0.554	0.504	−0.149	0.516	0.143	1
Health expenditure per capita														
Angola	1													
Botswana	0.384	1												
Lesotho	0.331	0.306	1											
Madagascar	0.107	−0.167	0.166	1										
Mozambique	0.322	0.432	0.828	0.015	1									
Mauritius	0.374	0.622	0.631	0.280	0.550	1								

Table 5 continued

	Ang	Bots	Leso	Mdg	Moz	Mus	Malw	Nam	Swaz	Seych	Tanz	S. Afric.	C. DRep.	Zamb
Malawi	0.261	0.374	0.114	−0.032	0.373	0.379	1							
Namibia	0.250	0.217	0.085	0.011	0.356	0.251	0.356	1						
Swaziland	0.389	0.295	0.785	0.078	0.915	0.546	0.372	0.250	1					
Seychelles	−0.136	0.144	0.230	−0.231	0.363	0.071	0.008	0.048	0.147					
Tanzania	0.420	0.118	0.446	0.269	0.463	0.478	0.310	0.279	0.459	0.355	1			
South Africa	0.249	0.407	0.799	−0.137	0.962	0.439	0.370	0.221	0.898	0.417	0.364	1		
Congo D. Rep.	−0.010	−0.053	0.208	−0.133	0.276	0.163	0.293	0.473	0.365	−0.142	.233	0.260	1	
Zambia	0.751	0.476	0.332	0.115	0.443	0.538	0.421	0.344	0.477	0.224	0.604	0.348	−0.055	1

Table 6 CIPS panel unit roots tests

	CADF (0)	CADF (1)	CADF (2)	CADF (3)
With intercept only				
Real GDP per capita	−3.307[c]	−2.564	−3.615[b]	−4.039[b]
Health expenditure per capita	−2.520	−3.154[c]	−3.250[c]	−3.041
With intercept and linear trend				
Real GDP per capita	−3.490	−2.992	−4.239[b]	−4.405[b]
Health expenditure per capita	−2.732	−3.570	−3.855[c]	−4.836[b]

Critical values are taken from Pesaran (2007)
[a,b] and [c] indicate statistical significance at 1, 5 and 10% level respectively

$(\widehat{e}_{it})$ were defactored. Further, in case (A), the reported CD statistics derive from the residuals $\widehat{u}_{it} = \Delta q_{it} - \widehat{a}_i - \widehat{b}_i q_{i,t-1} - \widehat{c}_i t - \sum_{j=1}^{p} \widehat{d}_{ij} \Delta q_{i,t-j}$ while in case (B) the residuals used are defactored; that is, $\hat{e}_{it} = \Delta q_{it} - \widehat{a}_i - \widehat{b}_i q_{i,t-1} - \widehat{c}_i t - \sum_{j=1}^{p} \widehat{d}_{ij} \Delta q_{i,t-j} - \widehat{g}_i' \overline{z}_t$ (see Eq. (18)).

Table 7 also illustrates that comparing case (A) with (B), all CD statistics show significant reduction in the level of cross section dependence. The average pairwise correlation coefficient ranges from approximately 26% for GDP per capita and 18% for health expenditure to close to zero respectively. This implies inclusion of the cross section average $\overline{z}_t$ from Eq. (18) might have resolved the problem. This suggests that the efficiency of the CIPS in correcting the dependency between the cross sections.

Case (B) also shows Moran's I statistic on the error term that checks for the presence of geographical concentration, both in the residuals of GDP per capita and health care expenditure, controlling for common factors. The results indicate significant amount of geographical concentration—existence of spatial correlation—in the former, compared to the latter. This is consistent with our earlier tests for the presence of geographical concentration in health expenditure and income ("Preliminary analysis" section).

In Table 8, our results reveal elasticity of greater than unity for only two countries, Angola and Lesotho; implying health care is a luxury good for these countries. For others—Democratic Republic of Congo, Madagascar, Malawi, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Tanzania and Zambia—income elasticity of less than unity is obtained, indicating that health care is a necessity; consistent with the result of Freeman (2003) and other earlier studies.

For Botswana, Mauritius and Tanzania, the coefficients are positive but statistically insignificant; a problem that appears more pronounced at the individual country level since averaging tends to cancel out estimation error due to cross border movements. It is worth noting too that estimating the coefficients country by country reduces the degrees of freedom, implying wider confidence intervals. Similar results were reported by Freeman (2003) for individual States in the US; Dreger and Reimers (2005) and Baltagi and Moscone (2010) for OECD countries; Costa-Font and Pons-Novell (2007) for decentralized nations; and Elmi and Sadeghi (2012) for some developing countries.

The relatively low income elasticity obtained in our analysis supports the idea that while ability to pay is an important factor in seeking health care services in many developing countries, the existence of publicly financed programmes in SADC weakens the link between GDP per capita and the standard of care.

In Table 9, results from three different estimators are compared: the fixed effects (FE) estimator; the common correlated pooled (CCEP) estimator that controls for unobserved

Table 7 Cross section dependence in residuals from CADF regression

Variables	CADF (0)	CADF (1)	CADF (2)	CADF (3)
Case (A): use of $\widehat{u}_{it}$				
$\bar{\rho}_{AVPC}$				
Real GDP per capita	0.256	0.189	0.165	0.146
Health expenditure per capita	0.179	0.158	0.157	0.093
CD_P				
Real GDP per capita	10.374	7.666	6.693	5.911
Health expenditure per capita	7.228	6.387	6.353	3.762
CD_{LM}				
Real GDP per capita	15.045	12.630	10.802	10.352
Health expenditure per capita	7.663	7.339	7.130	7.834
Case (B): use of $\widehat{e}_{it}$				
$\bar{\rho}_{AVPC}$				
Real GDP per capita	−0.030	−0.007	−0.012	0.009
Health expenditure per capita	−0.050	−0.055	−0.029	−0.015
CD_P				
Real GDP per capita	−1.195	−0.269	−0.498	−0.358
Health expenditure per capita	−2.024	−2.212	−1.189	−0.623
CD_{LM}				
Real GDP per capita	18.246	14.489	16.873	19.748
Health expenditure per capita	5.422	7.070	8.242	9.977
Moran				
Real GDP per capita	0.221	0.263	0.325	0.331
Health expenditure per capita	0.227	0.169	0.133	0.316
Standardized Moran				
Real GDP per capita	1.544	1.641	2.957	2.719
Health expenditure per capita	1.436	1.256	0.799	1.253
Mantel				
Real GDP per capita	−0.008	0.036	0.031	−0.013
Health expenditure per capita	0.009	0.034	0.111	0.070

common factors, individual and time heterogeneity and individual trend, and the common correlated effects mean group (CCEMG) estimator. Among the three, the FE produces an income elasticity of 0.598 while the CCEMG produces an income elasticity of 0.745. The CCEP estimate yields the lowest income elasticity (0.455) after controlling for cross section dependence. These results are lower than what was obtained by Baltagi and Moscone (2010) and Freeman (2003), confirming that health care in SADC is a necessity. Since the CCEP and the CCEMG account for unobservable common factors, they tend to be more appropriate for estimating income elasticity of health expenditure, especially in developing countries.

Table 10 reports results of robustness check for income elasticity, controlling for non-income factors suggested in the literature (Baltagi and Moscone 2010; Hitiris and Posnett 1992; Gerdtham and Löthgren 2000; De Mello-Sampayo and De Sousa-Vale 2014; Tang 2010). The FE estimator, the CCEMG estimator and the CCEP estimator were employed

Table 8 CCE estimate of the coefficients by country

Country	Estimate coefficient	Standard error
Angola	1.123[a]	0.340
Botswana	0.550	0.440
Lesotho	1.157[a]	0.303
Madagascar	0.759[a]	0.131
Mozambique	0.878[a]	0.070
Mauritius	0.530	0.257
Malawi	0.672[a]	0.148
Namibia	0.703[a]	0.286
Swaziland	0.990[a]	0.109
Seychelles	0.802[a]	0.421
Tanzania	0.091	0.060
South Africa	0.754[a]	0.092
Congo D. Rep.	0.629[a]	0.256
Zambia	0.793[a]	0.132

The superscript "a" means that the coefficient is significant at the 5% level

Table 9 Income elasticity of health expenditure

	Fixed effect (+)		CCE mean group		CCE pooled	
Variable	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Real GDP per capita	0.598[a]	0.049	0.745[b]	0.218	0.455[a]	0.0249
CD statistics						
Case (A): use of $\widehat{u}_{it}$						
$\bar{\rho}_{AVPC}$			0.397		0.982	
CD_P			16.065		39.761	
CD_{LM}			83.622		110.515	
Case (B): use of $\widehat{e}_{it}$						
$\bar{\rho}_{AVPC}$			0.185		1.000	
CD_{P}			7.505		40.455	
CD_{LM}			5.537		114.570	
Moran's I Statistic			0.578		152.228	
Standardized Moran's I Statistic			1.248		8.569	
Mantel's Test Statistic			0.979		0.983	

(+) Time dummies were included

a, b and c indicate statistical significance at the 1, 5 and 10% level respectively

(A) The CD statistics are computed with $\widehat{u}_{it} = h_{it} - \widehat{\alpha}_i - \widehat{\beta} y_{it}$

B The CD statistics are computed on $\widehat{e}_{it} = h_{it} - \widehat{\alpha}_i - \widehat{\beta} y_{it} - \widehat{g}_i' \overline{z}_t$ where $\overline{z}_t = \left(\overline{h}_t, \overline{y}_t\right)'$

using the following variables: GDP per capita (*lgdppc*), the percentage of population below 15 years old (*lady*), the percentage of population above 65 years old (*lado*), immunization of measles (*limu*) and urbanization *(lurbt)*. The CCEMG and CCEP estimates of income elasticity are robust to the introduction of non-income determinants—in the range of 0.759–

Table 10 Income elasticity of health expenditure controlling for other regressors

	Model 1			Model 2			Model 3		
	Fixed effects (+)	CCEMG	CCEP	Fixed effects (+)	CCEMG	CCEP	Fixed effects (+)	CCEMG	CCEP
Lgdppc	0.953[a]	0.781[a]	0.414[a]	0.763[a]	0.759[a]	0.373[a]	0.784[a]	0.849[a]	0.343[a]
Lady	−0.404[b]	2.747	−1.282[a]	−0.393[c]	−35.734[c]	−0.938[a]	−0.375[b]	−31.693[b]	−0.460[c]
Lado	–	–	–	0.836[a]	27.083	0.210	0.809[c]	74.564	0.253
Lurbt	–	–	–	1.479[c]	−23.955	0.564[a]	1.544[c]	43.801	0.881[a]
Limu	–	–	–	–	–	–	−0.147[a]	−0.398	1.383[a]

(+): Time dummies were included. [a], [b] and [c] indicate statistical significance at the 1, 5 and 10% level respectively

Table 11 CIPS panel unit roots tests on residuals from CCE and FE estimations

	CADF (0)	CADF (1)	CADF (2)	CADF (3)
With intercept only				
CCE mean group				
$\hat{u}_{it}$	−2.085	−2.118[c]	−2.116[c]	−3.170[b]
CCE pooled				
$\hat{u}_{it}$	−2.194[c]	−2.618[c]	−2.312[c]	−2.158[c]
Fixed effects model				
$\hat{u}_{it}$	−1.838	−1.830	−1.512	−1.671
With intercept and trend				
CCE mean group				
$\hat{u}_{it}$	−2.268[c]	−2.100[c]	−2.000	−1.898
CCE pooled				
$\hat{u}_{it}$	−2.710[c]	−2.585[c]	−2.131[c]	−2.112[c]
Fixed effects model				
$\hat{u}_{it}$	−2.361[c]	−2.508[c]	−2.181[c]	−2.337[c]

a, b and c indicate statistical significance at the 1, 5 and 10% levels respectively

0.849 and 0.343–0.414 respectively. The FE estimate of income elasticity also remains lower than unity. The results for FE and CCEP estimators imply that almost all the non-income factors are significant at the appropriate level.

CIPS panel unit root test results on the residuals for the FE, CCEMG and CCEP estimators are shown in Table 11. Based on the intercept and trend assumptions, the CCEMG, CCEP and FE residuals are stationary for $p = 1, 2, 3$ suggesting that we can rely on the statistics of the long run estimates. The results also corroborate the existence of a long run relationship between health expenditure and income in SADC and consistent with Freeman (2003), Millo (2016), Baltagi and Moscone (2010), Moscone and Tosetti (2010), and De Mello-Sampayo and De Sousa-Vale (2014). However, our results contrast with those of Wang and Rettenmaier (2006), who reported weak evidence of cointegration between states in the USA.

Having established the long run relationship between health care expenditure and income, we also estimated the error correction model specified as,

$$\Delta h_{it} = \alpha_i + \theta_i \left(h_{i,t-1} - \widehat{\beta}' y_{i,t-1} \right) + \vartheta_i \Delta h_{i,t-1} + \delta_i' \Delta y_{it} + u_{it} \tag{25}$$

where θ_i measures the speed of adjustment of health expenditure to a deviation from the long run equilibrium relation between health expenditure and GDP per capita, and $\left(h_{i,t-1} - \widehat{\beta}' y_{i,t-1} \right)$ is the cointegrating relation in the previous period.

We estimated Eq. (24) by FE and then by CCE methods, where factors are approximated by $\Delta \overline{h}_t$, $\Delta \overline{h}_{t-1}$, $\Delta \overline{y}_t$ and, $\left(\overline{h}_t - \widehat{\beta}' \overline{y}_{t-1} \right)$; $\widehat{\beta}$ is the estimated income elasticity with either the FE, the CCEMG or the CCEP estimator. Table 12 shows results of the analyses. As expected, all estimators of the ECM show negative coefficients. The FE estimator records a speed of adjustment of −0.667, greater than what is obtained when we control for cross section dependence using the CCEMG and the CCEP; that is −0.911 and −0.371 respectively. The higher coefficient value of the FE estimator reflects the effect of distortions as it ignores cross cross-section dependence.

Finally, we estimated spatial correlation coefficient due to unobserved spillovers as specified in Eq. (3), adjusting for cross section dependence due to common factors. As in Moscone and Tosetti (2010), the residuals are:

Table 12 Error correction model

Variable	Fixed effect Coefficient	Fixed effect Std. error	CCE mean group Coefficient	CCE mean group Std. error	CCE pooled Coefficient	CCE pooled Std. error
ECM(-1)	-0.667^{c}	0.366	-0.911^{b}	0.339	-0.371	0.235
D(health(-1))	0.171	0.269	0.208	0.213	0.083	0.240
D(income)	0.728^{b}	0.257	0.844^{c}	0.230	0.720^{b}	0.263
CD statistic						
Case (A): use of $\hat{u}_{it}$						
$\bar{\rho}_{AVPC}$			0.059		0.055	
CD_P			2.372		2.219	
CD_{LM}			3.147		4.145	
Case (B): use of $\hat{e}_{it}$						
$\bar{\rho}_{AVPC}$			-0.047		-0.047	
CD_P			-1.919		-1.900	
CD_{LM}			4.157		3.662	
Moran's I statistic			0.218		0.274	
Stdzed Moran's I statistic			1.521		2.310	
Mantel's test statistic			0.379		0.396	

a, b and c indicate statistical significance at the 1, 5 and 10% levels respectively

$$\widehat{e}_{it} = h_{it} - \widehat{\beta}_{MG} y_{it} - \widehat{g}_i' \overline{z}_t \tag{26}$$

where the common factors are estimated by $\overline{z}_t$, the cross section averages of h_{it} and y_{it}. Following from Anselin (1988), the estimated model is therefore:

$$\widehat{e}_{it} = \rho \overline{\overline{\widehat{e}}}_{it} + \varepsilon_{it} \tag{27}$$

The results indicate a significant spatial coefficient $\widehat{\rho}$ of 0.336, with a standard error of 0.1002, and a z-value of 3.359. This implies the presence of geographically concentrated unobservable risk factors that may affect health expenditure. Our result is consistent with Case et al. (1993) who also found per capita expenditure to be positively and significantly influenced by patients' neighbors' spending.

Final remarks

This paper examines the long-run relationship between health expenditure and GDP per capita (income) in the Southern African Development Community (SADC) sub-regional bloc using panel data for the period 1995–2012. The non-stationarity and cointegration properties of the two variables and other non-income determinants of health expenditure were also investigated. The paper fills a gap in the literature by using up-to-date econometric techniques that take into account cross-country dependence and heterogeneity. Our results suggest that a long run relationship exists between the variables.

Furthermore, controlling for cross section dependence and heterogeneity, we estimated an income elasticity of health expenditure that is below unity. This result suggests that health care in the SADC region is a necessity. This is further reinforced by individual country income elasticities that turned out much higher than those obtained by Acemoglu et al. (2013) and Moscone and Tosetti (2010).

The income elasticity of health expenditure has some critical implications for policy. Health care being a necessity implies that governments should intervene by regulating the market, expanding the flow of drugs and new medical techniques to cover the whole population, curbing health care costs by regulating out-of-pocket charges (OOP) and introduce reforms to define priorities and refine policies. The results also show the presence of geographical concentration of health expenditure and its determinants which needs to be taken into consideration when formulating policy to avoid failure.

The empirical analysis also reveal a significant amount of cross section dependence that arise through the inclusion of a factor structure and unobserved heterogeneity. This, if not controlled for, may yield misleading results and incorrect policy recommendations.

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