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Health Expenditure, Environmental Degradation and Economic Growth in ECOWAS: Evidence from Panel ARDL Approach

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Abstract *- Using annual data from 2000 to 2020, we investigate the relationship between health expenditure (HE), economic growth, and environmental pollution variables used for the Economic Community of West African States (ECOWAS) fifteen countries. We use IPS (2003) and Breitung (2000) unit root tests. To study the long and short-run relationship of economic growth and environmental pollution on health expenditure, the PMG estimator using the ARDL model has been retained. At last, a Panel Vector Error Correction Model is used to show the direction of causality. The results show a long-run significant and negative effect of economic growth on health expenditure, but in the short-run, the relation is not significant. Environmental pollution variables have a statistically significant long-run positive effect on health expenditure. The PVECM results indicate a one-way causal link from economic growth to health expenditure, a bidirectional relationship between economic growth and environmental pollution variables. Surprisingly, the PVECM indicate no Granger causal relationship between HE and* co_2 *emissions contrary to the PMG result where there is a long-run causality. These results imply that investments in the health sector and low carbon technologies should be encouraged.*

Keywords *- Health expenditure,* Co_2 *Emissions, Economic growth, PMG, PVECM Granger causality.*

JEL Classification Codes: H51; Q54; O44;C23; C33;

I. INTRODUCTION

In recent years, the relationship between environmental degradation, economic growth, and health expenditure stands out as a popular topic of research in economic literature. The studies covering developed and developing countries can be classified into many groups.

The first aspect relates to the relationship between the environment and economic growth, with most studies (Grossman, 1995; Grossman and Krueger, 1995, Torras and Boyce, 1998; Blázquez-Fernández et al., 2019) focusing on validating or invalidating a U-shaped relationship. Environmental economists analyzed this relation mostly in a bidirectional way. Since the 1990s, many empirical types of research have found an inverted-U curve, the so-called Environmental Kuznets Curve (EKC), describing the decline between environmental quality and income (Grossman, 1995; Grossman and Krueger, 1995, Torras and Boyce, 1998). Acharyya (2009) note that the hypothesis link to environmental problems and economic development is more complex. Improving economic growth causes environmental problems because environmental pollution increases with production levels increase (Panayotou, 2016; Pao and Tsai, 2010; Arouri and al., 2012). Conversely, some authors found that economic growth may improve environmental quality (Hao, Liu & Huang, 2015).The second aspect focuses on the relationship between economic growth and health expenditure (Baltagi and Moscone, 2010; Piabuo and Tieguhong, 2017; Ye and Zhang, 2018). In fact, Health economists are mostly interested in the effects of private and public health expenditure on economic activity and its reverse linkage. Good health improves human capital through education because health motivates high schooling levels (Thuilliez, 2009). Good health also encourages saving and then investment and per capita productive capital (Chakraborty, 2004; Drabo, 2011). Good health is generally recognized to contribute to economic growth, but some authors reject this hypothesis (Acemoglu, 2007). Empirical studies show mixed results. Some of them found a significant positive effect of good health on economic growth (Bloom and al. 2019), and others found a negative effect of GDP per capita on health spending.

Another group of researchers focused on the relationship between environmental quality and health expenditure (Assadzadeh et al., 2014; Yahaya et al., 2016; Raeissi et al., 2018) in many countries of the world. In addition, the relationship between health expenditures and environment degradation measures by CO_2, SO4, and N2O emission is analyzed. An increase in air pollution increases health expenditure (Jarrett and al., 2003). This relationship is generally qualified to be negative. Boachie and al. (2018) found an adverse correlation between health expenditure and carbon dioxide emissions. The same result is obtained by Beatty and al. (2014) with carbon monoxide and health treatment. Mehrara and al. (2011) found a short and long-run direct connection between health spending and environment quality. Nevertheless, in many cases, findings have been mixed and contradictory.

The last category is a combination of the first two categories. It can be categorized as studies investigating environmental degradation, economic growth, and health expenditure (Chaabouni et al., 2016; Drabo, 2011; Gövdeli, 2019). However, the relationship among these three variables (health expenditure, environment, and economic growth) remain less explored and studied specifically for developing countries. The main objective of this paper is to investigate the relationship between health expenditure (HE), economic growth, and environmental pollution variables used for the Economic Community of West African States (ECOWAS) in fifteen countries.

The rest of the article is organized as follows: the second section presents Data and Econometric Methodology, while the third section is devoted to the Econometric results and discussions. Finally, conclusions are made in Section 4.

II. DATA AND ECONOMETRIC METHODOLOGY

A. Data

To conduct the econometric analysis, we use annual data from 2000 to 2020 for the Economic Community of West African States (ECOWAS), fifteen countries. In this paper, six variables are collected, namely health expenditure (HE), real gross domestic product per capita (GDP per capita), nitrous oxide emissions (N), carbon dioxide emissions (co_2), Measles (MEAS), and urban population (UP). HE measures public expenditure on health from domestic sources, real GDP per capita as economic growth (constant 2010 US$), N measures Nitrous oxide emissions (thousand metric tons of co_2 equivalent excluding), co_2emissions (metric tons per capita). co_2N represents environmental variables. Measles represents child immunization as a percentage of children ages 12-23 months who received measles vaccination. UP refers to people living in urban areas. All data are from World Development Indicator (2018), and all variables are in logarithm form. Table 1 represents the descriptive statistics with the smallest standard deviation obtained with MEAS (0.250) while the highest with N (1.480) and each variable have 315 observations. Table 2 represents the correlation matrix of variables. It shows that variables are not perfectly correlated.

Table 1. Descriptive statistics

	HE	GDP	N	CO2	MEAS	UP
Mean	0.0824	6.7751	7.8469	-1.3341	4.2560	15.0170
Median	0.0798	6.6267	8.0583	-1.3810	4.3040	14.9861
Minimum	-1.4243	5.6094	4.2484	-2.9369	3.4011	12.3405
Maximum	1.2845	8.2706	10.5299	0.1333	4.5951	18.4893
Std. Dev.	0.5908	0.5748	1.4806	0.7062	0.2503	1.2719
Jarque-Bera	2.4964	26.7448	17.8739	5.2900	51.9851	11.3709
Probability	0.2870	0.0000	0.0000	0.0710	0.0000	0.0033
Observations	315	315	315	315	315	315

Table 2. Correlation matrix of variables

	HE	GDP	N	MEAS	CO2	UP
HE	1.0000					
GDP	0.1010 0.0736	1.0000				
N	-0.2990* 0.0000	-0.0608 0.2819	1.0000			
MEAS	0.4301* 0.0000	0.1162* 0.0392	-0.4652* 0.0000	1.0000		
CO2	-0.0229 0.6853	0.8854* 0.0000	-0.1340* 0.0173	0.1235* 0.0284	1.0000	
UP	-0.3584* 0.0000	0.2455* 0.0000	0.8558* 0.0000	-0.4019* 0.0000	0.2202* 0.0001	1.0000

Notes: ** denotes significance at 5%, and values in brackets are p-value.*

B. Econometric methodology

To investigate the relationship between health spending, environment degradation, and economic growth, we use the following linear panel framework (Narayan and Narayan, 2008; Roushdy and al. 2012):

$$HE_{it} = \gamma_0 + \gamma_{1t}GDP_{it} + \gamma_{2t}N_{it} + \gamma_{3t}MEAS_{it} + \gamma_{4t}CO2_{it} + \gamma_{5t}UP_{it} + \varepsilon_{it} i = 1, \dots, N; t = 1, \dots, T \quad (1)$$

Where HE_{it} represents health expenditure for i^{th}country at time t, x_{it} is a $k \times 1$ set of regressors, namely, per capita GDP (GDP_{it}), health-related environmental factors ($meas_{it}$), carbon dioxide emissions ($CO2_{it}$), Nitrous oxide emissions (N_{it}) and urban population (UP_{it}). ε_{it} is a country-specific error assumed to be identically and independently distributed across i and t.

C. ARDL approach

In this paper, we use a panel ARDL approach proposed by Pesaran et al. (1997), Pesaran et al. (2004) for co-integration analysis in single-equation models. Check for the optimal lag lengths for the model and variables. Two steps allow us to estimate the long-run relationship in the ARDL approach for co-integration. The first is to investigate the existence of a long-run relationship among the variables, and the second is to estimate, by ARDL model, the long-run coefficients. The second step is achieved if there exists a co-integration (long-run relationship) between variables. The Hausman (1978) test is then used to determine the appropriate estimator between the Pooled Mean Group (PMG), the Mean Group (MG), and the Dynamic Fixed Effects (DFE). PMG gives the average of unrestricted single country coefficients and represents a good estimator to the others for a panel like Dynamic OLS and FMOLS (Bildirici, 2014).

The PMG estimator indicates homogenous long-run slope coefficients and heterogeneous short-run coefficients. The panel autoregressive distributed lag (ARDL)(p, q... q) model is a variety of the ARDL (p, q) model in the Pesaran et al. (1999). ARDL-UECM model with the long-run relationship between variables is written as follows:

$$\Delta HE_{it} = \lambda_i HE_{i,t-1} + \beta_i{}' X_{i,t-1} + \sum_{j=1}^{p-1} \phi_{ij}^* \Delta HE_{i,t-j} + \sum_{j=0}^{q-1} \gamma_{ij}^*{}' \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (2)$$

Where $\lambda_i = -\left(1 - \sum_{j=1}^{p} \phi_{ij}\right)$; $\beta_i = \sum_{j=0}^{q} \gamma_{ij}$ for $i = 1, \dots, N; t = 1, \dots, T$

and $\phi_{ij}^* = -\sum_{m=j+1}^{p} \phi_{im}$, $j = 1, \dots, p-1$; $\gamma_{ij}^* = -\sum_{j=0}^{q} \omega_{ij}$, $j = 1, \dots, q-1$

μ_i is the country-specific coefficient, all variables contained in X_{it} are dependent variables, γ_{ij} and ϕ_{ij} Are $k \times 1$ vectors for explanatory variables. ϕ_{ij}^* and γ_{ij}^* Are the coefficients of the short-run dynamic relative to each country.

The Hausman (1978) restrictions test is presented as follows:

$$h = T\hat{q}'\hat{v}(\hat{q})^{-1}\hat{q} \quad (3)$$

Where $\hat{q} = \hat{\eta}_u - \hat{\eta}_r$ Is the difference between unrestricted MG and restricted PMG. The restricted estimation is consistent under the null hypothesis of homogeneity $Cov(\hat{\eta}_r, \hat{q}) = 0$.

The next step is the estimation of the conditional ARDL long-run model if the hypothesis of co-integration is confirmed as follows:

$$HE_{it} = \sum_{j=1}^{p-1} \phi_{ij} HE_{i,t-j} + \sum_{j=0}^{q-1} \gamma_{ij}{}' X_{i,t-j} + \delta_i + \varepsilon_{it} (4)$$

Another step is the estimation of an error correction model involving obtaining the short-run dynamic parameters and the long-run estimates as below:

$$\Delta HE_{it} = \alpha_i + \sum_{j=1}^{p-1} \phi_{ij} \Delta HE_{i,t-j} + \sum_{j=0}^{q-1} \gamma_{ij}{}' \Delta X_{i,t-j} + \mu_{ij} ECT_{i,t-1} + \varepsilon_{it} \quad (5)$$

Where ε_{it} are independently and normally distributed, ECT_{t-1} is the error correction term and μ_i is the speed of adjustment to the equilibrium.

In the last step, if variables are cointegrated, the Engle Granger (1987) causality test can be used. The two-step procedure is adopted. That test can be done with PMG as well as other estimators. The Vector Error Correction Model (VECM) was used to analyze the short-run relationship between variables. The coefficient of the ECT should be statistically significant and negative.

Before doing the panel ARDL and Granger causality test, some preliminary tests should be done.

a) Cross-section dependence tests

To examine the cross-sectional dependence, we consider the sample estimate of the pair-wise correlation of the residuals, $\hat{u}_{it}$ and $\hat{u}_{jt}$ for $i \neq j$

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \hat{u}_{it} \hat{u}_{jt}}{\left(\sum_{t=1}^{T} \hat{u}^2{}_{it}\right)^{1/2} \left(\sum_{t=1}^{T} \hat{u}^2{}_{jt}\right)^{1/2}}$$

$$i = 1, \dots, N, t = 1, \dots, T \quad (6)$$

Under the null hypothesis of no cross-sectional dependence

$$H_0: \rho_{ij} = 0 \text{ for } i \neq j \quad (7)$$

Where ρ_{ij} Is the pair-wise correlation coefficient of the residuals.

For N fixed and$T \rightarrow \infty$, Breusch and Pagan (1980) proposed an LM test to test the null of no

$T \to \infty$, Breusch, and Pagan (1980) proposed an LM test to test the null of no cross-sectional correlation in (7) without imposing any structure on this correlation. It is given by:

$$LM_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \quad (8)$$

LM_{BP} is asymptotically distributed as a Chi-squared distribution with $N(N-1)/2$ degrees of freedom under the null. However, for a micro-panel dataset, N is larger than T. Breusch-Pagan LM test statistic is not valid under this large N, small T setup. Pesaran (2004) proposed a scaled version of this LM test as follows:

$$LM_P = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{ij}^2 - 1\right) (9)$$

Pesaran (2004) shows that LM_P is distributed as $N(0,1)$ with $T \to \infty$ first, then $N \to \infty$ under the null hypothesis. However, $E\left(T\hat{\rho}_{ij}^2 - 1\right)$ is not correctly centered at zero with fixed T and large N. Hence, Pesaran and al. (2008) propose a bias-adjusted version of this LM test, denoted by M_{PUY} :

$$LM_{PUY} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{V_{Tij}} \ (10)$$

Where μ_{Tij} and V_{Tij} Depends on on T, k. Pesaran and al., (2008) show that LM_{PUY} is asymptotically distributed as $N(0,1)$ under the null (7) and the normality assumption of the disturbances as $T \to \infty$ followed by $N \to \infty$ (Baltagi and al. 2017). Pesaran (2004) proposes a test based on the average of pair-wise correlation coefficients rather than their squares, and the test statistic is given by:

$$CD_P = \sqrt{\frac{2}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}\right) \quad (11)$$

This test has exactly mean zero for fixed values of T and N. As N, $T \to \infty$ in any order, CD_P Tends approximately to a standardized normal. One important advantage of the CD_P The test is that it is also applicable to autoregressive heterogeneous panels(Baltagi, 2013; Kouassi, 2018).

b) Unit roots tests

Im, Pesaran and Shin (IPS, 2003)

They begin their specification by separating ADF regression for each cross-section as follows:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + X_{it}'\lambda + \varepsilon_{it} \quad i = 1,2,\dots,N;\ t = 1,2,\dots,T_i \quad (12)$$

Where y_{it} Is it either the logarithm of health care expenditure, the logarithm of GDP per capita, the logarithm of other regressors, or regression residuals from equation (1)? p_i is the lag order, ϕ the autoregressive coefficient, X_{it} represent the exogenous variables in the model, ε_{it} Is the idiosyncratic disturbance independent of each other.

The null hypothesis is written like this:

$$H_0: \phi_i = 0, \text{ for all } i \quad (13)$$

And the alternative hypothesis is:

$$H_1: \begin{cases} \phi_i = 0 & for i = 1,2,\dots,N_1 \\ \phi_i < 0 & for i = N+1, N+2, \dots, N \end{cases} \quad (14)$$

c) Breitung (2000)

Breitung's (2000) method is similar to those of Levin Lin Chu (LLC), with two distinct differences.

The first is removing only the autoregressive portion when constructing the standardized proxies:

$$\Delta y_{it} = \left(\Delta y_{it} - \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j}\right)/s_i \quad (15)$$

$$y_{i,t-1} = \left(y_{i,t-1} - \sum_{j=1}^{p_i} \dot{\beta}_{ij} \Delta y_{i,t-j}\right)/s_i \quad (16)$$

Where β, $\dot{\beta}$ are the estimated coefficients from these two regressions, respectively and s_i Are the estimated standard errors from estimating each ADF (12).

The second is the proxies transformation and detrending

$$\Delta y_{it}^* = \sqrt{\frac{(T-t)}{(T-t+1)}} \left(\Delta y_{it} - \frac{\Delta y_{i,t+1} + \dots + \Delta y_{iT}}{T-t}\right) (17)$$

$$y_{it}^* = y_{it} - y_{i1} - \frac{t-1}{T-1}(y_{iT} - y_{i1}) \quad (18)$$

A pooled proxy equation below allows the estimation of the parameter α like follows:

$$\Delta y_{it}^* = \alpha y_{i,t-1}^* + v_{it} \quad (19)$$

d) Panel co-integration tests

Given the findings of panel unit root tests that conclude that the variables are integrated of order one, we apply the panel co-integration test to examine the long-run relationship between the variables. We perform two-panel co-integration tests, namely Pedroni (1999, 2004), Kao (1999). Pedroni (1999, 2004) introduces seven-panel co-integration statistics based on both homogeneity and heterogeneity assumptions. Assuming a panel of N countries, T observations and m regressors

$$y_{it} = \alpha_i + \delta_i t + \sum_{j=1}^{m} \theta_{ji} X_{j,it} + u_{it} \quad (20)$$

Where y_{it} and $X_{j,it}$ Are assumed to be integrated of order one in levels, e.g., $I(1)$. α_i and δ_i Are individual and trend effects that can be set to zero. The seven statistics can be divided into two sets. The first one consists of four-panel statistics (pooled or within dimension). The second set consists of three *group* panel statistics (between dimensions) (Jardon. and al. 2017). Under the null hypothesis that, all the seven tests indicate the absence of co-integration $H_0: \rho_i = 1 \forall i$, whereas the alternative hypothesis is given by $H_1: \rho_i = \rho < 1 \forall i$, where ρ_i is the autoregressive term of the estimated residual under H_1 given by $\hat{u}_{it} = \rho_i \hat{u}_{i,t-1} + \xi_{i,t}$.

The test of Kao (1999) follows the same approach as the Pedroni (1999) test, but it is based on the assumption of homogeneity across panels with:

$$y_{it} = \alpha_i + \beta x_{it} + \omega_{it} \qquad (21)$$

Where $i = 1, \ldots, N$, $t = 1, \ldots, T$, α_i is an individual constant term, β slope parameter and ω_{it} the stationary distribution, x_{it} and y_{it} Our integrated processes of order $I(1)$ for all i. Kao (1999) derives two (DF and ADF) types of panel co-integration tests. Both tests can be calculated from:

$$\mu_{it} = \rho \mu_{i,t-1} + v_{it} \qquad (22)$$

And $\mu_{it} = \rho \mu_{it-1} + \sum_{j=1}^{p} \Phi_j \Delta \mu_{i,t-j} + v_{it}$ (23)

Where μ_{it-1} is obtained from the equation (21). The null hypothesis is $H_0: \rho = 1$ (no co-integration), while the alternative hypothesis is $H_1: \rho < 1$.

III. ECONOMETRIC RESULTS

This section presents the cross-section dependence (CD), the unit root, panel co-integration tests, and PMG (Pool Mean Group) estimation results.

A. Cross-section dependence tests

Based on the residuals, Breusch-Pagan's (1980) LM test exhibits evidence of cross-section dependence while Pesaran and al. (2008) bias-adjusted and Pesaran (2004) scaled version of LM tests an absence of dependence in cross-sections (table 3A). To check for robustness, the Friedman (1937) and Frees (1995, 2004) tests are made (table 3B). These tests conclude to cross-section independence. In this case, we should employ the first generation unit root tests to analyze variables stationary.

Table 3A. Residual CD test

Test	Statistic
$LM_{BP}(BP, 1980)$	179.6***
LM_{PUY}(2008)Bias adjusted	7.75***
$CD(Pesaran, 2004)$	0.0466

***Notes**: The null hypothesis is no cross section dependence. ***, ** and * represent 1%, 5% and 10% rejections respectively.*

Table 3B. Residual CD test

CD tests	CD Statistic	abs (corr)
Friedman (1937)	10.268	0.384
Frees (1995, 2004)	2.094	0.384
Pesaran CD (2004)	-1.372	0.384

***Notes**: ***, ** and * represent 1%, 5% and 10% rejections respectively.*

Panel unit root tests

To avoid the problems of fallacious regression, which can occur when variables are not stationary, we performed the IPS and Breitung unit root tests, and the results are reported in table 4. The knowledge of the order of integration is necessary before using the co-integration techniques. We can see that all the variables are $I(1)$ i.e., variables are not stationary in level and become stationary in the first difference. The null hypothesis (H_0) of no stationary is rejected in level. No variable is $I(2)$.

Table 4. Unit root tests

	IPS test		Breitung	
	Level	First difference	Level	First difference
HE	-0.1520	-9.5542***	-0.5329	-4.8818***
GDP	1.8433	-4.4327***	1.2219	-2.5385***
N	-0.9386	-10.6263***	2.8024	-6.3034***
MEAS	-3.5257*	-8.2614***	0.0853	-6.2423***
CO2	-0.6521	-7.9961***	0.8116	-6.1504***
UP	3.2040	-5.2270***	-4.7002**	-1.4843*

***Notes**: *, **, *** indicate the significance at 10%, 5% and 1% levels respectively.*

We could know to perform the co-integration test to show if there is a long-term relationship or not among variables.

B. Panel co-integration tests

Tableau 5 contains the results of two-panel co-integration tests. The first is those of Pedroni (1999), which proposes 7 tests statistics both within and between dimensions. We realized a kind of sensitivity analysis of Pedroni's (1999) panel co-integration test. All statistics are significant except for panel v and group rho statistics, and the null hypothesis of no co-integration is rejected. Variables are co-integrated.

These results are confirmed by Kao (1999) panel co-integration test. Variables move together, and the next step is to estimate the long-term relationships between these variables.

Table 5. Panel co-integration tests

	Specification	HE GDP	HE GDP NITR	HE GDP NITR MEAS	HE GDP NITR MEAS CO2	HE GDP NITR MEAS CO2 UP
Pedroni panel co-integration tests	**Within dimension**					
	$Panel v - stat$	0.807	0.394	-0.953	-1.637	-2.562
	$Panel \rho - stat$	-3.049***	-1.204*	0.734	1.217	2.369*
	$Panel pp - stat$	-4.258***	-3.281***	-1.798**	-2.265**	-1.375**
	$Panel ADF - stat$	-3.193***	-1.375**	0.721	1.145*	1.726*
	Between dimension					
	$Group \rho - stat$	-1.633*	-0.353	1.327	2.546	3.536
	$Group pp - stat$	-4.160***	-4.064***	-3.200***	-4.242***	-6.076***
	$Group ADF - stat$	-1.801**	-0.648*	0.235*	0.486	-0.273**
Kao panel co-integration test	$ADF t - stat$	0.133*	-0.304**	-0.326*	-0.354*	-0.847*

Notes: *The null hypothesis is that there is no co-integration. ***, ** and * represent 1%, 5% and 10% rejections respectively. Within the dimension, tests presuppose common autoregressive coefficients among cross-sections, and between dimensions presupposes individual autoregressive coefficients. Pedroni's (1999) tests included deterministic intercept and trend.*

Before doing the estimation of the long-term relationships among variables, we performed Hausman (1978) test to make a choice between the PMG, the MG, and the DFE. Hausman (1978) test p-value is 0.7603, and we can not reject the null hypothesis of homogeneity. PMG is the consistent model to use. Compared with the DFE (dynamic fixed effects) model, the PMG is retained.

C. Pooled Mean Group (PMG) estimation results

After the confirmation that variables are cointegrated, we now estimate the long-run and short-run relationships using the PMG estimator in the ARDL model. The long-run and short-run coefficients are based on the elasticity of HE (health expenditure) with respect to the analyzed variables.

As we can see, in the long-term, only nitrous oxide emissions, co_2emissions and urban population have a positive and significant effect on health expenditure. In fact, an increase of 1% of Nitrous emissions, co_2emissions and urban population lead to health expenditure increase by 0.314% and 0.133% and 1.716%, respectively. This result means that when co_2 and nitrous oxide emissions increase health expenditure increases. Our findings are in line with those of (Yahaya et al. 2016; Narayan and Narayan, 2008; Jerrett et al. 2003).

Economic growth and measles have a negative effect on health expenditure. An increase of 1% level of real GDP per capita and measles lead to a decrease of health expenditure by 0.890% and 0.653%, respectively. When the number of children ages 12-23 months who received the measles vaccination decrease, health expenditure increase.

In the short-run dynamic, real economic growth, nitrous oxide emissions, measles, co_2 emissions and urban population have no significant effect on health expenditure. The urban population has a significant and positive effect on health expenditure. An increase of 1% level of urban population increases real GDP per capita by 2.961%. When measles increase to 1%, co_2 also, increase by 0.385%. In the last equation of short-run dynamic, one can see that only the real GDP per capita is significant and positive. All things being equal, a percentage increase in real GDP per capita will give rise to the urban population by 0.022%.

In terms of health-economic growth relationships, a bilateral causal link exists between health expenditure and real GDP per capita only in the long term. Furthermore, when we look at the causal relationships between health-nitrous oxide emissions, health-co_2emissions, health-measles and health-urban population it is found to be significant and bilateral in the long term and have no causal link in the short run. In terms of economic growth-nitrous oxide emissions, economic growth -co_2 emissions relationships (i.e., growth-environment pollution), a bilateral causal link is found.

There are bilateral relationships between health and environmental pollution in the long term. This result is similar to Zaidi and Saidi's (2018) findings. A contrary result, i.e., a one-way causality relationship from carbon dioxide emission to health expenditure, is found by (Usman et al.,2019; Wang et al., 2019). The same result (bilateral link) is found between economic growth-air pollution and health-economic growth in the long term. The PMG estimation results table (6) also shows that the variables health expenditure, real GDP per capita, nitrous oxide emissions, co_2 emissions, measles, and urban population are significant with the corresponding adjustment rates 40.3%, 16%, 63.3%, 47.1%, 45.2%, and 0.3%, respectively, which indicate that each variable responds speedily to deviances in the long-run equilibrium.

Table 6. **PMG long and short run estimates (1, 0, 0, 0, 0, 0)**

Dependent variab	HE	GDP	N	$MEAS$	CO_2	UP
Long-run coeff.						
HE		-0.890***	0.314***	-0.653***	0.133**	1.716***
GDP	0.110***		0.319***	0.351***	0.338***	0.336***
N	0.053***	0.307***		0.010	0.195***	0.018
$MEAS$	0.098***	-0.258***	0.269***		0.099*	0.188***
CO_2	0.080***	-0.430***	1.160***	-0.314***		0.239***
UP	-0.802**	6.646***	-3.129**	5.956***	-1.744	
ECT	-0.403***	-0.160***	-0.633***	-0.471***	-0.452***	-0.003*
Short-run coeff.						
ΔHE		-0.118	0.434	-0.370	-0.033	14.121
ΔGDP	-0.028		-0.069	0.060	0.009	2.961**
ΔN	0.030	-0.038		-0.146	0.039	-7.093
$\Delta MEAS$	-0.028	-0.007	-0.007		-0.041	1.131
ΔCO_2	-0.039	0.153	-0.002	0.385***		7.438
ΔUP	0.003	0.022***	0.002	0.004	-0.002	

***Notes**: ***, ** and * indicate statistical significance at 1%, 5% and 10% level respectively.*

D. Panel VECM Granger causality test

To test the robustness of the PMG estimation, the panel vector error correction technique (PVECM) Granger causality tests were applied. Even if the estimated parameters of the PMG estimator using the ARDL model are different from those of Granger causality among variables, results are generally consistent. It gives signs that the PMG estimator results concerning causalities are robust. Table 7 report the PVECM results. In Granger's sense, the causal link between HE and real GDP per capita is a one-way from GDP to HE. Our findings are in line with (Neycheva 2008; Zaidi and Saidi, 2018). Results show a bidirectional relationship between real GDP per capita and co_2emissions. This outcome is similar to those of (Arouri and al. 2008). The results also present a two-way relationship between real GDP per capita and nitrous oxide emissions. Surprisingly, the PVECM indicate no Granger causal relationship between HE and co_2 emissions.

The rest of the results show a one-way relationship from Measles to real GDP; from measles to nitrous oxide emissions; from nitrous oxide emissions to co_2 emissions and a bidirectional between measles and urban population; urban population and nitrous oxide emissions.

Table 7. **Panel VECM Granger causality test**

	HE	GDP	N	MEAS	CO2	UP
HE	-	1.904	0.340	11.245	0.120	1.198
GDP	0.458*	-	7.502***	0.548	2.407*	4.251**
N	0.455	2.947**	-	2.137	0.231	5.239***
MEAS	0.760	2.454*	3.622**	-	1.403	11.146***
CO2	0.538	2.912**	4.826***	0.804	-	1.737
UP	0.588	1.731	4.217**	3.059**	0.136	-

***Notes**: ***, ** and * indicate statistical significance at 1%, 5% and 10% level respectively.*

IV. CONCLUSION

The aim of this paper is to analyze the causality (long and short-run relationship) between health expenditure, real GDP per capita (economic growth), and environmental pollution variables using annual data from 2000 to 2020 for the Economic Community of West African States (ECOWAS) fifteen countries. Several tests have been done. The results of cross-section dependence tests highlight an absence of cross-section dependence leading us to use first-generation unit root tests. Both IPS (2003) and Breitung (2000) unit root tests used indicate that variables are stationary at the first difference. We then perform Pedroni (1999, 2004) and Kao (1999) co-integration tests, and results from exhibit evidence of the long-run relationship between variables. To study the long and short-run relationship of economic growth and environmental pollution on health expenditure, the PMG estimator using the ARDL model has been retained as a consistent estimator compared to the Mean Group (MG) and Dynamic Fixed Effects (DFE) using the Hausman (1978) test. At last, a Panel Vector Error Correction Model is used to show the direction of causality.

The PMG approach shows a long-run significant and negative effect of economic growth on health expenditure, but in the short-run, the relation is not significant. Nitrous oxide emissions and co_2 emissions representing environmental pollution have a statistically significant long-run positive effect on health expenditure. When the number of children ages 12-23 months who received the measles vaccination decrease, health expenditure increase. Policymakers should encourage the measles vaccination. Another finding is that when co_2 and nitrous oxide emissions increase health expenditure increases. ECOWAS governments should preserve the environment against pollution in order to reduce pressure on health spending.

The PVECM results indicate a one-way causal link from economic growth (real GDP per capita) to health expenditure (HE); a bidirectional relationship between real GDP per capita and co_2 emissions; a two-way relationship between real GDP per capita and nitrous oxide emissions. This means that there is a bidirectional relationship between economic growth and environmental pollution variables. Surprisingly, the PVECM indicate no Granger causal relationship between HE and co_2 emissions contrary to the PMG result where there is a long-run causality. The findings emphasize the need for the transformation of low-carbon technologies aimed at reducing emissions and sustainable economic growth. ECOWAS countries should prioritize their socio-economic development, but without neglecting environmental protection, as the principles of sustainable development suggest.

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