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Tajul Masron, Mduduzi Biyase, Talent Zwane, Thomas Udimal, Frederich Kirsten

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Ecological footprint and population health outcomes: an analysis of E7 countries

TAJUL ARIFFIN MASRON
School of Management, Universiti Sains Malaysia, Malaysia
Email: tams@usm.my

MDUDUZI BIYASE*
School of Economics and Econometrics, University of Johannesburg.
Email: mbiyase@uj.ac.za

TALENT ZWANE
School of Economics and Econometrics, University of Johannesburg.
Email: ttzwane@uj.ac.za

THOMAS UDIMAL
Southwest forestry University, Kunming China
Email: tbudimal2007@yahoo.com

FREDERICH KIRSTEN
School of Economics and Econometrics, University of Johannesburg.
Email: fkirsten@uj.ac.za

Abstract

This study investigates the relationship between ecological footprint and health outcomes in E7 countries from 1990 to 2017. The study makes use of panel fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS) models to assess the relationship between the ecological footprint and health outcomes. Although the findings show that ecological footprint has a positive effect on life expectancy, implying that the current levels of ecological footprints support life expectancy, failure to strictly observe the level of ecological footprint in the long run may result in a negative impact on life expectancy. Therefore, a more serious efforts and strategies are needed to keep the size of ecological footprints to be favorable to human life.

Keywords: *Ecological footprint, CO2, CH4, N2O, life expectancy, mortality, E7*

*Corresponding author. School of Economics and Econometrics University of Johannesburg.
Address: Protea Glen ext. 12, 1818, South Africa. Email: mbiyase@uj.ac.za

1. Introduction

A healthy population is a key to the country's productivity and economic growth. The economic development, living environment and social welfare systems are crucial factors that can have a direct link with life expectancy (Lomborg, 2002). Improved life expectancy is attributable to improvement in education, and health care among others. An improved living environment or environmental quality is also expected to cause an improvement in life expectancy. Under the environmental factors, ecological footprint could serve as one crucial indicator. Rees (1992) defines ecological footprint as a '*[total] area of productive land and water ecosystems required to produce the resources that the population consumes and assimilate the wastes that the population produces, wherever on Earth that land and water may be located*.' Ecological footprint can be used as an indicator of sustainability that a larger ecological footprint than the land area under one's direct control may mean overutilization or unsustainable use of resources (Costanza, 2000). In an area or country that suffers from ecological deficits, a situation the ecological footprint exceeds the area's biocapacity, over suppressing its own ecological assets (e.g., overfishing), and emitting carbon dioxide could be inevitable[1]. The critique on ecological footprint has been added by Fiala (2008) that most measurements of footprint put a strong assumption of zero greenhouse emissions.[2]

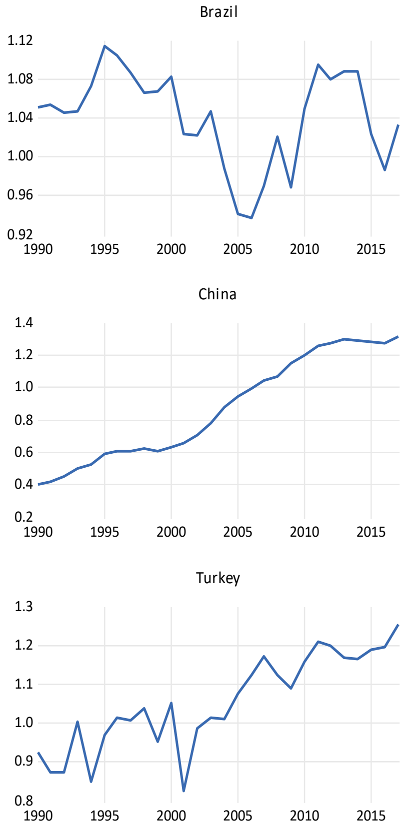
Figure 1 below shows the trends in ecological footprint for the E7 member countries for the period 1990 to 2015. On a positive note, the level of ecological footprint in all E7 countries is generally at an acceptable point. The average ecological footprint in Brazil is merely 1.04 while Mexico is around 1.1 and Russia is around 1.7. These figures are far below Qatar (14.72), Luxembourg (12.79), and the United Arab Emirates (8.95) in 2017 and could be ideal to support life expectancy of the population[3]. Similarly, the ecological footprint in China, India, Indonesia, and Turkey is currently under control with the highest level still below 1.4 in the case of China and Turkey.

[1] see https://www.footprintnetwork.org/our-work/ecological-footprint

[2] Fiala (2008) also reminds us of the weak representation of sustainability that ecological footprint can serve since the correlation between ecological footprint and land degradation is weak. Another interesting debate is the uselessness of ecological footprint for future prediction in the presence of technology that could turn the future production beyond expectation (van den Bergh & Verbruggen, 1999).

[3] See https://worldpopulationreview.com/country-rankings/ecological-footprint-by-country.

FIG. 1: ECOLOGICAL FOOTPRINT IN E7 COUNTRIES



Nonetheless, the uprising trend in these countries could induce health problems in the future if the level is not strictly monitored and controlled. For instance, the quality of air has deteriorated over the years and poses a serious threat to human existence. It is estimated that about 3.4 million child mortality each year is caused by air pollution (WHO, 2019). Reduction in air quality has led to an increase in diseases such as cancer, heart disease, stroke, chronic obstructive pulmonary disease (COPD), pneumonia, allergy, asthma, etc. It is estimated that 3.8 million and 4.4 million people die from indoor air pollution and outdoor air pollution each year, respectively (WHO, 2019). In the developing world, most respiratory diseases are caused by indoor air pollution (Leowski, 1986). The impact of air pollution on human health is much of a challenge with the rapid population growth coupled with industrialization that has led to the reduction in the quality of air attributable to an increase in emissions and high ecological footprint (Pena and Rollins, 2017). Interestingly, people with low socioeconomic backgrounds are more susceptible to the harmful effect of air pollution (Deguen et al., 2015; Di et al. 2017). With the industrial sector becoming the main driver of economies across the globe, sustainability erosion is inevitable that reflects a high ecological footprint. Given the mixed results of past studies regarding the effect of the ecological footprint on life expectancy, this study hypothesizes that it could be due to the size of the ecological footprint. In other words, low ecological footprints are expected to positively support life expectancy, and vice versa. Efforts to establish the link between life expectancy against ecological footprints, and life expectancy against emissions, particularly when the ecological footprint is getting weaker to fully support human health, its finding will hint at the future threats to the ecological footprint that urge for the formulation of strategic environmental policies to maintain optimal ecological footprint (Tanaka, 2015, Kiross et al., 2020, Rasoulinezhad et al., 2020).

Therefore, it is the objective of this study to examine the potential impact of a high ecological footprint in the E7 countries, namely China, Brazil, Turkey, India, Russia, Indonesia, and Mexico. Expecting that the high ecological footprint may induce more damage to environmental quality, this study also examines the impact of higher emissions (i.e., carbon dioxide, nitrogen and methane) on life expectancy due to the failure to monitor the size of ecological footprint properly.

The organization of this study is as follows. The next section reviews relevant past studies, followed by the methodology section. Results are displayed and discussed in the fourth section. Fifth section concludes.

2. Literature Review

Life expectancy is widely accepted as a good measurement of the health status of any country's population as well as comparative national development (see UNDP, 1997; Barlow and Vissandjee, 1999). According to Frenk (2004), a 10 percent improvement in life expectancy can generate 3-4 percent economic growth. Life expectancy was constantly rising about 2 decades ago, but discrepancy exists between developing and developed countries, which is rooted in differences in socioeconomic and environmental conditions in each country (Bilas et al., 2014). Since improvement in life expectancy should also mean improvement in socioeconomic and environmental factors, they form the foundation for the life expectancy model.

The critique on ecological footprint by Fiala (2008) that most measurements of footprint put a strong assumption of zero greenhouse emissions has led Long et al. (2020) to propose a new ecological well-being performance (EWP) index, as opposed to ecological footprint by combining ecological footprint (EFP) and human development index (HDI) as $EWP = \frac{HDI}{EFP}$ in the four islands, namely Chongming, Zhoushan, Hainan, and Taiwan. Prior to the calculation of EWP, the early correlation between HDI and EFP suggests that while most of the four islands are enjoying high HDI, the main contribution comes from high life expectancy, only in Taiwan that 'acceptable' ecological footprint leads to high HDI. Hainan island suffers from a high ecological footprint that likely explains the low HDI. Some of the arguments could suggest a positive connection between ecological footprint and health, especially life expectancy. First, viewing and connecting to the natural green environment such as trees can lead to faster recovery among surgical patients (Ulrich, 1984; Maas et al. 2006; de Vries et al. 2013). Second, physical activities in the forests and outdoor parks could improve health conditions (Hansmann et al. 2007). Third, health issues should not be addressed by referring to medicine alone as the ever-growing stress-related diseases may suggest that environmental elements could be useful to mediate the situation (Nilsson and Berglund, 2006; Velarde et al. 2007). Fourth, indirectly, natural resources can maintain clean water and air that are suitable to naturally cure physical and mental conditions of people (Kim and Kim, 2017). Fifth, environmental amenities could also offer physically challenging jobs and be capable to enhance health and life longevity (Poudyal et al. 2009).

Barlow and Vissandjee (1999) observe that income has a positive effect on life expectancy in several countries. Obviously, income allows individuals to afford healthy food, and water supply. Income, which is also one of the indicators of economic development determines improvement in social conditions and is expected to improve life expectancy (Bilas et al. 2014). Among the classic sources of income leading to better life expectancy could be health care spending and transfer payment (e.g., unemployment compensation, disability pay, and maternity pay), which is called welfare effort by Crepaz and Crepaz (2004). Daniels et al. (2000) and Crepaz and Crepaz (2004) highlight that the issue of life expectancy could stem from the issue of health inequalities, or the unhealthy is generally among the poor and could be addressed by overcoming the issue of income inequality. Crepaz and Crepaz (2004) particularly show that income inequality has a non-linear relationship with life expectancy. At the low-income inequality level, it does affect life expectancy too much that life expectancy keeps on increasing. Nonetheless, after income inequality reaches a certain level of high, life expectancy starts to decline. Regardless of whether income or income inequality, the key to the results on life expectancy lies in the psycho-social stress which tends to be low when income is high or more equally distributed and vice versa.[4] Interestingly, although life expectancy could be higher among the rich rather than the poor (Wilkinson, 1996), some diseases are more pertinent to the high-class people such as coronary heart attack (Marmot and Mcdowall, 1986). Finally, the detailed analysis among workers with a similar type of work suggests a higher incidence of heart disease among the lower class or income earner of civil servants (Singh-Manoux and Marmot, 2005).

Considering another perspective, GDP, which can represent the political tension, crimes, and internal conflict, may have an unfavourable consequence on life expectancy if low GDP is primarily due to conflict and war, either domestic or across the border (WHO, 2002; Halicioglu, 2011). As estimated by WHO (2002), 90 million people are living in critical situations due to conflicts, combined with disasters and sanctions. Hence, if high GDP may mean strong security enforcement, and well-designed laws, leading to a minimum or zero social unrest and violence, then, life expectance can be predicted to be positively improved (Halicioglu, 2011). Sabri (2008) offers another fascinating idea that the imports and exports in the era of globalization, not only affect GDP but could also have a positive and negative impact on life expectancy. The positive aspect of globalization could be due to the installation of new medical devices, emigration of skilled health professionals, as well as practices of taking healthy diets, and in contrast, the negative influence could be the consumption of unhealthy diets and restriction of new medical technologies. Government spending on health also does not seem to exert a significant impact on life expectancy in Bangladesh (Zaman et al. 2017) and Sub-Saharan Africa (Arthur and Oaikhenan, 2017). One key answer could be due to the corresponding governance that facilitates access to equitable and quality health services (Osakede, 2021) and efficiency in the allocation and management of health funds to target the desired goal of accessibility to all (Owumi and Eboh, 2021). In other words, out-of-pocket is still the main factor in the improvement in life expectancy even in developing countries, implying their income is strongly determining the decision to get medical treatment. Within private health spending, two strands of empirical findings can also be observed positive significance (Arthur and Oaikhenan, 2017; Duba et al. 2018) and non-significance (Rezapour et al., 2019).

Bilas et al. (2014) argue that countries with improper education and health care developments tend to suffer from achieving sustainable development. Most countries in the world are

[4] Nonetheless, Mellor and Milyo (2001), Deaton (2003) and Mackenbach (2002) cannot find any systematic or robust correlation between income inequality and life expectancy. In line with the suggestion by Wilkinson (1996), a level of chronic anxiety is the key to mediate the relationship between income inequality and life expectancy.

considering health care as a basic right for everyone that could improve the individual's welfare. As a result, health expenditure and literature on the health economy have increased during the last decade. Cremieux et al. (2005) examines the markedly increased drug expenditures, which also reflect higher healthcare costs on health outcomes in Canada. The growing utilization of pharmaceutical products may also be a result of the cost-containing strategy of a more outpatient-focused. Moreover, quality pharmaceutical products' availability may also help to promote life expectancy for those suffering from lymphoma, leukaemia, and AIDS as well as upgrade quality of life by comforting issues such as anaemia, pain, and depression. With the call for millennium development goals (MDGs) in 2000, a strong commitment such as water services, urban planning, and so on has pushed the agendas to successfully generate positive outcomes on health like life expectancy. Halicioglu (2001) suggests that proper urban development equipped with health facilities and information installed completely may help to improve life expectance. Nonetheless, it is also possible that, as in the case of most cities in developing countries, congestion, pollution, and expensive access to medical care may hamper the aim to expand the life expectancy of urban dwellers. Similar conclusions by Fuchs (1984), Bokhari et al. (2007), and Kulkarni (2016) and that although the contribution of healthcare spending could be big, the contribution to health outcomes is minimal. Quality of delivery and establishment of a financial system are among the conditions that need to be improved first.

Hauck et al. (2016) also share the conclusion that poor sanitation and water quality could be the primary breeding grounds for contagious diseases. Although efforts have been made to prepare a community-level water infrastructure, poor countries generally suffer a shortage of funds to maintain them. Private healthcare could have been confirmed by Moreno-Serra & Smith (2015) as capable to bring down child and adult mortality but could be too expensive for everyone to have access to it. Owumi and Eboh (2021) echo the idea that overdependence on out-of-pocket health expenditure could push the poor to the precipice of catastrophic health spending, especially if their spending on health exceeds their income, individually or collectively as a household.

3. Methodology

3.1. Data and model specification

As indicated in the introduction, this study uses a panel data of the emerging seven countries: China, India, Brazil, Turkey, Russia, Mexico and Indonesia for the period 1990 to 2017. The period was carefully chosen based on data availability for the variables and sample of emerging seven countries in question. The data comprise health outcomes, measured by life expectancy at birth, total (years) and mortality rate, infant (per 1,000 live births). The independent variable of interest is ecological footprint—EFConsPerCap (constant per capita), including alternative degrading indicators such as CO2 emissions (metric tons per capita), CH4-Nitrous oxide emissions (thousand metric tons of CO2 equivalent) and N2O-Methane emissions (kt of CO2 equivalent). We also control for GDP per capita (constant 2015 US$) and life preservative measures such as Current health expenditure per capita (current US$), people using at least basic drinking water services (% of population), and Urban population growth (annual %). Most of the variables are obtained World Bank Development indicators except for EFConsPerCap (constant per capita) which was sourced from Global Footprint Network. The abbreviations and measurement methods of these variables are displayed in Table 2 below: The baseline model (premised on) expresses health outcome as the function of LEF, LEFSQ, LGDPPC, WA, Hexp, URB as follows:

$lnHO = f(LEF\ , LEFSQ, LGDPPC, WA, Hexp, URB)$ (1)

The above model can be converted into regression model as shown below. Equation 2 regresses health outcome (life expectancy) on ecological footprint and its squared term, with two control variables (GDP per capita and one life preservative measure variable proxied by water access). Equation 3 studies the effect of ecological footprint on health outcomes by adding alternative measures of life preservative (proxied by current health expenditure). While equation 4 incorporates urbanization variable (as an additional measure of life preservative). Supplementary analyses were carried out to test whether the effects of ecological footprint on health outcome is sensitive to alternative proxy measures of health outcome (such as mortality rate)—life expectancy and mortality rate were used as dependent variables in order to test the robustness of the findings. Last but not least, we used dynamic ordinary least squares to check the robustness of FMOLS estimators.

Model 1

$$lnHO = \alpha_0 + \alpha LEF_{it} + \alpha LEFSQ_{it} + \alpha GDPPC_{it} + \alpha WA_{it} + \varepsilon \quad (2)$$

Model 2

$$lnHO = \alpha_0 + \alpha LEF_{it} + \alpha LEFSQ_{it} + \alpha GDPPC_{it} + \alpha Hexp_{it} + \varepsilon \quad (3)$$

Model 3

$$lnHO = \alpha_0 + \alpha LEF_{it} + \alpha LEFSQ_{it} + \alpha GDPPC_{it} + \alpha URB_{it} + \varepsilon \quad (4)$$

In all the models, subscripts i and t represent the cross-sectional units (i.e., emerging seven countries in this case) and t is the year of study (1990 to 2017), respectively. HO is the health outcome variables (measured by life expectancy and mortality rate), LEF is the ecological footprint, $LEFSQ$ is the squired term of ecological footprint, $LGDPPC$ is the GDP per capita, WA measures water access, $Hexp$ represents current health expenditure, α_0 represents intercept and the rest of the alpha's represent the slope of LEF , LEFSQ, LGDPPC, WA, Hexp, URB, respectively. εt is the error term of the regression.

In panel data setting cross-sectional dependency issues are not uncommon. Accordingly, the cross-section dependence (CD) test advanced by Pesaran (2004) is used to detect any correlation among the cross sections. Other standard specification tests such panel unit root tests were carried out to ascertain the absence or presence of long-run features of the variables used in this paper. We specifically used second generation panel unit root test (based on Pesaran, 2007) to identify a presence of stationarity in the data series. We also undertook Pedroni cointegration tests to establish whether or not there exist a long-run association for those variables with long-run appearances Pedroni (1999, 2004).

3.2. Estimation strategy

To estimate the precise impact of the independent variables (*LEF, LEFSQ, LGDPPC, WA, Hexp, URB,*) on the health outcomes, this study employed panel fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS). A notable advantage of using FMOLS and DOLS is that they account for serial correlation and endogeneity issues, thus providing reliable long-run estimations. Following Zhang et al. (2022) FMOLS and DOLS are expressed through Eq. (3) and Eq. (4) & (5), respectively.

$$\hat{\varphi}_{FM} = \left(\sum_{t=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)^1 \right) \left(\sum_{t=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)\hat{y}_{it}^{*} + T.\widehat{\triangle}_{\varepsilon\mu}\right) \quad (3)$$

where $\widehat{\Delta}_{\varepsilon\mu}$ signifies the serial correlation of correction term, while $\hat{y}^{*}_{it}$ denotes endogeneity correction. DOLS estimator has also been used to correct for serial correlation as well as endogeneity. Panel DOLS on the other hand can be expressed as follows:

$$Y_{it} = \alpha_i + x_{it}\delta \sum_{j=q1}^{j=q2} x_{it}\Delta x_{it+j} + \nu_{it} \qquad (4)$$

where cij is the coefficient of a lead or lag of first differenced explanatory variables. The estimated coefficient of DOLS is given by

$$\hat{\varphi}_{DOLS} = \sum_{t=1}^{N} \left(\sum_{t=1}^{T} Z_{it} Z^{1}_{it} \right) \left(\sum_{t=1}^{T} Z_{it} \hat{y}^{*}_{it} \right) \qquad (5)$$

Where Z_{it}=($x_{it} - \bar{x}_i$, Δx_{it+q}) is 2(q+1)

X1 represent the independent variables.

4. Empirical results and discussion

4.1 Descriptive statistics

Before discussing the empirical results obtained from the estimation of PFMOLS and PDOLS models, we first report the descriptive analysis. Precisely, table 1 presents the mean statistics for all the examined variables. From this table, it is evident that the mean of LGDPPC is the largest (70.070) and differs significantly across countries (maximum = 87.963 and minimum = 39.290). Average CH4 is 12.800 in the countries, and the standard deviation is 0.886. As of logN2O, LHEXP and percentage of LWATER show a mean of 11.543, 5.278 and 4.508, respectively. Over the period, the average of logLE and MORT of selected countries is 4.241 and 3.220. In terms of standard deviation, the highest value is for the LGDPPC variable with 13.637, followed by URB and logHEXP by 1.279 and 1.183, respectively.

TABLE 1: SUMMARY STATISTICS

	LEF	LCO2	LCH4	LN2O	LLE	LMORT	LGDPPC	LWATER	LHEXP	URB
Mean	0.829	1.045	12.800	11.543	4.241	3.220	70.070	4.508	5.278	2.292
Median	0.984	0.986	12.937	11.408	4.247	3.248	76.124	4.540	5.696	2.418
Maximum	1.922	2.683	14.032	13.212	4.346	4.484	87.963	4.594	6.939	5.081
Minimum	-0.273	-0.440	10.517	10.153	4.058	1.705	39.290	4.322	2.755	-0.467
Std. Dev.	0.540	0.784	0.886	0.869	0.064	0.626	13.637	0.068	1.183	1.279
Skewness	-0.347	0.270	-0.971	0.284	-0.521	-0.144	-0.743	-0.818	-0.535	-0.243
Kurtosis	2.340	2.285	3.247	1.960	2.684	2.334	2.198	2.527	1.973	2.939
Jarque-Bera	7.423	6.550	29.391	10.754	9.668	4.305	23.304	15.210	11.549	1.957
Probability	0.024	0.038	0.000	0.005	0.008	0.116	0.000	0.000	0.003	0.376
Observations	194	196	184	184	196	196	196	126	126	196

Source: Computed by the authors

4.2 Results of cross-sectional dependence and panel unit root tests

As a standard procedure in this field, before implementing some econometric methods which deal with panel data assessments, it is a common practice to begin by checking the presence of cross-sectional dependence or independence among the variables. The literature is full of evidence suggesting that the findings from a conventional unit root tests might be spurious and misleading if the variables are found to be cross-sectional dependence because it is based on the assumption of cross-sectional independence (Ummalla et al. 2019). For this purpose, this study applied the cross-sectional dependence test promulgated by Pesaran (2004) to examine the presence of cross-sectional dependence and heterogeneity issues. The null hypothesis of cross-sectional independence is tested against the alternative hypothesis of cross-sectional dependence consistent with the literature (Ummalla et al. 2019; Faisal et al. 2020). If we reject the null hypotheses, it suggests that there is a presence of cross-sectional dependence among all of the variables (Pesaran, 2004). Interestingly, table 2 shows that there is a presence of cross-sectional dependence across all models, hence we reject the null hypotheses.

Given the fact that the conventional unit root tests are not appropriate in the presence of cross-sectional dependence across all models, the study then employed Pesaran's (2007) CADF and CIPS cross-sectional augmented panel unit root tests which account for cross-sectional dependence consistent with the work of Ummalla et al. (2019). Table 3 present the results of the second-generational unit root test since the first-generation unit root test fails to account for the cross-sectional dependency. The results reveals that the data series are all stationary at first difference.

TABLE 2: PESARAN CROSS-SECTIONAL DEPENDENCE TEST

	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
LEF	157.060***	20.995***	20.865***	6.285***
LEFSQ	129.254***	16.704***	16.574***	0.164
GDPpc	470.733***	69.395***	69.266***	21.576***
Water	376.340***	54.830***	54.624***	19.399***
Hexp	314.232***	45.247***	45.041***	17.687***
URB	251.967***	35.639***	35.509***	11.084***
Lmort	570.852***	84.844***	84.714***	23.891***
LCO2	345.167***	50.020***	49.890***	12.866***
LCH4	222.122***	31.034***	30.904***	-1.728*
LN20	338.852***	49.046***	48.916***	-2.388**

Probabilities *p < 0.1, **p < 0.05, ***p < 0.01 *Source: Computed by the authors*

TABLE 3: PANEL UNIT ROOT TEST RESULTS FOR THE E-7 COUNTRIES

	Level	1st difference
LEF	-1.22899	-3.94728***
LEFSQ	-2.18931	-4.58504***

GDPpc	-0.66552	-3.27755***
Water	-4.48847***	-3.31874***
Hexp	-1.65101	-3.067***
URB	-0.05321	-3.31874***
Lmort	-0.69333	-2.10836***
LCO2	-1.56472	-3.69986***
LCH4	-1.10243	-2.26065**
LN20	-0.56507	-3.69986***

Source: Computed by the authors

4.3 Panel cointegration test

The cointegration test predicts the existence of a long-run relationship provided that the series is integrated of unique order (Faisal et al. 2020). Westerlund panel cointegration is often preferred since it accounts for cross-sectional dependency. Panel cointegration test was proposed by Westerlund (2007) and Persyn and Westerlund (2008), in which the hypothesis is investigated using two different tests. Westerlund (2007) formulated the to establish the long-run association in the presence of cross-sectional dependency. Table 4 present the results of the Westerlund panel cointegration test. The results suggest that the null hypothesis of no cointegration can be rejected under the cross-sectional dependency.

TABLE 4: PANEL COINTEGRATION TESTS

Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-0.365304	0.6426	0.967374	0.1667
Panel rho-Statistic	1.621181	0.9475	0.930278	0.8239
Panel PP-Statistic	0.001367	0.5005	-1.883249***	0.0298
Panel ADF-Statistic	-3.272337***	0.0005	-2.567167***	0.0051
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	1.449549	0.9264		
Group PP-Statistic	-2.735723	0.0031***		
Group ADF-Statistic	-3.622141	0.0001***		

Source: Computed by the authors

4.4 Empirical results

In this section, we begin our discussion by presenting the estimates (reported in Table 5 through Table 9) carried out using both the PFMOLS and PDOLS estimators described in the methodology section. All control variables are converted into logarithmic form for the empirical estimation. Besides, these variables are added in a stepwise manner for robustness analysis. Model (1) through to (6) of Table 5 regresses life expectancy as a dependent variable against economic factors and health outcomes — ecological footprint, squared ecological footprint, GDP per capita, access to clean drinking water, healthcare expenditure and urbanisation.

We begin our analysis by discussing the empirical results of PFMOLS presented in Model (1) to (3) below. Except for squared ecological footprint, economic factors such as ecological footprint, GDP per capita, access to drinking water, healthcare expenditure and urbanisation, displayed a positive influence on life expectancy. In respect to ecological footprint, the results in Table 5 shows that ecological footprint present a significant positive effect on life expectancy from Model (1) to (3), which are supported by the past studies (Maas et al. 2006; Hansmann et al. 2007; Velarde et al. 2007; de Vries et al. 2013). The results suggest that the current levels of ecological footprints support life expectancy. The literature is full of evidence suggesting that the positive coefficient of ecological footprint on life expectancy might be attributed to natural green environment such as trees, which can lead to faster recovery among surgical patients (Maas et al. 2006; de Vries et al. 2013). An alternative reason might be that physical activities in the forests and outdoor parks could improve health conditions (Hansmann et al. 2007). However, Dietz et al. (2007) found opposite results and argued that when people utilise an area of land to produce its waste material, the land turns into soil deterioration and land degradation that have a negative impact on the climate and thus reduce the human life longevity. Squared ecological footprint have been associated with a decrease in life expectancy, implying that in the long run, life expectancy might have significant negative influence on life expectancy.

Meanwhile, the effect of GDP per capita on life expectancy is observed to be significantly positive in all PFMOLS models, as expected and consistent with Miladinov (2020), Luo and Xie (2020) Wang et al. (2020), to mention only few. From Model (1) to (3), the results demonstrate that a 1% rise in GDP per capita increases the life expectancy by 0.0099%, 0.0039% and 0.0397%, respectively. Implicitly, increased levels of income permit increased access to consumption of improved quality goods and services, better housing, and medical care services that affect the health status (Bayati et al. 2013). The results are in line with the findings of Halicioglu (2011) who concluded that if high GDP is an indication of a strong security enforcement, and well-designed laws, leading to a minimum or zero social unrest and violence, then, life expectancy can be predicted to be positively improved.

Next is access to drinking water. Access to drinking water enters with positive and significant impact on life expectancy, and the impact of access to water is substantial in Model (1), indicating that a 1% rise of this variable improve the life expectancy by 11.804%. These results reinforcing the UN General Assembly declaration that clearly state that every person has the right to enough, continuous, safe, acceptable, physically accessible and affordable water for personal and domestic use.

In Model (2) and (3,) we repeated the investigation by adding healthcare expenditure and urbanisation as a control variables. Interestingly, the results demonstrate that healthcare expenditures (viewed as a measure of the provision of the health facilities to the society) is positive and statistically correlated with life expectancy confirming the findings of Cervantes et al. (2019) and Bein et al. (2017). The finding shows that a 1% increase in health expenditure increases the life expectancy by 0.0204%. The results suggest that that increased healthcare expenditure is associated with greater availability of healthcare services in E7 member countries.

The results further demonstrate that urbanisation has a positive and significant effect on life expectancy in the PFMOLS model, which confirm the findings of Kalediene and Petrauskiene (2000) for Lithuania. The results suggest that urban population often enjoy better-quality medical care and means of life, improved education system, and other enhanced socio-economic amenities, which influence positively on health outcomes (see for example, Beyene and Kotosz, 2021).

For robustness checks, we further estimate an alternative model using DOLS. Table 5 Model (4) to (6) reports the factors influencing life expectancy. Remarkably, the results of PDOLS model appeared to mimic the same pattern in terms of the direction of the impact and the level of significance as those presented by the FMOLS estimator. For instance, ecological footprint appears to possess a significantly positive impact on life expectancy in all models supporting the results of PFMOLS estimator. The square ecological footprint is shown to have negative impact on life expectancy. In line with the results of the PFMOLS model, GDP per capita, healthcare expenditure and access to water appear to have significant and positive effects on life expectancy in the PDOLS. Overall, the findings from PDOLS demonstrate consistent results with PFMOLS estimates. Therefore, the conclusions advanced earlier for significant variables from PFMOLS also apply to the findings displayed in this part.

TABLE 5: THE RELATIONSHIP BETWEEN ECOLOGICAL FOOTPRINT AND LIFE EXPECTANCY

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS
LEF	0.003025	0.033815	1.900560	3.423167	0.058489	1.977547
	(0.197337)	(1.820636)	(7.832250)	(10.59543)	(3.147480)	(6.700282)
LEFSQ	-0.041981	-0.045458	-1.272778	-1.714644	-0.038208	-1.278722
	(-6.691832)	(-5.912860)	(-4.840666)	(-10.40755)	(-4.271505)	(-3.661089)
LGDPPC	0.009925	0.003978	0.039753	0.025001	0.004796	0.039550
	(22.90750)	(6.292790)	(18.95265)	(13.23841)	(6.165650)	(13.75878)
LIFE_PRES(LWATER)	11.80400			182.8188		
	(12.03149)			(182.8188)		
LIFE_PRES(health exp)		0.020475			0.012985	
		(6.074764)			(3.937852)	
LIFE_PRES(URB)			0.146962			0.155483
			(4.360190)			(3.288151)
R-squared	0.957749	0.948585	0.943142	0.938207	0.948244	0.880416

Note: numbers in ( ) denotes t-statistics
Source: Computed by the authors

Table 6 presents the empirical results of PFMOLS and PDOLS estimators from Model (1) to (6). In this section, we regress mortality rate on ecological footprint, GDP per capita, access to drinking water, healthcare expenditure and urbanisation. There are some noticeable differences between the results presented earlier to the estimates presented in this part. Apart from the levels of significance, the major differences are in terms of the direction of the impact of the coefficients. For instance, ecological footprint has a negative and strongly significant impact on mortality rate across the three first models., The results indicate that an increase in ecological footprint by 1% leads to a reduction in mortality rate by -3.8210% The reason might be that there are strong environmental outcomes that are not polluted and exposing individuals to an unhealthy setting, which might make them sick, leading to increased death (Mays and Smith, 2011). These results align the findings of Mays and Smith (2011) who showed that increases in ecological footprint correlate with a decrease in mortality rate. A closer look at the squared ecological footprint–mortality nexus indicates a positive and strongly significant relationship. We conclude that in the short run, ecological footprint might have a negative impact on mortality rate; however, the relationship can be positive in the long run.

GDP per capita appear to have the opposite impact in this model — enters with positive and statistically significant coefficients in all models, thus Model (1) to (3). The findings implies that a 1% increase in GDP per capita in Model (1) to (3) results in an increases mortality rate by 0.0717%, 0.1144% and 0.5059% respectively. These results are unexpected given the fact that GDP per capita is often assumed to improve life expectancy at birth through improved economic growth and development and hence results to the prolongation of longevity (Rahman et al., 2022). Access to drinking water is an important factor influencing mortality rates — enters positively and significantly, suggesting that that provision of poor water quality to the general public could be the primary breeding grounds for contagious waterborne diseases like malaria, lower respiratory infections, which have important implications for burden of diseases and contributes to higher mortality (Hauck et al., 2016).

Total healthcare expenditure is perceived to have significant influence on life expectancy because it directly helps reduce mortality and morbidity (Mays and Smith, 2011). Consistent with this thinking, healthcare expenditure appears to enter with expected negative sign, at 1% level of significance. The results suggest that an increase in healthcare expenditures by 1% is correlated with a reduction in mortality rate of -0.6051%, an indication that higher healthcare expenditure has a long-lasting effect on low-resource communities (see also, Mays and Smith, 2011). These findings are similar to those of Maruthappu et al. (2015) who reported that a higher public healthcare expenditure is negatively associated with HIV mortality.

Urbanisation is one of the critical determinants of mortality rate in the current study — enters with positive and significant impact on mortality rate, demonstrating that urbanisation is largely related to unhealthy conditions such as pollution and congestion, which both have adverse effects on health and ultimate dearth in these countries under investigation (see also).

Conceivably, what is more interesting is a comparison of the results of the FMOLS and the DOLS model. In this study, DOLS estimator was estimated as robustness check and produces results that are qualitatively similar to those of PFMOLS. For instance, coefficients for ecological footprint reported in Model (4) to (6) once again matter in explaining mortality rate and enter with negative coefficients. Squared ecological footprint, GDP per capita, access to water still matters in explaining mortality rate — enters positive and significantly rated to mortality rate.

General, the findings from DOLS demonstrate consistent results with FMOLS estimates. Therefore, the conclusions arrived at earlier for the FMOLS estimates for significant variables also apply to the estimates displayed in this part.

TABLE 6 THE RELATIONSHIP BETWEEN ECOLOGICAL FOOTPRINT AND MORTALITY RATE

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Variable	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS
LEF	-3.821028	-3.480078	-2.877505	-1.072385	-3.692982	-4.170474
	(-468.0943)	(-11.18255)	(-64.47403)	(-1.112951)	(-5.874420)	(-17.55965)
LEFSQ	0.972053	0.811258	0.542049	0.041199	0.818766	1.105779
	(1676.274)	(4.986692)	(11.41772)	(0.115862)	(3.552718)	(6.180057)
LGDPPC	0.071738	0.114402	0.505915	0.042060	0.090110	0.078013
	(189.3385)	(14.43167)	(32.50776)	(5.052975)	(12.57060)	(63.71295)
LIFE_PRES(LWATER)	66.16504			138.0408		
	(177859.5)			(4.119692)		
LIFE_PRES(health exp)		-0.605185			-0.263385	
		(-5.579743)			(-2.741833)	
LIFE_PRES(URB)			2.025386			-0.712374
			(32.80083)			(-1.828610)
R-squared	0.280465	0.628862	0.321786	0.862407	0.991158	0.780180

Note: numbers in ( ) denotes t-statistics
Source: Computed by the authors

Table 7 reports the PFMOLS and PDOLS estimation results where we replace ecological footprint with CO_2 emission (proxy environmental degradation). What is evident from Model (1) to (3) is that CO_2 emission have a significant positive effect on life expectancy, suggesting that higher CO_2 emission increases the life expectancy. Precisely, a 1% increase in CO_2 emission, keeping all other variables unchanged, increases life expectancy by 0.0292%,2.7633% and 0.1223% respectively. Therefore, this study finds that CO_2 emissions is detrimental to life expectancy, since the release of CO_2 into the air can result in numerous environmental problems, with devastating impact on human health. On the other hand, squared CO_2 emission was found to have a strong negative effect on life expectance. More specifically, a 1 percent increase of squared CO_2 emission, holding all other factors constant, decreases life expectancy by -0.0113613 percent. In fact, the results imply that after CO_2 emission reaches a certain level of high; life expectancy starts to decline.

Remarkably, GDP per capita present negative but insignificant coefficients on life expectancy in Model (1) but the direction of the impact changes to positive in Model (2) and (3). Access to basic drinking water have significantly positive effect on life expectancy and the effect is extensive suggesting that 1% rise of this variable rises the life expectancy by 0.2758%. These results are to be expected since maintaining a healthy water intake might also improve longevity (Rahman et al., 2022).

Likewise, we conduct some robustness checks to make certain that the estimates discussed thus far are consistent. Model (4) to (6) in Table 7 shows the results of DOLS. Based on the DOLS analysis, it is found that CO_2 emission have a significant and positive effect on life expectancy in Model (4) to (6). This indicates that a 1% increase in CO_2 emission increases life expectancy by 0.0353%, 2.3014% and 0.2764%, respectively. These positive estimates are supported by the results of FMOLS. In contrast, squared CO_2 emission has a negative impact on expectancy in all models. This suggests that a 1% increase in squared CO_2 emission in model 4 to model 6 will reduce life expectancy by -0.0115%, -1.3222% and -0.1230% respectively. GDP per capita is negative and insignificant in Model (4) consistent with the estimates of Model (1). However, Model (5) and (6) present positive but insignificant coefficients. Access to water, health expenditure and urbanisation present positive and significant impact on life expectancy.

TABLE 7: THE IMPACT OF CO_2 EMISSION ON LIFE EXPECTANCY

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Variable	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS
LCO2	0.02924	2.763361	0.122318	0.035384	2.301468	0.276488
	(3.495887)	(4.077127)	(11.6799)	(4.678023)	(2.727815)	(2.059994)
LC2OSQ	-0.013613	-1.784397	-0.040823	-0.011567	-1.32227	-0.123017
	(-4.140001)	(-3.807759)	(-15.77026)	(-4.12169)	(-2.39951)	(-1.99453)
LGDPPC	-0.000183	0.035136	0.003751	-0.000261	0.019102	0.006489
	(-0.376062)	(3.84817)	(6.840984)	(-0.57793)	(0.784438)	(3.19803)
LIFE_PRES(LWATER)	0.275835			0.106542		
	(2.633877)			(0.845113)		
LIFE_PRES(health exp)		0.181071			0.401552	
		(1.731325)			(1.261441)	
LIFE_PRES(URB)			0.001593			0.001183
			(0.734524)			(0.11743)
	0.985833	0.981196	0.917373	0.985833	0.981196	0.917373

Note: numbers in ( ) denotes t-statistics
Source: Computed by the authors

Table 8 present the results of life expectancy focusing more on nitrous oxide (N_2O). We applied PFMOLS as a preferred estimation technique and PDOLS for robustness check. Interestingly, nitrous oxide (N_2O) enters with positive and statistically significant coefficient when PFMOLS estimator is used, suggesting that a 1% increase in N_2O will increase life expectancy by 0.6707%, 0.6289% and 0.6897% from Model (1) to (3). On the other hand, squared nitrous oxide present negative and statistically significant coefficients across Model (1) to (3). The results seem to suggest that nitrous oxide might be influencing the life expectancy positive up to a certain point, but negatively affecting life expectancy in the long run. GDP per capita remain an important determinant of life expectancy — enters positively and significantly in all Models (1) to (3). Thus, a 1% increase in GDP per capita increases life expectancy by 0.0038%, 0.0043% and 0.0041% respectively. Access to drinking water, health care expenditure and urbanisation all enter with positive impact on life expectancy. These results are also in line with those presented earlier.

For robustness analysis, we further estimate a model using DOLS. Model (4) to (6) reports the factors influencing life expectancy. In these models, the results follow the same direction and pattern from those presented in Model (1) to (3). For instance, nitrous oxide, GDP per capita, access to water, healthcare expenditure and urbanisation still present positive effects on life expectancy. Correspondingly, squared nitrous oxide once again matters in explaining life expectancy — enters with negative and statistically significant coefficients in all models. These results are consistent with the results of model 1 to model 3. Overall, the estimates from DOLS demonstrate consistent results with FMOLS estimates. The conclusions advanced earlier in Table 1 and Table 3 for significant variables also apply to the results presented in this part.

TABLE 8: THE IMPACT OF N2O EMISSION ON LIFE EXPECTANCY

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Variable	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS
LN2O	0.670746	0.628971	0.689704	0.712738	0.648873	0.690736
	(47.94549)	(37.82371)	(52.50428)	(43.17605)	(29.20665)	(42.56002)
LN2OSQ	-0.028163	-0.025076	-0.029641	-0.030698	-0.026694	-0.02999
	(-25.00704)	(-16.72581)	(-37.34581)	(-21.7448)	(-13.1655)	(-24.4102)
LGDPPC	0.003859	0.004376	0.004156	0.002158	0.004056	0.004577
	(6.488724)	(4.668389)	(6.34085)	(3.691752)	(3.385148)	(8.560194)
LIFE_PRES(LWATER)	31.56068			62.29815		
	(1.081839)			(1.689509)		
LIFE_PRES(health exp)		0.006482			0.006012	
		(1.374553)			(1.008065)	
LIFE_PRES(URB)			0.000831			0.006306
			(0.13776)			(0.842855)
	0.953504	0.311095	0.535746	0.845966	0.763682	0.943909

Note: numbers in ( ) denotes t-statistics
Source: Computed by the authors

Table 9 present the results of life focusing more precisely on methane (CH_4) which is positively and significantly related to life expectancy in Model (1) to (3), a sign that capturing and using CH_4 presents prospects to produce new sources of clean energy and alleviate global climate change and hence improved quality of life. However, squared methane enters with negative and statistically significant coefficients. In keeping with the results of presented earlier, GDP per capita, access to water, healthcare expenditure and urbanisation remains important determinants of life expectancy — enters positively in all models.

Closer look at the results of PDOLS model, the results are similar in direction of the impact to those of the PFMOLS model. As can be observed, CH_4 still matters in explaining life expectancy — enters positively and significantly in PDOLS model. Alternatively, squared CH_4 have continuously been negative and significantly related to life expectancy in all models. Other control variables such as GDP per capita, healthcare expenditure and urbanisation still present still enters with positive coefficients.

TABLE 9: THE IMPACT OF CH4 EMISSION ON LIFE EXPECTANCY

	Mode 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variable	FMOLS	FMOLS	FMOLS	DOLS	DOLS	DOLS
LCH4	0.515385	0.67101	0.609259	0.541428	0.554911	0.700116
	(4.474911)	(479.5764)	(296.0696)	(4.594426)	(27.53364)	(30.31017)
LCH4SQ	-0.021371	-0.027706	-0.024153	-0.022488	-0.019441	-0.02976
	(-4.544725)	(-319.8015)	(-195.2354)	(-4.68272)	(-9.89613)	(-17.2211)
LGDPPC	0.002766	0.003207	0.005207	0.002362	0.003958	0.003589
	(2.787775)	(17.34819)	(59.78653)	(2.196454)	(2.201246)	(5.738434)

LIFE_PRES(LWATER)	0.216896			0.191426		
	(1.282149)			(1.09782)		
LIFE_PRES(health exp)		0.000961			0.005072	
		(0.484928)			(0.909726)	
LIFE_PRES(URB)			0.023918			0.002318
			(26.29132)			(0.333845)
	0.443538	0.327946	0.416181	0.950036	0.676004	0.910753

Note: numbers in ( ) denotes t-statistics
Source: Computed by authors

5. Conclusion

The interlinkages between economic development, increased ecological footprints and health outcomes are a major talking point in E7 nations. Not only are these developing countries in a heightened era of industrialization, urbanization and economic growth, but the source of this development relies mainly on fossil fuel consumption. This level of energy consumption has shown increasing patterns of the ecological footprint in these countries, patterns that might influence health outcomes. However, the current level of acceptably low ecological footprints in E7 nations has led to conflicting results when observing the casual relationship between ecological footprint and health outcomes, especially over the long run. The aim of this study was to build on the existing literature and further assess the impact of the ecological footprint on health outcomes for E7 nations in the long run.

The results of the FOMLS and DOLS models show that environmental degradation measures like ecological footprint, CO2 and N2O all have a positive impact on life expectancy in E7 countries. These results show support for a strong positive relationship between environmental demands and health outcomes for developing countries, consistent with some development studies (Dietz et al. 2012; Knight, 2014). The positive relationship could be linked with the social benefits that are associated with an increased ecological footprint; with still an acceptably low level of ecological footprint, these benefits still outweigh the negative health effects of environmental degradation. The social benefits, through a larger ecological footprint, include urbanization, improved public health and an overall improvement of living standards that all result in higher life expectancy. However, observing the relationship over time we find a decoupling relationship between environmental demands and well-being. We find that the square ecological footprint has a negative and significant impact on life expectancy. Indicating that over time the positive relationship between environmental degradation and life expectancy breaks down and becomes negative. We can therefore conclude that after reaching a certain threshold a higher level of ecological footprints would lead to lower life expectancy in E7 countries, mimicking the current decoupling environmental degradation-health outcome nexus in developed nations.

Although the relationship between ecological footprint and well-being is still positive in these E7 nations, our results suggest a decoupling relationship over time and provide evidence that in the overtime the relationship between environmental degradation and health outcomes could become negative and further environmental degradation would harm well-being in these countries. This provides an incentive for policymakers to fast track the shift to more renewable and calls for more serious efforts and strategies are needed to keep the size of ecological footprints to be favorable to human life. All before these countries' own ecological footprint becomes a real burden on the health outcomes of their citizens.

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