Determinants of Life Expectancy in Most Polluted Countries: Exploring the Effect of Environmental Degradation

Mafiz Rahman

University of Southern Queensland Faculty of Business Education Law and Arts

Rezwanul Rana

University of Southern Queensland Faculty of Business Education Law and Arts

Rasheda Khanam (✉ rasheda.khanam@usq.edu.au)

University of Southern Queensland Faculty of Business Education Law and Arts

Research

Keywords: Life Expectancy, Most Polluted Countries, Environmental degradation, Panel Data, Preston Curve.

Posted Date: September 22nd, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-77014/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Version of Record: A version of this preprint was published at PLOS ONE on January 21st, 2022. See the published version at <https://doi.org/10.1371/journal.pone.0262802>.

Determinants of Life Expectancy in Most Polluted Countries: Exploring the Effect of Environmental Degradation

Mohammad Mafizur Rahman,

Email: mafiz.rahman@us.edu.au

School of Commerce, Centre for Health Research, University of Southern Queensland
Toowoomba | Queensland | 4350 | Australia

Rezwanul Rana

Email: Rezwanul.Rana@usq.edu.au

School of Commerce, University of Southern Queensland
Toowoomba | Queensland | 4350 | Australia

Rasheda Khanam, corresponding author

Email: rasheda.khanam@usq.edu.au

School of Commerce, Centre for Health Research, University of Southern Queensland
Toowoomba | Queensland | 4350 | Australia

Determinants of Life Expectancy in Most Polluted Countries: Exploring the Effect of Environmental Degradation

Abstract

Background: Better understanding of the determinants of national life expectancy is crucial for economic development, as healthy nation is a prerequisite for a wealthy nation. Many socioeconomic, nutritional, lifestyle, genetic and environmental factors can influence a nation's health and longevity. Environmental degradation is one of the critical determinants of life expectancy, which is still under researched as the literature suggests

Objectives: This study aims to investigate the determinants of life expectancy in 31 world's most polluted countries with particular attention on environmental degradation using the World Bank annual data and British Petroleum data over the period of 18 years (2000-2017),

Methods: The empirical investigation is based on the model of Preston Curve where panel corrected standard errors (PCSE) and feasible general least square (FGLS) estimates are employed to explore the long run effects. Pairwise Granger causality test is also used to have short run causality among the variables of interest taking into account the cross sectional dependence test and other essential diagnostic tests.

Results: The results confirm the existence of Preston Curve, implying the positive effect of economic growth on the life expectancy. Environmental degradation is found as a threat while health expenditure, clean water and improved sanitation affect the life expectancy positively in the sample countries. The causality test results reveal one-way causality from carbon emissions to life expectancy and bidirectional causalities between drinking water and life expectancy, and sanitation and life expectancy.

Conclusion: Our results reveal that environmental degradation is a threat for having the improved life expectancy in our sample countries. Based on the results of this study, we recommend that: (1) policy marker of these countries should adopt policies that will reduce carbon emissions and thus will improve public health and productivity; (2) environment-friendly technologies and resources, such as renewable energy, should be used in production process; (3) healthcare expenditure on national budget should be increased; and (4) clean drinking water and basic sanitation facilities must be ensured for all people.

Keywords: Life Expectancy; Most Polluted Countries; Environmental degradation; Panel Data; Preston Curve.

Background

Life expectancy is the average outstanding years of life at a specific age of an individual which captures the prevailing patterns of mortality for various age groups [1] concluded that longer life expectancy is desirable for its inherent value as well as for the important life achievements of each individual. It is considered as one of the most important parameters of the Human Development Index, and improvement of life expectancy is principal to many medical research. In addition, good health and longevity are related to higher productivity which is an essential stimulus for sustainable economic growth [2]. Income level is considered as one of the major drivers of life expectancy, and many researchers have concluded that higher income leads to greater life expectancy in a country [3-5]. However, significant disparities in life expectancy are predominant among countries with identical per capita income [6]. For example, according to the World Bank [7] data, life expectancy in Bangladesh (72 years) and Nepal (70 years) are higher than India (69 years) and South Africa (64 years), despite having lower per capita income [7]¹.

Understanding the determinants of national life expectancy is a complex issue. Many socioeconomic, nutritional, lifestyle, genetic and environmental factors can influence people's health and longevity [8, 9]. For example, Mackenbach and Looman [10] found that rising national income reduced the mortality from infectious diseases in European countries over the period of 1990 to 2008 while they studied the upward shift of the Preston curve (link between life expectancy and per capita real income) for the selected European countries. This reduction in mortality has significantly contributed to the rise in life expectancy in Europe. Healthcare expenditure is also found to have strong positive impact on life expectancy in the studies of Bein et al [11], Jaba et al

¹ The World Bank (2018). World Development Indicators. Washington DC.: The World Bank. Available from <https://data.worldbank.org/indicator/SP.DYN.LE00.IN> cited on 29th May 2020.

[12] and Ranabhat et al [13]. In another study on 40 countries of sub Saharan Africa (SSA), Arthur and Oaikhenan [14] also revealed the improved life expectancy due to increased healthcare expenditure. However, van del Heuvel and Olaroiu [15] and Rahman et al. [16] found no impact of healthcare expenditure on the life expectancy of 31 European countries and SAARC-ASEAN regions, respectively. The studies of Filmer [17] and Barlow and Vissandjee [18] also support this no impact result.

Sanitation is also linked to the life expectancy. Poor sanitation causes transmission of many diseases such as cholera, diarrhea, hepatitis A, typhoid, etc. that reduces life expectancy [19]. According to this report, around 432,000 deaths each year occur mainly due to poor sanitation. Similarly, unclean or contaminated drinking water transmits various diseases that adversely affect life expectancy via infant mortality (16, 20). WHO Report [21] also notes that there are 485, 000 diarrheal death each year which is mostly related to unclean drinking water.. Islam et al. [22] used healthy life expectancy (HALE) data to estimate the health status and quality of life in low and lower-middle income countries. Along with other known factors, they have found economic freedom, level of corruption, carbon dioxide emission and success in achieving millennium development goal are highly correlated to higher life expectancy.

Numerous recent studies labelled environmental degradation as the most critical determinant of life expectancy in the world today. According to the World Health Organization [23], 4.2 million premature deaths in the world in 2016 were caused by ambient air pollution and this is projected to increase further as 9 out of 10 of the world's population resides in places with hazardous air

quality². Environmental degradation can adversely impact population health in several ways. Severe outdoor air pollution is responsible for rising chronic diseases (e.g. Asthma, heart diseases and lung cancer) [24, 25] and increasing premature mortality [26]. Others concluded that environmental degradation increases the likelihood of waterborne diseases [27] such as malaria and dengue fever [28, 29]. Previous studies also concluded that environmental degradation increases the variability in the ecosystem, hence, increasing the probability of floods and droughts [30]. As a result, environmental degradation might cause adverse variations in food production and water quality, which contributes to higher mortality particularly among infant and elderly population, as well as vulnerable people from the lower socioeconomic background. Wen and Gu [31] and Wang et al. [32] found that air quality critically impacts the longevity of elderly population who has minimal ability to cope with environmental degradation due to other comorbidities. Similarly, Majeed and Ozturk [33] demonstrated that countries with a higher level of environmental degradation experience greater infant mortality and vice-versa.

Despite the above empirical evidence, many developing countries continue to disregard decisive actions against environmental degradation. Chasing higher economic growth, these developing countries exert a lot of pressure on environmental resources (e.g. water, land and forest), and their increasing production fosters higher CO₂ emission and industrial wastes [2, 34-36]. Countries with high level of environmental degradation fails to realize the long-run positive impact of strong environmental law on economic growth and health [37]. Their lack of focus on environment warrants further considerations. No study so far has examined the determinants of life expectancy

² The World Health Organization (2018). Ambient air pollution: health impacts. Department of Public Health, Environmental and Social Determinants of Health (PHE), World Health Organization, Geneva, available from <https://www.who.int/airpollution/ambient/health-impacts/en/> cited on 29th May 2020.

in most polluted countries³ with particular attention of the adverse effect of environmental degradation on population's longevity. This motivates us to pursue this research to fill up the current research gap.

This paper used life expectancy as public health outcome, and, the objective of this research is to examine the key determinants of life expectancy in the most polluted countries of the world. Our main variables of interest are GDP per capita (proxy for economic growth) and CO₂ emissions per capita (proxy for environmental degradation). Other controlled/explanatory variables are health expenditure per capita, people's access to basic drinking water services and sanitation services. The rationale for selecting these 31 most polluted countries is all of these countries are developing countries where average life expectancy is lower (70 years) compared to that of developed countries (around 80 years). The justification for selecting other explanatory variables in this study are: average per capita CO₂ emissions are 6 metric tons in these sample countries; average per capita health expenditure is lower (US\$700) compared to high income (US\$ 5,600) and OECD (US\$ 5,041) countries; still 15% of population have no basic drinking water service; and 29% of population do not use basic sanitation facilities [7]. Moreover, the variables used in this paper are along the line of past literature. The basic hypothesis of the study is that the positive correlation between economic growth and life expectancy will persist, and environmental degradation will have significantly higher negative impact on life expectancy than often estimated in the empirical studies. Hence, the aim is to measure the validity of the Preston's curve and the impacts of CO₂ emission on longevity. Other hypothesis is that health expenditure per capita [4, 16, 38], availability of safe drinking water and sanitation facilitates [39-41] will influence longevity

³ 31 most polluted countries are selected where average PM_{2.5} (mg/m³), an air pollutant, is greater than 20, and these data are collected from World Population Review (WPR, 2020). See further details in section 3.1.

positively. Following the studies of Majeed and Ozturk [35], Ebenstein et al. [42] and Mohammed et al. [43], CO₂ emission is used as a measure of environmental pollution.

The main contributions of this paper to the existing literature are as follows: (i) the paper has used longitudinal data to determine the factors impacting life expectancy, and longitudinal data provide multiple observations for each individual item which facilitates reliable research method, eliminates estimation bias and reduces the problem of multicollinearity [44]; (ii) the study has also used appropriate diagnostic tests to check the accuracy of the model; (iii) to the best of knowledge of the authors, this is the first study of its kind that used long-term data to estimate the determinants of life expectancy in the world's most polluted countries; (iv) the findings of health outcomes at the individual country level revealed by clinical and epidemiological studies are seldom used for macroeconomic policy implications [45]; this study addressed this issue. Our findings will be critically important to implement effective public health and environmental policies, in particular with increasing number of elderly populations in these countries. In addition, the outcome of this study will also assist in executing focused health interventions for the most at-risk groups of the community, develop environmental pollution monitoring system and strengthen environmental laws and regulations.

Data and Methods

Data

This study uses balanced panel data over the period of 2000 - 2017 for 31 world's most polluted countries. The countries are Afghanistan, Bahrain, Bangladesh, Bulgaria, Cambodia, Chile, China, Croatia, Czech Republic, Ethiopia, India, Indonesia, Iran, Kazakhstan, Korea Republic, Kuwait, Mexico, Mongolia, Nepal, Nigeria, Pakistan, Peru, Poland, Serbia, Sri Lanka, Thailand, Turkey, Uganda, United Arab Emirates, Uzbekistan and Vietnam. The data were acquired from the World Development Indicator [7], World Bank database. The carbon emissions data for the period from 2015 to 2017 are not available in the WDI; therefore, these are sourced from the British Petroleum (BP) Statistical Review of World Energy [46]. The world's most 31 polluted countries are selected where average PM_{2.5} (mg/m³), an air pollutant, is greater than 20, and these data are collected from World Population Review [47]. In this study, the dependent variable is life expectancy at birth, total years (LIF) and the independent variables are GDP per capita (GDP), CO₂ emissions metric ton per capita (CO₂), health expenditure per capita (HEX), percentage of population using at least basic drinking water services (WAT) and percentage of population using at least basic sanitation services (SAN). Table 1 presents the summary statistics of the variables used in the study. The average life expectancy at birth is around 70 years, GDP per capita is \$8,566 and per capita health expenditure is \$701. On average, 85% of population have access to basic drinking water and 71% population use sanitation service. Average per capita CO₂ emissions are 6 metric tons in the sample countries.

Table 1: Descriptive statistics of the variables

Variables	Mean	Median	Standard Deviation	Minimum	Maximum
LIF	70.39	72.75	7.17	46.23	82.63
CO ₂	5.93	3.94	7.27	0.04	35.92
GDP	8565.45	4188.70	11319.38	194.87	63251.52
HEX	700.51	420.11	688.33	21.38	3070.09
WAT	85.27	92.29	18.86	18.70	100.00
SAN	71.25	85.89	29.47	3.40	100.00

Model

Preston [5] develops a model, known as Preston Curve, to examine the relationship between life expectancy and real GDP per capita and found a positive relationship between these two variables.

The basic model of the Preston Curve is noted below:

$$\text{LIF} = f(\text{GDP}) \quad (1)$$

Where LIF and GDP represent life expectancy and real GDP per capita (a proxy for economic growth), respectively. The coefficient of GDP is expected to have a positive sign. This study uses the augmented model of Preston Curve by adding some other relevant explanatory variables as stated above. Therefore, the used model for the study is as follows:

$$\text{LIF} = f(\text{GDP}, \text{CO}_2, \text{HEX}, \text{WAT}, \text{SAN}) \quad (2)$$

CO₂ emissions are believed to impact human life expectancy [43, 48, 49] as a major determinant. It is expected that CO₂ emissions have a negative relationship with life expectancy. We expect a positive relationship between LIF and the rest of the explanatory variables. This study uses panel data so that our baseline model will be re-written as follows:

$$\text{LIF}_{it} = \beta_0 + \beta_1 \text{GDP}_{it} + \beta_2 \text{CO}_{2it} + \beta_3 \text{HEX}_{it} + \beta_4 \text{WAT}_{it} + \beta_5 \text{SAN}_{it} + \varepsilon_{it} \quad (3)$$

Subscripts i and t represent country and year, respectively. $\beta_1 - \beta_5$ are the vectors of coefficients for time-varying explanatory variables. ε_{it} is the error terms for country i at year t . All variables used in this study are transformed into natural logarithms in order to reduce heteroscedasticity.

$$\ln LIF_{it} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln CO_{2it} + \beta_3 \ln HEX_{it} + \beta_4 \ln WAT_{it} + \beta_5 \ln SAN_{it} + \varepsilon_{it} \quad (4)$$

Econometric approach

This research conducts panel data approach as this analysis has certain advantages. First, it has both time-series and cross-sectional dimensions. Second, the panel data analysis addresses the individual heterogeneity issue. Third, this analysis reduces multi-collinearity and increases the degrees of freedom. Lastly, it overcomes the problems associated with time-series analysis [50].

Panel unit root tests

The test for panel unit root is the first necessary step to identify the stationary properties of the variables. A range of panel unit root tests is available in the literature. In this study, we use four first- and second-generation panel unit root tests for increasing the robustness of results. They are Pesaran [51] test, Im, Pesaran and Shin (IPS) [52] test, Fisher (53) augmented Dickey–Fuller (ADF) test and Harris and Tzavalis [54] unit-root test. The null hypothesis of the above panel unit root tests is: each series is non-stationary across countries at the level and stationary at the first difference.

Pesaran [51] suggests the following Augmented Dickey-Fuller regression with the cross-section average of lagged and first differences of the individual series:

$$\Delta y_{it} = \alpha_i + p_i \bar{y}_{t-1} + \sum_{j=0}^k \gamma_{ij} \Delta \bar{y}_{it-1} + \sum_{j=0}^k \delta_{ij} y_{it-1} + \varepsilon_{it} \quad (5)$$

where $\bar{y}_{t-1}$ and $\Delta\bar{y}_{it-1}$ are the cross-sectional averages of lagged levels and first differences individual series, respectively. Once running the CADF (covariate-augmented **Dickey Fuller**) statistics, the CIPS (cross sectionally augmented IPS) statistic can be obtained as follows:

$$CIPS = \left(\frac{1}{N}\right) \sum_{i=1}^N t_i(N, T) \quad (6)$$

Im, Pesaran and Shin (2003) propose the t-bar test using the following equation.

$$t - bar = \sqrt{N(t_\alpha - k_t)} / \sqrt{v_t} \quad (7)$$

where N is the size of the panel, t_α is the average of the individual ADFt- statistics for the cross-sectional unit, with and without a trend, and k_t and v_t are, respectively, estimates of the mean and variance of each t_{ai} statistics, and they are generated by simulations and tabulated exact critical values for various combinations of N in Im, Pesaran and Shin [54] test.

Fisher (55) augmented Dickey–Fuller (ADF) test is as follows:

$$y_t = \beta' D_t + \phi y_{t-1} + \sum_{j=0}^p \psi_{ij} \Delta y_{t-j} + \varepsilon_{it} \quad (8)$$

Where D_t is a vector deterministic term. The p lagged difference terms, Δy_{t-j} are used to approximate the ARMA structure of the errors.

The Harris-Tsavalis test statistic based on the OLS estimator, p, in the regression model is:

$$y_{it} = p y_{i,t} + z'_{i,t} \gamma_i + \varepsilon_{it} \quad (9)$$

where the term $z'_{i,t} \gamma_i$ allows for panel means and trends.

Cross-sectional dependence, autocorrelation and heteroscedasticity

Panel data with autocorrelation, cross-sectional dependence and heteroscedasticity make serious problems for econometric analysis. The presence of cross-sectional dependence in a panel study suggests that there exists a common unobserved shock among the cross-sectional variable over a time period [55].

Pesaran [56] recommends that if the cross-sectional size is larger than the time dimension, the following test statistic can be used instead.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \widehat{p}_{ij}^2 \quad (10)$$

Where $\widehat{p}_{ij}$ indicates a correlation between the errors. The null hypothesis of this test is H_0 : no cross-sectional dependence. The alternative hypothesis of this test is H_1 : cross-sectional dependence.

Khan et al. [57] define autocorrelation as “the disturbance term correlated with any variable of the model that has not been affected by the disturbance term related to other variables in this model.” Heteroscedasticity arises when the variance of the disturbance differs across samples [58].

Parks [59] proposes Feasible Generalized Least Squares (FGLS), which is efficient in overcoming group-wise heteroscedasticity, time-invariant cross-sectional dependence and serial correlations. Beck and Katz [60] suggest an alternative panel-corrected standard error (PCSE) estimates to deal with the panel nature of the data. It is believed that FGLS and PCSE effectively deal with heteroscedasticity, serial correlations and cross-sectional dependence. Le and Nguyen [61] advocate that PCSE and FGLS are two techniques that correct for heterogeneity and autocorrelation and produce robust standard errors. Ikpesu et al. [62] incorporate the PCSE

approach to address autocorrelation, correct standard error estimate and overcome outlier estimates. Some previous studies use FGLS, which overcomes heteroscedasticity and autocorrelation [57, 63]. Alonso et al. [64] use PCSE and FGLS estimates for their panel data set and report similar results.

This study uses the time-series-cross-sectional Prais-Winsten (PW) regression with panel-corrected standard errors (PCSE) as a baseline estimate, which allow for disturbances that are heteroskedastic and contemporaneously correlated across the panel. The PCSE correction helps avoid statistical overconfidence that is often associated with the feasible generalized least-square estimator in which the total periods are smaller than total sample countries [60, 65].

Results

This study sample consists of 31 countries and the period of study is for 18 years, 2000 – 2017. First, this study tests for the existence of heteroscedasticity, cross-sectional dependence and autocorrelation. Also, to investigate the stationary of the variables, this study adopts the Pesaran [51] CIPS, the Im-Pesaran-Shin unit root test [52] and the Levin-Lin-Chu unit root test [66].

Table 2: The results of cross-sectional dependence and stationary test

	CD test	Pesaran (2007) CIPS	Im-Pesaran-Shin unit-root test		Fisher unit root test		Harris-Tzavalis unit-root test	
			Z-t-tilde-bar Statistics	p-value	Inverse chi-squared	p-value	Statistics	p-value
lnLIF	84.872***	-2.521***	-2.983***	0.001	213.070***	0.000	0.955	0.999
lnCO ₂	18.237***	-2.438***	2.055	0.980	123.292***	0.000	0.908	0.988
lnGDP	62.742***	-2.027	5.207	1.000	122.378***	0.000	0.962	1.000
lnHEX	77.525***	-2.201*	-1.774**	0.038	186.735***	0.000	0.787**	0.029
lnWAT	58.409***	-1.723	-9.732***	0.000	170.471***	0.000	0.968	1.000
lnSAN	68.482***	-2.312**	-13.904***	0.000	227.404***	0.000	0.9246	0.998

Note: ***, **, and * denote significance level at 1%, 5% and 10%, respectively.

Table 2 shows that the cross-sectional dependence exists in all of the variables. Besides, most of the variables are stationary at the levels.

Table 3: The results of heteroscedasticity and autocorrelation

Test	Test statistic	P-value	Decision
Modified Wald test for groupwise heteroskedasticity	$X^2 = 44115.37$	0.0000	There is heteroscedasticity in the panel
Wooldridge test for autocorrelation in panel data	F-statistic = 84.29	0.0000	The autocorrelation is present in the panel.

Table 3 presents the results of heteroscedasticity and autocorrelation, indicating that heteroscedasticity and auto-correlation exist in our used panel data. In this context, this study adopts the Panel-Corrected Standard errors model (PCSE) to examine the long-run effects of carbon emissions on life expectancy following the panel data estimation as shown in equation 4. This method has been adopted following Bailey and Katz [67], Jönsson [68], Le et al. [69], and Marques and Fuinhas [70] to address the heteroscedasticity, cross-sectional dependence and autocorrelation of variables in a small data with short period (T) and large cross-sectionals (N). Following the previous studies, this study also uses the FGLS method for checking the robustness of results [69, 71-73]. Following Asongu et al. [74] and Bergh and Nilsson [75], this study also uses the fixed effect regressions that adjust for clustering over countries as a complementary analysis because it can correct within panel heteroscedasticity and autocorrelation.

Table 4: The results of PCSE regression

	PCSE
_Constant	3.0065 (125.00)***
lnGDP	0.0139 (4.39)***
lnCO ₂	-0.0119 (-7.83)***
lnHEX	0.0241 (6.07)***
lnWAT	0.2069 (37.61)***
lnSAN	0.0200 (4.62)***
R-squared	0.9999
Wald chi ²	5186.23
Probability	0.0000
N	558

Note: *** denotes significance at 1% level. .. Figures in the parentheses are z-statistics

Table 4 reports the PCSE long-run estimation results concerning the impact of life expectancy for 31 countries over the period 2000-2017. Economic growth has a significant positive association with life expectancy, supporting Preston Curve. This means that the economic growth of a country would likely to increase the life expectancy. This finding is consistent with theory and the previous research evidence that higher the economic growth increases more years for life expectancy. Carbon emissions have a significantly negative impact on life expectancy, suggesting that higher the carbon emissions lower the life expectancy. More specifically, a 1% increase of carbon emissions, keeping all other variables constant, decreases life expectancy by 0.012%. Therefore, this study finds that carbon emissions is a vital driver of life expectancy. The healthcare expenditure has a significant positive impact on life expectancy, implying that higher healthcare expenditure would increase life expectancy. This result is consistent with previous studies [76], indicating that healthcare expenditure is an important factor of life expectancy. Drinking water and sanitation have significantly positive impacts on life expectancy as well, and the effect of access to drinking water is substantial implying that 1 percent increase of this variable increases the life expectancy by 0.21%.

Table 5: Robustness check: The results of FGLS regression

	FGLS
Constant	3.1052 (79.19)***
lnGDP	0.0228 (10.49)***
lnCO ₂	-0.0116 (-7.97)***
lnHEX	0.0126 (6.57)***
lnWAT	0.1622 (15.29)***
lnSAN	0.0426 (9.78)***
Wald chi ²	2866.08
Probability	0.0000
N	558

Note: *** denotes significance at 1% level. Figures in the parentheses are z-statistics.

For robustness checks, this study also estimates a model using FGLS. Table 5 reports the determinants of life expectancy. Economic growth appears to have significantly positive effects on life expectancy supporting Preston Curve. The carbon emissions are shown to have negative effects on life expectancy; health care expenditure, water and sanitation appear to have significant and positive effects on life expectancy. Overall, the results from FGLS show consistent results with PCSE estimates.

The results of causality test

Table 6: Pairwise Granger Causality Tests

Null Hypothesis:	F-Statistic	Causality
lnCO ₂ → lnLIF	4.271**	One-way causality from lnCO ₂ to lnLIF
lnLIF → lnCO ₂	2.133	
lnGDP → lnLIF	0.323	No causality between lnGDP and lnLIF
lnLIF → lnGDP	2.196	
lnHEX → lnLIF	0.084	No causality between lnHEX and lnLIF
lnLIF → lnHEX	1.580	
lnWAT → lnLIF	21.482***	Two-way causality between lnWAT and lnLIF
lnLIF → lnWAT	8.872***	
lnSAN → lnLIF	11.265***	Two-way causality between lnSAT and lnLIF
lnLIF → lnSAN	11.941***	

Table 6 shows the short-term causality between life expectancy, carbon emissions, economic growth, healthcare expenditure, drinking water and sanitation. This study finds that there is a one-way causality running from carbon emissions to life expectancy. In other words, more carbon emissions threaten life expectancy. Additionally, this study reveals that there are bidirectional causalities between drinking water and life expectancy as well as sanitation and life expectancy. The study, however, found no short-run causality between GDP and life expectancy and between health expenditure and life expectancy.

Discussions

This paper investigates the determinants of life expectancy in 31 most polluted countries of the world with a special focus on environmental degradation (measured by CO₂ emissions). Taking the World Bank annual data and BP data over the period of 18 years (2000-2017), we have used the PCSE model to estimate the long run effects of environmental degradation on life expectancy. Then we have applied FGLS regression to check the consistency of the results found in PCSE regression. We also check the cross-sectional dependence and perform other essential diagnostic tests for panel data. The results from both PCSE and FGLS regressions confirm a significant negative effect of CO₂ emissions on life expectancy, whilst all other variables (GDP per capita, health expenditure per capita, people's access to basic drinking water services and improved sanitation services) are positively correlated with life expectancy. The Pairwise Granger Causality Tests show one-way causality from carbon emissions to life expectancy and bidirectional causalities between drinking water and life expectancy, and sanitation and life expectancy. Thus, our results reveal that environmental degradation is a threat for having the improved life expectancy in our sample countries.

Based on our findings several policy recommendations can be drawn. First, the policy makers should implement strong environment policies that reduce pressure on environmental resources such as water, land, forest and air quality. Evidently, the most polluted countries feature the weakest environmental policies, and they often fail to implement public policies to downgrade environmental damages caused by rapid economic growth. Since, environmental pollution results in a poor quality of life, it often impedes the positive impact of economic growth on life expectancy [77]. Numerous past studies have concluded that healthier nations have higher per capita productivity and are able to accumulate more wealth compared to those with poor health [78, 79]. Therefore, policy maker of these countries should adopt effective public health and environmental policies that will pay off in the long run in terms of better health from reduced CO₂ emission and thus increases productivity and economic growth. They should also invest in research and innovation to invent and produce technologies that will reduce environment degradation in addition to developing environmental pollution monitoring system and strengthening environmental laws and regulations. Second, production activities for higher economic growth should continue using environment-friendly technologies and resources such as renewable energy. Third, since income and health expenditure have positive effects on the life expectancy, budgetary allocation on health care expenditure must be increased. Finally, for all people clean drinking water and basic sanitation facilities must be ensured to improve the life expectancy in these countries. The joint efforts through public-private initiatives will really be helpful in this regard.

Conclusions

Overall, this study used the latest and sophisticated econometric techniques to estimate the determinants of life expectancy for the most polluted countries in the world. In this context, carbon

emission was confirmed as the key determining factor. For these 31 countries, rising CO₂ emission had a significant negative impact on life expectancy both in short as well as in the long-run. Variables such as the availability of safe drinking water, and improved sanitation facility, increased the life expectancy. Although rising GDP and expenditure on health promote higher life expectancy, this study did not find a short-run causal relationship from the direction of GDP to life expectancy or health expenditure to life expectancy. This would suggest that countries with very high pollution level may not achieve a higher life expectancy in the short-run, despite having positive GDP growth and expanding healthcare expenditure.

References

1. Sen A. Mortality as an indicator of economic success and failure. *The Economic Journal*. 1998; 108(446):1-25.
2. Raffin N, Seegmuller T. Longevity, pollution and growth. *Mathematical Social Sciences*. 2014; 69:22-33.
3. Bloom DE, Canning D. Commentary: The Preston Curve 30 years on: still sparking fires. *International Journal of Epidemiology*. 2007; 36(3):498-499.
4. Kabir M. Determinants of life expectancy in developing countries. *The Journal of Developing Areas*. 2008:185-204.
5. Preston SH. The changing relation between mortality and level of economic development. *Population Studies*. 1975; 29(2):231-248.
6. Chowdhury AMR, Bhuiya A, Chowdhury ME, Rasheed S, Hussain Z, Chen LC. The Bangladesh paradox: exceptional health achievement despite economic poverty. *The Lancet*. 2013; 382(9906):1734-1745.
7. World Bank: World Development Indicators. Washington DC: The World Bank; 2018. <https://data.worldbank.org/indicator/SP.DYN.LE00.IN>. Accessed on 29th May 2020.
8. Christensen K, Vaupel JW. Determinants of longevity: genetic, environmental and medical factors. *Journal of Internal Medicine*. 1996; 240(6):333-341.
9. Yang YC, Boen C, Gerken K, Li T, Schorpp K, Harris KM. Social relationships and physiological determinants of longevity across the human life span. *Proceedings of the National Academy of Sciences*. 2016; 113(3):578-583.
10. Mackenbach JP, Looman CW. Life expectancy and national income in Europe, 1900-2008: an update of Preston's analysis. *International Journal of Epidemiology*. 2013; 42(4):1100-1110.
11. Bein MA, Unlucan D, Olowu G, Kalifa W. Healthcare spending and health outcomes: evidence from selected East African countries. *African Health Sciences*. 2017; 17(1):247-254.
12. Jaba E, Balan CB, Robu I-B. The relationship between life expectancy at birth and health expenditures estimated by a cross-country and time-series analysis. *Procedia Economics and Finance*. 2014; 15:108-114.

13. Ranabhat CL, Atkinson J, Park M-B, Kim C-B, Jakovljevic M. The influence of universal health coverage on life expectancy at birth (LEAB) and healthy life expectancy (HALE): a multi-country cross-sectional study. *Frontiers in Pharmacology*. 2018; 9:960.
14. Arthur E, Oaikhenan HE. The effects of health expenditure on health outcomes in Sub-Saharan Africa (SSA). *African Development Review*. 2017; 29(3):524-536.
15. van Den Heuvel WJA, Olaroju M. How Important Are Health Care Expenditures for Life Expectancy? A Comparative, European Analysis. *Journal of the American Medical Directors Association*. 2017; 18(3):276.e279-276.e212.
16. Rahman MM, Khanam R, Rahman M. Health care expenditure and health outcome nexus: new evidence from the SAARC-ASEAN region. *Globalization and Health*. 2018; 14(1):113.
17. Filmer D. Child mortality and public spending on health: How much does money matter?: The World Bank; 1999.
18. Barlow R, Vissandjee B. Determinants of national life expectancy. *Canadian Journal of Development Studies/Revue canadienne d'études du développement*. 1999; 20(1):9-29.
19. World Health Organisation: Sanitation, Key Facts. Online publication: WHO; 2019. <https://www.who.int/news-room/fact-sheets/detail/sanitation>. Accessed on 2 June 2020.
20. Alemu AM. To what extent does access to improved sanitation explain the observed differences in infant mortality in Africa? *African journal of Primary Health Care & Family Medicine*. 2017; 9(1):1-9.
21. World Health Organisation: Drinking Water, Key Facts. Online Publication: WHO; 2019. <https://www.who.int/news-room/fact-sheets/detail/sanitation>. Accessed on 14 June 2019.
22. Islam MS, Mondal MNI, Tareque MI, Rahman MA, Hoque MN, Ahmed MM, Khan HT. Correlates of healthy life expectancy in low-and lower-middle-income countries. *BMC Public Health*. 2018; 18(1):476.
23. World Health Organization: Ambient air pollution: health impacts. Department of Public Health, Environmental and Social Determinants of Health (PHE). Geneva: WHO; 2018. <https://www.who.int/airpollution/ambient/health-impacts/en/>. Accessed on 29th May 2020.

24. Apergis N, Bhattacharya M, Hadhri W. Health care expenditure and environmental pollution: a cross-country comparison across different income groups. *Environmental Science and Pollution Research*. 2020:1-15.
25. Kampa M, Castanas E. Human health effects of air pollution. *Environmental Pollution*. 2008; 151(2):362-367.
26. Pope III CA, Ezzati M, Dockery DW. Fine-particulate air pollution and life expectancy in the United States. *New England Journal of Medicine*. 2009; 360(4):376-386.
27. Comrie A. Climate change and human health. *Geography Compass*. 2007; 1(3):325-339.
28. Hales S, De Wet N, Maindonald J, Woodward A. Potential effect of population and climate changes on global distribution of dengue fever: an empirical model. *The Lancet*. 2002; 360(9336):830-834.
29. Tanser FC, Sharp B, Le Sueur D. Potential effect of climate change on malaria transmission in Africa. *The Lancet*. 2003; 362(9398):1792-1798.
30. Haines A, Kovats RS, Campbell-Lendrum D, Corvalán C. Climate change and human health: impacts, vulnerability and public health. *Public health*. 2006; 120(7):585-596.
31. Wen M, Gu D. Air pollution shortens life expectancy and health expectancy for older adults: the case of China. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences*. 2012; 67(11):1219-1229.
32. Wang L, Li Y, Li H, Zhang F, Rosenberg M, Yang L, Huang J, Krafft T, Wang W. A study of air pollutants influencing life expectancy and longevity from spatial perspective in China. *Science of the Total Environment*. 2014; 487:57-64.
33. Majeed MT, Ozturk I. Environmental degradation and population health outcomes: a global panel data analysis. *Environmental Science and Pollution Research*. 2020:1-11.
34. Kasman A, Duman YS. CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. *Economic Modelling*. 2015; 44:97-103.
35. Sapkota P, Bastola U. Foreign direct investment, income, and environmental pollution in developing countries: Panel data analysis of Latin America. *Energy Economics*. 2017; 64:206-212.

36. Sebri M, Ben-Salha O. On the causal dynamics between economic growth, renewable energy consumption, CO2 emissions and trade openness: Fresh evidence from BRICS countries. *Renewable and Sustainable Energy Reviews*. 2014; 39:14-23.
37. Pautrel X. Pollution and life expectancy: How environmental policy can promote growth. *Ecological Economics*. 2009; 68(4):1040-1051.
38. Rana RH, Alam K, Gow J. Development of a richer measure of health outcomes incorporating the impacts of income inequality, ethnic diversity, and ICT development on health. *Globalization and Health*. 2018; 14(1):72.
39. Howard G, Bartram J, Water S, Organization WH. Domestic water quantity, service level and health. In.: World Health Organization; 2003.
40. Kumar S, Vollmer S. Does access to improved sanitation reduce childhood diarrhea in rural India? *Health Economics*. 2013; 22(4):410-427.
41. Peter G. Impact of rural water projects on hygienic behaviour in Swaziland. *Physics and Chemistry of the Earth, Parts A/B/C*. 2010; 35(13-14):772-779.
42. Ebenstein A, Fan M, Greenstone M, He G, Yin P, Zhou M. Growth, pollution, and life expectancy: China from 1991-2012. *American Economic Review*. 2015; 105(5):226-231.
43. Mohammed A, Li Z, Arowolo AO, Su H, Deng X, Najmuddin O, Zhang Y. Driving factors of CO2 emissions and nexus with economic growth, development and human health in the Top Ten emitting countries. *Resources, Conservation and Recycling*. 2019; 148:157-169.
44. Hsiao C. Benefits and limitations of panel data. *Econometric Reviews*. 1985; 4(1):121-174.
45. Shaw JW, Horrace WC, Vogel RJ. The determinants of life expectancy: an analysis of the OECD health data. *Southern Economic Journal*. 2005:768-783.
46. British Petroleum: BP Statistical Review of World Energy. 2007.
<https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>. Accessed on 1 March 2020.
47. World Population Review: Most Polluted Countries 2020.. Online publication: WPR; 2020. <http://worldpopulationreview.com/countries/most-polluted-countries>. Accessed on 1 March 2020.

48. Bayati M, Akbarian R, Kavosi Z. Determinants of life expectancy in eastern mediterranean region: a health production function. *International Journal of Health Policy and Management*. 2013; 1(1):57.
49. Jorgenson AK, Givens J. The changing effect of economic development on the consumption-based carbon intensity of well-being, 1990–2008. *PloS one*. 2015; 10(5):e0123920.
50. Rahman MM, Velayutham E. Renewable and non-renewable energy consumption-economic growth nexus: New evidence from South Asia. *Renewable Energy*. 2020; 147:399-408.
51. Pesaran MH. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*. 2007; 22(2):265-312.
52. Im KS, Pesaran MH, Shin Y. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*. 2003; 115(1):53-74.
53. Fisher, R.A., 1938. *Statistical Methods for Research Workers*, seventh ed. Rev. and Enl., Edinburgh Oliver and Boyd.
54. Harris RD, Tzavalis E. Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of Econometrics*. 1999; 91(2):201-226.
55. Akadiri SS, Akadiri AC. Examining the causal relationship between tourism, exchange rate, and economic growth in tourism island states: evidence from second-generation panel. *International Journal of Hospitality & Tourism Administration*. 2019:1-16.
56. Pesaran MH. General diagnostic tests for cross section dependence in panels. 2004.
57. Khan SAR, Jian C, Zhang Y, Golpîra H, Kumar A, Sharif A. Environmental, social and economic growth indicators spur logistics performance: from the perspective of South Asian Association for Regional Cooperation countries. *Journal of Cleaner Production*. 2019; 214:1011-1023.
58. Simpson D. Knowledge resources as a mediator of the relationship between recycling pressures and environmental performance. *Simpson, D (2012) Knowledge resources as a mediator of the relationship between recycling pressures and environmental performance Journal of Cleaner Production*. 2012; 22(1):32-41.
59. Parks RW. Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated. *Journal of the American Statistical Association*. 1967; 62(318):500-509.

60. Beck N, Katz JN. What to do (and not to do) with time-series cross-section data. *American Political Science Review*. 1995;634-647.
61. Le T-H, Nguyen CP. Is energy security a driver for economic growth? Evidence from a global sample. *Energy Policy*. 2019; 129:436-451.
62. Ikpesu F, Vincent O, Dakare O. Growth effect of trade and investment in Sub-Saharan Africa countries: Empirical insight from panel corrected standard error (PCSE) technique. *Cogent Economics & Finance*. 2019; 7(1):1607127.
63. Rao P, Griliches Z. Small-sample properties of several two-stage regression methods in the context of auto-correlated errors. *Journal of the American Statistical Association*. 1969; 64(325):253-272.
64. Alonso JM, Clifton J, Díaz-Fuentes D. The impact of government outsourcing on public spending: Evidence from European Union countries. *Journal of Policy Modeling*. 2017; 39(2):333-348.
65. Hao F. A study of ecologically unequal exchange for 89 countries between 1990 and 2015. *The Social Science Journal*. 2020; 57(2):245-257.
66. Levin A, Lin C-F, Chu C-SJ. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*. 2002; 108(1):1-24.
67. Bailey D, Katz JN. Implementing panel corrected standard errors in R: the pcse package. *Journal of Statistical Software*. 2011; 42(CS1):1-11.
68. Jönsson K. Cross-sectional dependency and size distortion in a small-sample homogeneous panel data unit root test. *Oxford Bulletin of Economics and Statistics*. 2005; 67(3):369-392.
69. Le T-H, Nguyen CP, Su TD, Tran-Nam B. The Kuznets curve for export diversification and income inequality: Evidence from a global sample. *Economic Analysis and Policy*. 2020; 65:21-39.
70. Marques AC, Fuinhas JA; Is renewable energy effective in promoting growth? *Energy Policy*. 2012; 46:434-442.
71. Liao H, Cao H-S. How does carbon dioxide emission change with the economic development? Statistical experiences from 132 countries. *Global Environmental Change*. 2013; 23(5):1073-1082.

72. Reed WR, Ye H. Which panel data estimator should I use? *Applied Economics*. 2011; 43(8):985-1000.
73. Zhang C, Nian J; Panel estimation for transport sector CO2 emissions and its affecting factors: A regional analysis in China. *Energy Policy*. 2013; 63:918-926.
74. Asongu SA, Efobi UR, Tanankem BV, Osabuohien ES: Globalisation and female economic participation in Sub-Saharan Africa. *Gender Issues*. 2020; 37(1):61-89.
75. Bergh A, Nilsson T; Good for living? On the relationship between globalization and life expectancy. *World Development*. 2010; 38(9):1191-1203.
76. Nixon J, Ulmann P. The relationship between health care expenditure and health outcomes. *The European Journal of Health Economics*. 2006; 7(1):7-18.
77. Varvarigos D. Environmental degradation, longevity, and the dynamics of economic development. *Environmental and Resource Economics*. 2010; 46(1):59-73.
78. McClellan MB. Health events, health insurance, and labor supply: Evidence from the health and retirement survey. In: *Frontiers in the Economics of Aging*. edn.: University of Chicago Press; 1998: 301-350.
79. Wu S. The effects of health events on the economic status of married couples. *Journal of Human Resources*. 2003; 38(1):219-230.

Declarations

- **Ethics approval and consent to participate:** This used secondary data from World Bank and British Petroleum data, so ethical approval and consent to participate are not needed.
- **Consent for publication:** Not applicable
- **Availability of data and materials:** The data used in this paper are available on World Bank and British Petroleum websites.
- **Acknowledgements:** Not Applicable
- **Competing interests:** We declare that they have no competing interest.
- **Funding:** We have not received any sponsorship/fund to conduct this research, so the publication of study results is not contingent on the sponsor's approval.
- **Authors' contributions:** MMR developed the concept, designed the study, performed statistical analysis and prepared the initial draft. RR wrote the background of the paper and reviewed the paper. RK helped in designing the study and analysing the results, and then reviewed the whole paper, and polished the paper throughout. All authors read and approved the final manuscript.