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The Impact of Climate Change on Life Expectancy in the UK: Empirical Evidence from Fourier Bootstrap ARDL Procedure

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Abstract
This study aims to determine the impact of surface temperature change, considered a proxy for climate change in the United Kingdom, on life expectancy using annual data from 1990–2021. Government expenditure is used as a control variable. The Fourier function-based bootstrap autoregressive distributed lag model is utilized to examine the cointegration among variables. The analysis outcomes reveal a long-term relationship between life expectancy, surface temperature change, and government expenditure. Furthermore, the findings reveal that surface temperature change significantly reduces life expectancy in the long run, while there is no significant relationship between the two variables in the short term. The Toda-Yamamoto causality analysis results show a unidirectional causality relationship between surface temperature change and life expectancy. Additionally, a significant bidirectional causality relationship is found between life expectancy and government expenditure.

Keywords
climate change, life expectancy; climate change and life expectancy; Fourier ARDL, Toda-Yamamoto causality test

Introduction

Climate change stands as a paramount global challenge of the 21st century, entailing far-reaching consequences for human health and well-being. According to the Intergovernmental Panel on Climate Change (IPCC), a body of the United Nations, greenhouse gas emissions predominantly caused by human activities have resulted in global warming, causing the global surface temperature to rise by 1.1°C above the period 1850–1900 during the years 2011–2020 (IPCC, 2023). Despite national commitments set by governments to reduce greenhouse gases, projections suggest that greenhouse gas emissions will increase in the future. Despite measures taken, greenhouse gas emissions are projected to contribute to an average global warming of 2.8°C by the year 2100 (IPCC, 2023). Climate experts anticipate more frequent and severe heat waves, extreme weather events, and rising sea levels as a result of climate change (Hansen et al., 2006). The escalating global warming elevates global surface temperatures and rapidly alters the world climate. This transformation is associated with adverse effects such as melting glaciers, diminishing winter snow cover, increasing droughts, rising sea levels, ocean acidification, elevated atmospheric water vapour, the proliferation of flood disasters, and an increased frequency of destructive storms. Changing climate and weather conditions negatively impact human lives in many parts of the world (Meierrieks, 2021). The aforementioned alterations in the physical environment pose substantial threats to human health, manifesting both directly and indirectly. Direct health consequences encompass heat-related illnesses and fatalities, injuries and fatalities arising from extreme weather events, and exposure to ultraviolet radiation (Harper et al., 2021). Indirect health consequences stem from the disruption of ecological and social systems, including the spread of infectious diseases, malnutrition, displacement, migration, conflict, and mental stress (Harper et al., 2021). Climate change increases the incidence of infectious diseases during both the summer and winter seasons, resulting in changes in morbidity and mortality rates (Goerre et al., 2007; Abrignani et al., 2012; Franchini & Mannucci, 2015). Furthermore, climate change arising from global warming adversely affects essential needs such as food and water, human health, national economies, and society (IPCC, 2023). These adversities negatively impact the quality of life and health of individuals. In summary, climate change is causing an increase in surface temperatures worldwide, and the potential effects of these changes on human health are becoming a growing source of concern. Air temperature emerges as a significant determinant affecting human life and health (Gasparrini et al., 2015). Moreover, climate-related temperature changes adversely affect household production activities, making lives more challenging. Therefore, the challenges mentioned above may indirectly result in negative implications for life expectancy.

Life expectancy epitomizes the cumulative effects of diverse factors that influence health, encompassing genetics, lifestyle, socioeconomic status, healthcare practices, and environmental exposures (Spiers et al., 2021). Therefore, life expectancy can be used as a measure of the health impacts of climate change. The negative impact of climate change varies geographically due to different local environmental conditions and the sensitivity of the local population (Watts et al., 2015). In this context, it is crucial to investigate the effects of climate change on life expectancy in the United Kingdom (UK), a geography where the impacts of industrialization, both pioneering and concluding, can be observed. In the UK, studies have shown that the extreme temperature threshold is exceeded in nearly every region (McCarthy et al., 2019). In the year 2019, the UK experienced a maximum temperature of 38.7 °C, a record-breaking maximum temperature (Sahani et al., 2022). A significant increase in mortality rates associated with this extreme temperature was observed (Brimicombe et al., 2021). Excessive urban heat, coupled with urbanization and population density increases, further elevates air pollutants, potentially making them more lethal.

According to the Human Development Index released by the United Nations Development Programme (UNDP) based on 2022 data, the life expectancy in the UK in 2019 was 81.7, dropping approximately by 1.22% to 80.7 in 2021 (UNDP, 2023). In this context, more efforts are required both in the UK and globally to minimize the adverse effects caused by extreme heat waves. Particularly, it is essential for further research on future climate changes in the UK and the impact of government policies on health. These efforts can be fostered through global initiatives and individual actions. Moreover, the utilization of eco-friendly materials in the construction of urban areas can effectively reduce the degradation of the global climate and environment (Imran et al., 2018; Debele et al., 2019). Raising awareness of environmentally friendly practices in production and consumption activities is another critical strategy.

Life expectancy is acknowledged as one of the key indicators reflecting a country's health and socioeconomic well-being (Nolte et al., 2002; Ho & Hendi, 2018). It signifies the average duration individuals are expected to live upon their birth, offering valuable insights into the overall quality of life within societies. Life expectancy, widely employed by prominent international organizations, typically constitutes a critical measure in conveying general health outcomes (World Health Organization, 2015; Salomon et al., 2012). Alongside per capita income and education, life expectancy serves as a crucial indicator of human development. Within the Human Development Index (HDI), measured and published by the UNDP, life expectancy at birth plays a role in calculations as a component of the health dimension of human development. As discussed above, the detrimental impacts of climate, particularly those related to temperature and surface conditions, may negatively impact life expectancy (Scovronick et al., 2018). Numerous factors can influence life expectancy at birth. However, climate change, which directly and indirectly affects many factors, can significantly affect life expectancy. Climate changes, leading to the deterioration of air quality and the spread of infectious diseases due to rising temperatures, may indirectly affect human health negatively (Haines et al., 2006). Furthermore, one of the factors that can influence life expectancy is government expenditures. These expenditures have been used as a control variable in the analyses. Government expenditures serve as an important reflection of a country's public policies and resource allocation. These expenditures encompass vital areas such as healthcare, education, environmental protection, and other social programs. In particular, healthcare expenditures and, consequently, a country's healthcare system are significant factors that influence life expectancy (Nixon & Ulmann, 2006).

In light of the crucial information provided above, the scientific investigation of the impact of climate change on health can be characterized as a current and significant topic. An important indicator of determining human life length is 'life expectancy.' Temperature changes have been utilized in numerous studies as an indicator of climate change. This study investigates the relationship between life expectancy and changes in surface temperature due to changes in air temperature and contributes to the health climate change literature. We believe that this study will contribute valuable insights into the complex relationship between climate change and life expectancy in the UK and will support the development of future policies. This study contributes to the existing literature in three ways. First, this is an attempt to examine the life expectancy-climate change nexus for the UK with current data. Second, the Fourier Function-based bootstrap autoregressive distributed lag approach is used to investigate the life expectancy-climate change nexus. This approach performs better than other methods because it more realistically analyzes the relationships between the dependent and independent variables with a nonlinear approach. Third, this study complements the limited knowledge available on the life expectancy-climate change nexus and contributes to a current topic being discussed.

This study is structured as follows: The literature review section provides a literature review on the topic. The Data and Methodology section explains the data used and the models applied. The Empirical Results section presents and interprets the findings. Finally, the Conclusion section explains the results, limitations, and contributions of this study to future research.

Literature Review

The relationship between climate change and life expectancy has become a significant research topic in recent years within the fields of environmental and health sciences. Several studies specifically focus on climate change's effects on human health, particularly its impact on life expectancy. These studies have investigated the association between climate change and life expectancy, employing diverse methodologies, data sources, and geographical scales.

Climate change can increase the frequency and intensity of heat waves. The adverse effects of heat waves on elderly individuals and those with chronic diseases can exert a substantial influence on life expectancy (Gasparrini et al., 2015). Climate change can result in a decrease in water resources and food insecurity. This situation can have an adverse impact on life expectancy by causing problems with nutrition and water supply (Wheeler & von Braun, 2013).

A substantial body of research examining the relationship between climate change and health demonstrates that climate change has direct and indirect effects on health. Notable among these impacts are factors such as the increased frequency of heat waves (Mitchell et al., 2016; Sahani et al., 2022), rising sea levels, and deteriorating air quality. Both extreme heat events and cold spells substantially elevate the risk of mortality by causing detrimental health consequences for individuals (Hajat et al., 2014). Investigations into the connection between temperature and health have been conducted using different methods in various countries. For instance, Scovronick et al. (2018) utilized the distributed lag nonlinear model (DLNM) methodology to investigate the relationship between daily maximum temperature and deaths in South Africa for the period 1997–2013. The analysis revealed a significant association between daily maximum temperature and mortality rate. Díaz et al. (2019), utilizing Generalized Linear Models (GLM) and meta-analysis techniques, analyzed the relationship between death rates and temperature in Spain from 1983 to 2013. Their analyses found that the impact of cold temperatures on mortality increased over time.

In the analysis conducted by Hauer and Santos-Lozada (2021), the potential impact of climate change on life expectancy in 31 European countries has been anticipated. It is projected that climate change extremes will reduce life expectancy by 0.24 years until the year 2100 for an average European country and may result in differences exceeding 1.0 years in some countries by 2100. Heo et al. (2019) analyzed the impact of temperature on mortality and morbidity in South Korea between 2011 and 2014 using DLNM and meta-analysis methods. The results of the analysis demonstrated that temperature significantly affects mortality and morbidity. Hu et al. (2019) conducted analyses using time series modelling (GLM) and random-effects meta-analysis methods, utilizing temperature variability and mortality rate data for the period 2005 –2009 in different regions of China. According to the results of the analysis, it was found that 5.33% of mortality rates were associated with temperature variability, with this percentage being 4.99% in urban areas and 6.02% in rural areas. Huber et al. (2020) predicted the significant impact of global warming on temperature-related deaths in Germany's 12 major cities during the period 1993 –2015 through their analysis of daily death counts and daily mean temperatures using the DLNM method. Khan et al. (2021), in their analysis using the DLNM method for the years 2003–2007 in the United States, investigated the relationship between exposure to outdoor temperatures in ageing adults and cognitive functions. Their analysis showed that individuals' exposure to temperature was associated with lower cognitive scores. Kewalani and Saifudeen (2021), using temperature as a measure of climate change, explored the impact of climate change on life expectancy. The study's results indicated that climate change has adverse effects on life expectancy. Ingole et al. (2022) examined the effect of daily mean temperature on mortality in India for the period 2004–2012 using the DLNM method. The study's findings suggested that the total number of deaths attributable to cold was higher than those attributable to heat.

A growing body of evidence suggests that health and social expenditures may play a role in determining life expectancy. For instance, Nixon and Ulmann (2006) and Jaba et al. (2014) have demonstrated a positive correlation between healthcare expenditures and average life expectancy. Linden and Ray (2017) have indicated that public expenditures are associated with higher life expectancy at higher levels. However, some studies have found that healthcare expenditures do not have an impact on health outcomes (Blázquez-Fernández et al., 2018).

Based on a comprehensive synthesis of the studies mentioned above, we may conclude that the frequency and intensity of heat waves brought on by climate change may impact life expectancy and contribute to reduced life expectancy for the elderly and people with chronic illnesses. Furthermore, as shown by several studies carried out using varied methodologies in various nations, this literature review methodically establishes a common foundation demonstrating the direct and indirect consequences of climate change on health. It also emphasizes the obvious need for more research in this area to lessen the severe and negative effects of global warming. In the studies discussed above, nonlinear methods were mostly preferred for analysis. The study topic was analyzed using nonlinear methods, which have become increasingly preferred in recent years.

The UK boasts a long-standing legacy of research and policy on climate change and health. It has deftly developed a range of frameworks and tools to assess and manage the health risks and opportunities presented by climate change. Nevertheless, a dearth of empirical evidence persists regarding the magnitude and direction of the climate-health nexus in the UK, particularly at the national level. Furthermore, the role of other influencing factors merits consideration, including government expenditure. Consequently, this study endeavours to bridge this knowledge gap by elucidating the impact of surface temperature change, a proxy for climate change, on life expectancy in the UK, utilizing annual data from 1990 to 2021. Government expenditure is incorporated as a control variable, given its potential to influence both population exposure and response to climate change.

Material and Method

a) Data Set

This study examines the effects of climate change and government expenditure on life expectancy using data in the UK from 1990-2021. The UK was chosen as a sample for four reasons. (i) The UK is vulnerable to various impacts of climate change, including extreme weather events, rising sea levels, and changes in temperature and precipitation patterns (Tsimplis et al. 2005). These factors can have significant implications for public health, including impacts on life expectancy. (ii) The UK has robust data collection systems, including healthcare records and meteorological data, which provide reliable information for conducting empirical research. (iii) The UK's advanced climate change policies make it an ideal case study for understanding the effects of climate change on life expectancy, offering valuable insights applicable to other regions with similar challenges. (iv) Finally, studying climate change's impact on life expectancy in the UK, with its advanced healthcare system and comprehensive climate data, can advance scientific understanding of this intricate relationship amid global climate concerns.

The variables used in this study, their definitions, and their sources are given in Table 1. STC and GEXP are considered independent variables, while LE is considered the dependent variable in the analysis. GEXP series is included in the model as a control variable and is obtained from the International Monetary Fund (IMF) Datamapper tool (IMF, 2023a). STC series were gathered from the IMF Climate Change Indicators Dashboard (IMF, 2023b). LE series were retrieved from UNDP (UNDP, 2023).

Tab. 1. Variables and their descriptions

Variables	Descriptions	Sources
LE	Life expectancy at birth	UNDP
STC	Surface Temperature Change	IMF
$GEXP$	Government Expenditure, per cent of GDP	IMF

To handle the dataset in detail, we plotted it from 1990 to 2021 in Figure 1. As can be seen in Figure 1, LE was at its highest level in 2019 but experienced a notable decline of approximately 1.6% in 2020 due to the impact of the pandemic. It can be said that the LE series has been in a significant increasing trend over the years, except for 2020. STC was at its lowest in 1996 but at its highest in 2014. Interestingly, STC exhibits a cyclical pattern, with periods of growth followed by periods of decline. It can be said that the reason for this trend is climate change due to global warming. Interestingly, GEXP displays a quasi-periodic pattern with an average cycle length of approximately 8 years, with its highest value in 2009. As Figure 1 shows, LE has increased over the years.

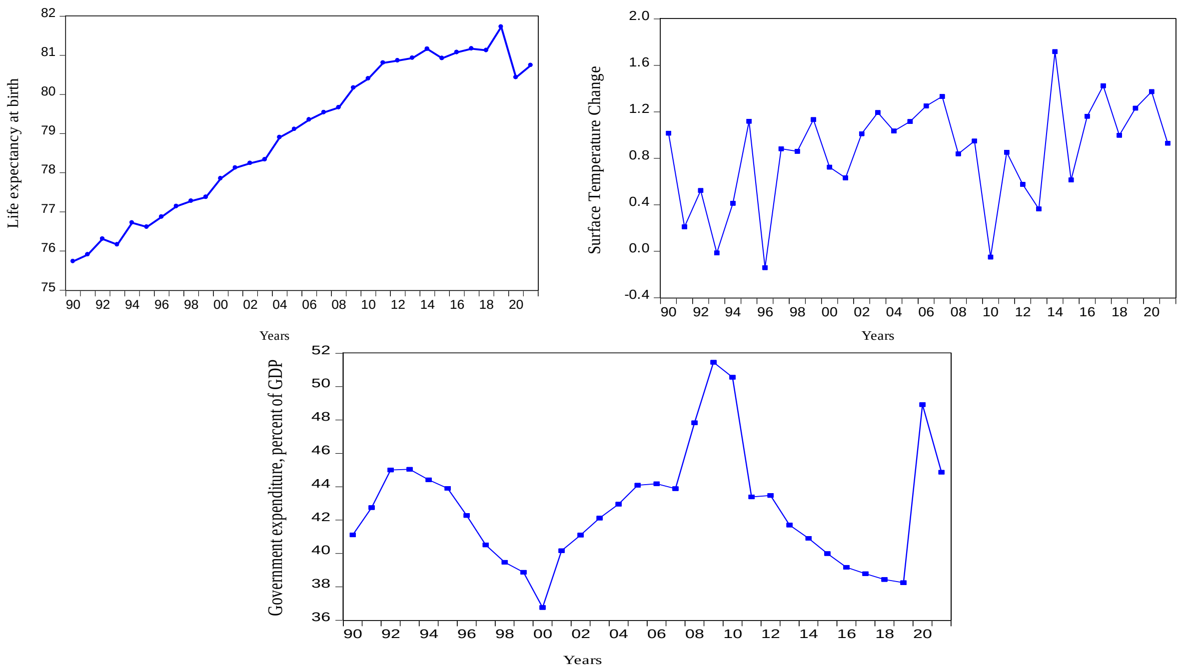

Fig. 1. Historical trends of dependent variable and independent variables

b) Fourier ARDL Cointegration Test

The model used for the long-term relationship between dependent and independent variables is assumed to be as given in Equation 2:

$$LE_t = \alpha_0 + \alpha_1 STC_t + \alpha_2 GEXP_t + \varepsilon_t \tag{1}$$

where α_0 is the constant term and ε_t is the error term. The parameters α_1 and α_2 represent slope coefficients values. Equation 1 can be tested using the Autoregressive Distributed Lag (ARDL) boundary test developed by Pesaran et al. (2001).To apply the Fourier function-based Bootstrap Autoregressive Distributed Lag (FARDL) procedure, equation (1) is rewritten within the framework of the error correction model to obtain equation (2).

$$\Delta LE_t = \varphi_0 + \sum_{t=1}^{p-1} \varphi_{1i} \Delta LE_{t-i} + \sum_{t=1}^{p-1} \varphi_{2i} \Delta STC_{t-i} + \sum_{t=1}^{p-1} \varphi_{3i} \Delta GEXP_{t-i}\, \alpha_2 + \theta_1 LE_{t-1} + \theta_2 STC_{t-1} + \theta_3 GEXP_{t-1} + \varepsilon_t \tag{2}$$

where Δ is the difference operator, and ε_t is the standard error term. φ_1, φ_2 and φ_3 is a short-term relationship, while θ_1, θ_2 and θ_3 are long-term relationships. Appropriate delay length is determined by the Akaike Information Criterion (AIC). To reject the null hypothesis, the F-test (F_A) and t-test (t) proposed by Pesaran et al. (2001) and the F-test (F_B) advanced by McNown et al. (2018) should be used (Yilanci et al. 2020). Accordingly, to test the joint significance of the delayed values of dependent and independent variables, the null hypothesis $H_{0A}: \theta_1 = \theta_2 = \theta_3 = 0$, should be rejected. To test the significance of only the delayed value of the dependent variable, the null hypothesis $H_{0t}: \theta_1 = 0$, and to test the significance of the delayed values of independent variables, the null hypothesis $H_{0B}: \theta_2 = \theta_3 = 0$ should be rejected. Using the Fourier function instead of dummy variables may lead to better results in capturing an unknown number of hard and soft structural breaks (Gallant and Souza, 1991). Therefore, to better capture structural breaks, Equation (3) uses the Fourier function (Yilanci et al. 2020).

$$d(t) = \sum_{k=1}^{n} \alpha_k sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k cos\left(\frac{2\pi kt}{T}\right) \tag{3}$$

In equation (3), π = 3.1416, and k represents the selected frequency value. Here, $d(t)$ denotes the deterministic trend, t represents the trend term, and T symbolizes the sample size. Based on this, a single-frequency equation, as formulated in equation (4), can be created, following the approach of Ludlow and Enders (2000) and Becker et al. (2006).

$$d(t) = \gamma_1 sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) \tag{4}$$

When the error correction model is appropriately adjusted to the Fourier function, equation (2) transforms into equation (5).

$$\Delta LE_t = \varphi_0 + \sum_{t=1}^{p-1} \varphi_{1i}\Delta LE_{t-i} + \sum_{t=1}^{p-1} \varphi_{2i}\Delta STC_{t-i} + \sum_{t=1}^{p-1} \varphi_{3i}\Delta GEXP_{t-i}\, \alpha_2 + \gamma_1 sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) + \theta_1 LE_{t-1} + \theta_2 STC_{t-1} + \theta_3 GEXP_{t-1} + \varepsilon_t \tag{5}$$

In Equation (5), when the frequency value (k) is an integer, the breaks are considered transient. Conversely, when the frequency value (k) is fractional, it indicates that the breaks are permanent (Christopoulos & Leon-Ledesma, 2011). All values within the range k = [0.1, ..., 5], with increments of 0.1, have been used to estimate equation (5) (Christopoulos & Leon-Ledesma, 2011; Omay, 2015). Critical values for F_A, F_B, and t have been calculated using bootstrap simulation.

c) Toda-Yamamoto Causality Test

To test causality, we used a modified Wald test developed by Toda and Yamamoto (1995). This test has two important advantages. First, by ignoring non-stationarity or cointegration between series, the modified Wald test avoids some problems associated with the ordinary Granger causality test (Zapata and Rambaldi, 1997; Wolde-Rufael, 2005). Second, in Toda and Yamamoto's (1995) approach, a VAR model is fitted to the levels of the variables, thereby minimizing the risk of incorrect identification of the order of integration (Mavrotas and Kelly, 2001). According to this method, the correct VAR order, k, is artificially enhanced by the maximal integration order, *dmax*. After these stages, the modified Wald hypothesis test is applied. To perform Toda and Yamamoto's (1995) causality test, the study model is specified with the VAR system below.

$$\boldsymbol{LE_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} LE_{t-i} + \sum_{j=k+1}^{d_{max}} \alpha_{2j} LE_{t-j} + \sum_{i=1}^{k} \beta_{1i} STC_{t-i} + \sum_{j=k+1}^{d_{max}} \beta_{2j} STC_{t-j} + \epsilon_{1t}} \tag{6}$$

$$\boldsymbol{STC_t = \gamma_0 + \sum_{i=1}^{k} \gamma_{1i} STC_{t-i} + \sum_{j=k+1}^{d_{max}} \gamma_{2j} STC_{t-j} + \sum_{i=1}^{k} \delta_{1i} LE_{t-i} + \sum_{j=k+1}^{d_{max}} \delta_{2j} LE_{t-j} + \epsilon_{2t}} \tag{7}$$

Eq (1) specifies Granger causality from STC_t to LE_t; similarly, Eq (2) implies Granger causality from LE_t to STC_t.

The Empirical Results

Table 2 reports the descriptive statistics of the dataset used in the analyses. It is worth noting that LE has the highest mean value, whereas STC contains the lowest mean value. GEXP has the lowest standard deviation, while the STC series contains the highest variation. Based on the *p*-value of the Jarque-Bera normality test, it can be stated that the series is not normally distributed.

Tab. 2. Descriptive statistics of variables

	LE	STC	GEXP
Mean	78.96169	0.852063	42.69959
Median	79.23330	0.938500	42.51265
Maximum	81.72500	1.718000	51.45880
Minimum	75.73590	-0.142000	36.76210
Std. Dev.	1.901536	0.445045	3.522169
Skewness	-0.232096	-0.581264	0.716100
Kurtosis	1.608469	2.864621	3.207222
Jarque-Bera	2.869109	1.826396	2.792181
Probability	0.238222	0.401239	0.247563

Sum	2526.774	27.26600	1366.387
Sum Sq. Dev.	112.0910	6.140008	384.5759
Observations	32	32	32

Prior to employing the Fourier Augmented Dickey-Fuller (FADF) unit root test, it is essential to evaluate the statistical significance of the Fourier function. If the Fourier function is statistically significant, the FADF unit root test can be applied; otherwise, the traditional ADF unit root test should be used to evaluate the stationarity properties of the series (Ozgur et al., 2022). The results of the tests in Table 3 demonstrate the significance of Fourier functions for all variables. Consequently, the null hypothesis value is tested for these variables using the Fourier ADF unit root test.

An examination of the FADF unit root test results in Table 3 reveals that the dependent variable, LE, is not stationary at the level. However, LE exhibits stationarity in its first difference. Additionally, the independent variables, STC and GEXP, are found to be stationary at the level. The critical value at the 5% significance level for a sample size of 100 is 7.58. The F-statistic values for all variables are greater than the critical value of 7.58 at the 5% significance level, leading to the rejection of the null hypothesis of no linear trend. Therefore, the FADF test can be used as a more robust alternative to the traditional ADF test in the presence of nonlinear trends.

Tab. 3. FADF and ADF unit root test results

Variables	Min RSS	k	FADF	F-statistic
LE	1.611813	1	-0.871010	9.457177
STC	3.411671	2	-5.219877	25.73465
GEXP	113.2523	2	-4.030509	11.57769
D(LE)	1.639496	1	-3.872216	8.305820

Note: At the 5% significance level, the FADF unit root test critical values are -3.81 for k=1 and -3.27 for k=2, and for the F-test, it is 7.58.

Since the variables have been confirmed to be stationary, we can use the FARDL cointegration test to examine the long-term relationship between variables, applying the model specified in Equation 2. The FARDL cointegration test results are presented in Table 4. Based on the test results, the optimal frequency value is identified as 0.5. Furthermore, the F_A and F_B test statistics are found to be significant at the 10% level, and the t-test statistic is also significant at the 1% level. These findings collectively indicate the presence of a long-term relationship between the variables. In conclusion, we establish the existence of a cointegration relationship between LE, STC, and GEXP.

Tab. 4. Fourier ARDL cointegration test results

Selected Model: FARDL(2, 1, 2)		Optimal Frequency: 0.5	AIC: -0.55277	
Test Statistics	Test Statistics Value	Bootstrap Critical Values		
		%10	%5	%1
F_A	6.513815*	5.6698515	6.8299749	10.72902
t	-4.244469**	−3.609565	-4.0502471	−5.114761
F_B	5.085515*	4.8706935	6.358044	9.866034

Note: * and ** indicate significance at 10% and 5% levels, respectively. We performed 4000 simulations to obtain the critical values.

In Table 5, there are long-term estimates that are statistically significant at the 5% level, except for GEXP. The STC coefficient is negative is negative, indicating that STC reduces LE. It shows that in the long run, a one-unit increase in STC also leads to a decrease of approximately 0.18 years in life expectancy. This result may suggest uncertainty in global climate policies in the long term and the government's perception of environmental degradation as a serious issue in the UK. Furthermore, this finding highlights the potential effects of global warming and environmental factors on human health. These findings are consistent with Sewe et al. (2018), Abdulkadir et al. (2018), Hauer and Santos-Lozada (2021), Kewalani and Saifudeen (2021), and Rahman et al. (2022). In recent years, global warming-induced disasters, manifested through human activities that contribute to environmental degradation, have become a reality, adversely impacting human health and quality of life. A trend variable representing this situation has been included in the model. In the long term, it is observed that global warming significantly reduces the life expectancy associated with this adverse trend (Table 5). This situation suggests a significant decrease in LE as a result of the intensification of disasters associated with global warming. This finding reinforces concerns about the health risks associated with climate change. The results of our study show that climate change could slow the increase in life expectancy in the UK if action is not taken. Forzieri et al. (2017) estimated that climate change-related disasters could affect approximately two-thirds of the European population by 2100. Furthermore, the study findings revealed that GEXP has no statistically significant long-term impact on LE. This finding suggests uncertainty about the impact of government expenditures on life expectancy. However, some studies indicate that health expenditures, rather than general public expenditures, contribute to improving life expectancy (Nixon and Ulmann 2006; Jaba et al. 2014; Nkemghae et al. 2021).

Tab. 5. Long-run estimation results (Dependent variable: LE)

Variables	Coefficient	Std. Error	Prob.
STC	-0.180482**	0.079500	0.0350
GEXP	-0.002336	0.007396	0.7556
TREND	-6.287728***	0.645936	0.0000

Note: ** $p < 0.05$; *** $p < 0.01$.

An error correction model (ECM) was estimated using the FARDL procedure to examine short-term dynamics. The short-term results are presented in Table 6. The results have not revealed a significant short-term relationship between STC and LE. This finding indicates that STC does not explain LE in the short term. Contrary to expectations, no statistically significant relationship between LE and GEXP was observed in the short term. The coefficient of GEXP exhibits a negative sign, indicating a potential adverse effect of government expenditures on LE in the short term. Namely, government spending does not align with the expected signs. Although coefficients in empirical studies may be statistically significant, they may not always have the expected signs according to a priori economic criteria. The control variable, GEXP, is found to have a negative impact on LE at a significance level of 10%. This result aligns with findings from Ogbonna and Ogbeide (2016) for Nigeria and Blazquez-Fernández et al. (2018) for a panel of the United States and some OECD countries, suggesting a potential inefficiency of public expenditures in the short term. Therefore, carefully considering cost-effectiveness analyses should guide public spending decisions rather than relying solely on increased expenditures (Blazquez-Fernández et al., 2018).

The error correction term ECT(-1) coefficient is statistically significant and negative, indicating that deviations from the long-term equilibrium tend to be corrected over time. Based on the cointegration equation, the value of ECT(−1) is another method used to confirm a long-term connection between variables. Thus, our findings underscore the importance of feedback mechanisms in stabilizing life expectancy (LE) in the UK. The coefficient of the ECT term (-1.91) indicates that the deviation in LE is corrected by approximately 191% in the following year. However, no significant relationship between STC and LE has been detected in the short term.

Tab. 6. Short-run estimation results.

Variable	Coefficient	Std. Error	Prob.
ΔLE_{t-1}	-0.504458**	0.212171	0.0281
ΔLE_{t-2}	-0.405098*	0.223899	0.0863
ΔSTC_{t}	-0.120002	0.092495	0.2100
ΔSTC_{t-1}	-0.224639**	0.093067	0.0260
$\Delta GEXP_{t}$	-0.025488*	0.013993	0.0843
$\Delta GEXP_{t-1}$	-0.008590	0.021429	0.6930
$\Delta GEXP_{t-2}$	0.029618	0.018852	0.1327
γsin	615.7111***	103.1513	0.0000
γcos	-167.6352***	30.97554	0.0000
C	313.0195***	53.22544	0.0000
ECT_{t-1}	-1.909556***	0.282649	0.0000
R^2	0.994691		
Adjusted R^2	0.991897		
F test	355.9915***		

Note: γsin and γcos show Fourier terms. * p<0.10; ** p<0.05; *** p<0.01.

Diagnostic tests of the model are presented in Table 7. The value of adjusted R-squared indicates that approximately 99% of the variation in LE is explained by STC and GEXP. The Ramsey RESET set suggests that the model is correctly specified, while the LM test demonstrates the absence of serial correlation. The Breusch-Pagan-Godfrey test confirms that heteroskedasticity is not an issue.

Tab. 7. Diagnostics tests

Adjusted R^2	F-statistic	Prob.
Ramsey RESET test	0.117221	0.9080
LM test	1.744020	0.5551
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.894925	0.5551

CUSUM and CUSUM-square tests showing the stability of the model are given in Figure 2. The findings from the CUSUM and CUSUM-square tests reveal that the estimated model is stable.

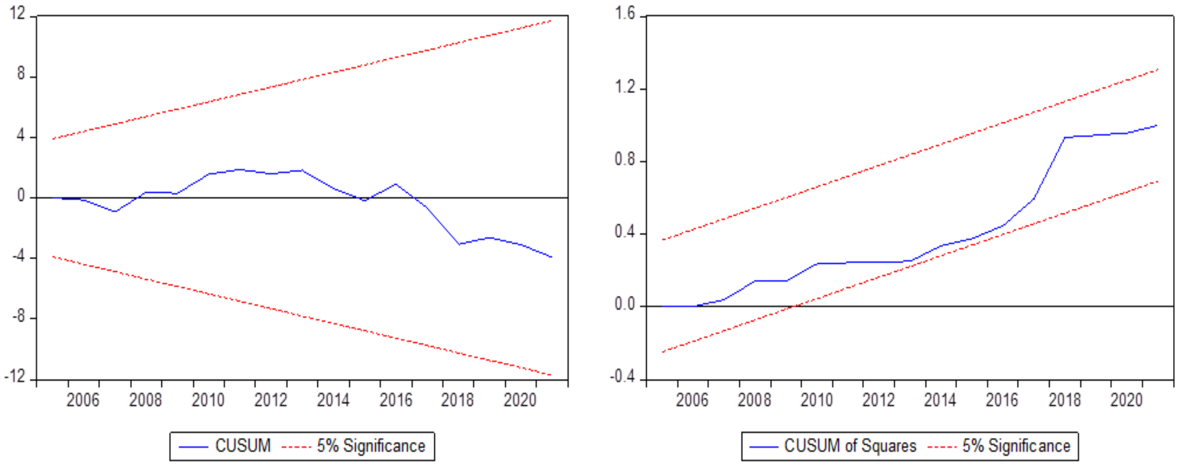

Fig. 2. CUSUM and CUSUM-square test.

Following the cointegration analysis that established a long-run relationship, we used the Toda-Yamamoto causality tests to investigate causal relationships. As shown in Table 8, the causality analysis results indicate a one-way causal relationship from STC to LE at a 5% significance level. This result is consistent with Rahman and Alam (2022) findings. Additionally, a significant bidirectional causal relationship exists between LE and GEXP. This finding aligns with the study by Ogunsakin and Olonisakin (2017). Both STC and GEXP can be considered causes of LE. A nexus between STC, GEXP, and LE can be inferred in this context. Furthermore, a unidirectional causality relationship from GEXP to STC at a 5% significance level is identified.

Tab. 8. Toda – Yamamoto Causality analysis results

Model	Lag Length (k+dmax)	Wald tests χ^2 statistic	χ^2 Table Value	Relationship and Direction
LE=f(STC)		0.039^{**}	9.081	STC → LE
STC=f(LE)		0.182	4.863	No
LE=f(GEXP)	2+1	0.032^{**}	8.780	LE ↔ GEXP
GEXP=f(LE)		0.009^{***}	9.342	
GEXP=f(STC)		0.390	1.885	No
STC=f(GEXP)		0.044^{**}	8.086	GEXP → STC

Note: $p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. The LM autocorrelation test statistic (LM stat: 12.53722, prob.: 0.8280) indicates that the probability value for the second lag length exceeds 10%, suggesting the absence of autocorrelation issues.

Conclusion

Research on the relationship between climate and life expectancy has been limited and inconsistent, highlighting the need for further investigation. This study investigated the impact of surface temperature change, which represents climate change, on life expectancy using an annual time series dataset for the UK. The Fourier ADF unit root test was used to evaluate the presence of a unit root in the dataset. Short- and long-term relationships were analyzed with the Fourier ARDL boundary test. The causality relationship between variables was examined using the Toda-Yamamoto causality test. The Fourier function-based Bootstrap ARDL model confirmed the existence of a long-run cointegration relationship among the variables. Also, using the Fourier ARDL test, a significant relationship between surface temperature change and life expectancy in the long term was confirmed. Findings obtained from the Fourier ARDL approach showed that surface temperature change reduced life expectancy in the long term, while there was no significant relationship between the two variables in the short term. These findings suggest that surface temperature change, and consequently life expectancy, has declined over time. Additionally, unlike in the short term, government expenditure was not found to affect life expectancy in the long term. Causality results indicated a unidirectional causal relationship between surface temperature change and life expectancy and a significant bidirectional causal relationship between life expectancy and government expenditure. Namely, the Toda-Yamamoto causality analysis indicated that there was a unidirectional causality running from surface temperature change to life expectancy, supporting the hypothesis that climate change affects human health and longevity.

In light of the findings mentioned above, several policy recommendations can be formulated. These findings suggest that policymakers need to take measures, especially in the long term, to balance variability in surface temperature change. To achieve this balance and curb the adverse effects of climate change, well-defined and long-term climate policies must be established and implemented. Fluctuations in surface temperature change in the UK are not solely attributable to domestic activities; they are also influenced by activities taken by other countries. In this context, policymakers should intensify their efforts to foster global unity of action in counteracting the negative impacts of surface temperature change.

To balance the variability and adverse effects of surface temperature change, UK policymakers should implement special incentives for increasing the production and consumption of renewable energy. In this regard, policies such as reducing tariffs on renewable energy imports, increasing research and development funding for renewable sources, and providing interest-free loans for renewable energy investments hold significant promise. Additionally, the UK government can alleviate the negative impact of climate change on healthcare systems by implementing more proactive measures aligned with the Sustainable Development Goals. Such policies can also curb the production and consumption of fossil fuels, which are primary contributors to global warming. Furthermore, policymakers and researchers should incorporate surface temperature change into development modelling and forecasting for the UK, as surface temperature change can, directly and indirectly, influence development trajectories. For future research directions, the impact of surface temperature change on other dimensions of development, such as education, income, and social structure, can also be explored.

Considering the limitations of the study, it is crucial to conduct a more in-depth examination of government spending and incorporate other potential influencing factors. Additionally, analyzing specific types of climate-related disasters can provide a more nuanced understanding of their impact.

References

Abdulkadir, A., Lawal, A. M., & Muhammad, T. (2018). Climate change and its implications on human existence in Nigeria: A review. *Bayero Journal of Pure and Applied Sciences*, *10*(2), 152-158. https://doi.org/10.4314/bajopas.v10i2.26

Abrignani, M. G., Corrao, S., Biondo, G. B., Lombardo, R. M., Di Girolamo, P., Braschi, A., Di Girolamo, A. & Novo, S. (2012). Effects of ambient temperature, humidity, and other meteorological variables on hospital admissions for angina pectoris. *European Journal of Preventive Cardiology*, *19*(3), 342-348. https://doi.org/10.1177/1741826711402741

Becker, R., Enders, W., & Lee, J. (2006). A stationarity test in the presence of an unknown number of smooth breaks. *Journal of Time Series Analysis*, *27*(3), 381-409. https://doi.org/10.1111/j.1467-9892.2006.00478.x

Blázquez-Fernández, C., Cantarero-Prieto, D., & Pascual-Saez, M. (2018). Does rising income inequality reduce life expectancy? New evidence for 26 European countries (1995–2014). *Global Economic Review*, *47*(4), 464–479. https://doi.org/10.1080/1226508X.2018.1526098

Brimicombe, C., Porter, J. J., Di Napoli, C., Pappenberger, F., Cornforth, R., Petty, C., & Cloke, H. L. (2021). Heatwaves: An invisible risk in UK policy and research. *Environmental Science & Policy*, *116*, 1-7. https://doi.org/10.1016/j.envsci.2020.10.021

Christopoulos, D. K. & Leon-Ledesma, M. A. (2011). International output convergence, breaks, and asymmetric adjustment. *Studies in Nonlinear Dynamics & Econometrics*, *15*(3), 1-33. https://doi.org/10.2202/1558-3708.1823

Debele, S. E., Kumar, P., Sahani, J., Marti-Cardona, B., Mickovski, S. B., Leo, L. S., Porcù, F., Bertini, F., Montesi, D., Vojinovic, Z., & Di Sabatino, S. (2019). Nature-based solutions for hydro-meteorological hazards: Revised concepts, classification schemes and databases. *Environmental Research*, *179*, 108799. https://doi.org/10.1016/j.envres.2019.108799

Díaz, J., Carmona, R., Mirón, I. J., Luna, M. Y., & Linares, C. (2019). Time trends in the impact attributable to cold days in Spain: Incidence of local factors. *Science of the Total Environment*, *655*, 305-312. https://doi.org/10.1016/j.scitotenv.2018.11.254

Forzieri, G., Cescatti, A., Silva, F. B., & Feyen, L. (2017). Increasing risk over time of weather-related hazards to the European population: a data-driven prognostic study. *The Lancet Planetary Health*, *1*(5), e200-e208. https://doi.org/10.1016/S2542-5196(17)30082-7

Franchini, M., & Mannucci, P. M. (2015). Impact on human health of climate changes. *European Journal of Internal Medicine*, *26*(1), 1-5. https://doi.org/10.1016/j.ejim.2014.12.008

Gallant, A. R., & Souza, G. (1991). On the asymptotic normality of Fourier flexible form estimates. *Journal of Econometrics*, *50*(3), 329-353. https://doi.org/10.1016/0304-4076(91)90024-8

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., ... & Armstrong, B. (2015). Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *The Lancet*, *386*(9991), 369-375. https://doi.org/10.1016/S0140-6736(14)62114-0

Goerre, S., Egli, C., Gerber, S., Defila, C., Minder, C., Richner, H., & Meier, B. (2007). Impact of weather and climate on the incidence of acute coronary syndromes. *International Journal of Cardiology*, *118*(1), 36-40.

https://doi.org/10.1016/j.ijcard.2006.06.015
Haines, A., Kovats, R. S., Campbell-Lendrum, D., & Corvalán, C. (2006). Climate change and human health: Impacts, vulnerability, and mitigation. *The Lancet*, *367*(9528), 2101-2109. https://doi.org/10.1016/j.puhe.2006.01.002.
Hajat, S., Vardoulakis, S., Heaviside, C., & Eggen, B. (2014). Climate change effects on human health: Projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s. *Journal Epidemiol Community Health*, *68*(7), 641-648. https://doi.org/10.1136/jech-2013-202449
Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D. W., & Medina-Elizade, M. (2006). Global temperature change. *Proceedings of the National Academy of Sciences*, *103*(39), 14288-14293. https://doi.org/10.1073/pnas.0606291103
Harper, S. L., Cunsolo, A., Babujee, A., Coggins, S., Aguilar, M. D., & Wright, C. J. (2021) Climate change and health in North America: Literature review protocol. *Systematic Reviews*, *10*(3), 1-13. https://doi.org/10.1186/s13643-020-01543-y
Hauer, M. E., & Santos-Lozada, A. R. (2021). Inaction on climate change projected to reduce European life expectancy. *Population Research and Policy Review*, *40*, 629-638. https://doi.org/10.1007/s11113-020-09584-w
Heo, S., Bell, M. L., & Lee, J. T. (2019). Comparison of health risks by heat wave definition: Applicability of wet-bulb globe temperature for heat wave criteria. *Environmental Research*, *168*, 158-170. https://doi.org/10.1016/j.envres.2018.09.032
Ho, J. Y., & Hendi, A. S. (2018). Recent trends in life expectancy across high income countries: Retrospective observational study. *British Medical Journal*, *362*. https://doi.org/10.1136/bmj.k2562
Hu, K., Guo, Y., Yang, X., Zhong, J., Fei, F., Chen, F., Zhao, Q., Zhang, Y., Chen, G., Chen, Q., Ye, T., Li, S., & Qi, J. (2019). Temperature variability and mortality in rural and urban areas in Zhejiang province, China: An application of a spatiotemporal index. *Science of the Total Environment*, *647*, 1044-1051. https://doi.org/10.1016/j.scitotenv.2018.08.095
Huber, V., Krummenauer, L., Peña-Ortiz, C., Lange, S., Gasparrini, A., Vicedo-Cabrera, A. M., Garcia-Herrera, R., & Frieler, K. (2020). Temperature-related excess mortality in German cities at 2° C and higher degrees of global warming. *Environmental Research*, *186*, 109447. https://doi.org/10.1016/j.envres.2020.109447
IMF. (2023a). Datamapper, https://www.imf.org/external/datamapper/exp@FPP/USA/FRA/JPN/GBR/SWE/ESP/ITA/ZAF/IND Accessed on 31 August 2023)
IMF. (2023b). Climate Change Indicators Dashboard, https://climatedata.imf.org/datasets/4063314923d74187be9596f10d034914/explore (Accessed on 31 August 2023)
Imran, H. M., Kala, J., Ng, A. W. M., & Muthukumaran, S. (2018). Effectiveness of green and cool roofs in mitigating urban heat island effects during a heatwave event in the city of Melbourne in southeast Australia. *Journal of Cleaner Production*, *197*, 393-405. https://doi.org/10.1016/j.jclepro.2018.06.179
Ingole, V., Sheridan, S. C., Juvekar, S., Achebak, H., & Moraga, P. (2022). Mortality risk attributable to high and low ambient temperature in Pune city, India: A time series analysis from 2004 to 2012. *Environmental Research*, *204*, 112304. https://doi.org/10.1016/j.envres.2021.112304
Intergovernmental Panel on Climate Change (IPCC) (2023). Climate Change 2023 Synthesis Report. Available at http://www.ipcc.ch/. 10.10.2023
Jaba, E., Balan, C., & Robu, I. (2014). The relationship between life expectancy at birth and health expenditures estimated by a cross-country and time-series analysis. *Procedia Economics and Finance*, *15*, 108–114. https://doi.org/10.1016/S2212-5671(14)00454-7
Kewalani, R., & Saifudeen, I. S. H. (2021). Exploring human longevity: The impact of climate on life expectancy. *International Journal of High School Research*, 28-34. https://doi.org/10.36838/v3i3.7
Khan, A. M., Finlay, J. M., Clarke, P., Sol, K., Melendez, R., Judd, S., & Gronlund, C. J. (2021). Association between temperature exposure and cognition: A cross-sectional analysis of 20,687 aging adults in the United States. *BMC Public Health*, *21*(1), 1-12. https://doi.org/10.1186/s12889-021-11533-x
Linden, M., & Ray, D. (2017). Life expectancy effects of public and private health expenditures in OECD countries 1970–2012: Panel time series approach. Economic Analysis and Policy, 56, 101–113. https://doi.org/10.1016/j.eap.2017.06.005
Ludlow, J., & Enders, W. (2000). Estimating nonlinear ARMA models using Fourier coefficients. *International Journal of Forecasting*, *16*(3), 333-347. https://doi.org/10.1016/S0169-2070(00)00048-0
Mavrotas, G., & Kelly, R. (2001). Old wine in new bottles: Testing causality between savings and growth. *The Manchester School*, *69*, 97-105. https://doi.org/10.1111/1467-9957.69.s1.6
McCarthy, M., Armstrong, L., & Armstrong, N. (2019). A new heatwave definition for the UK. *Weather*, *74*(11), 382-387. https://doi.org/10.1002/wea.3629
McNown, R., Sam, C. Y., & Goh, S. K. (2018). Bootstrapping the autoregressive distributed lag test for

cointegration. Applied Economics, 50(13), 1509-1521. https://doi.org/10.1080/00036846.2017.1366643
Meierrieks, D. (2021). Weather shocks, climate change and human health, *World Development*, *138*, 105228, https://doi.org/10.1016/j.worlddev.2020.105228.
Mitchell, D., Heaviside, C., Vardoulakis, S., Huntingford, C., Masato, G., Guillod, B. P., Frumhoff, P.Ç., Bowery, A., Wallom, D., & Allen, M. (2016). Attributing human mortality during extreme heat waves to anthropogenic climate change. *Environmental Research Letters*, *11*(7), 074006. https://doi.org/10.1088/1748-9326/11/7/074006
Nixon, J., & Ulmann, P. (2006). The relationship between health care expenditure and health outcomes. *The European Journal of Health Economics*, *7*(1), 7–18. https://doi.org/10.1007/s10198-005-0336-8
Nkemgha, G.Z., Tékam, H.O. & Belek, A. (2021). Healthcare expenditure and life expectancy in Cameroon. *Journal of Public Health*, *29*, 683–691. https://doi.org/10.1007/s10389-019-01181-2
Nolte, E., Scholz, R., Shkolnikov, V., & Mckee, M. (2002). The contribution of medical care to changing life expectancy in Germany and Poland. *Social Science & Medicine*, *55*(11), 1905–1921. https://doi.org/10.1016/S0277-9536(01)00320-3
Ogbonna, G., & Ogbeide, S. O. (2016). Government health expenditure and life expectancy in Nigeria empirical analysis. *Rhema University Journal of Management and Social Sciences*, *3*(2), 95-106.
Ogunsakin, S., & Olonisakin, T. (2017). Health expenditure distribution and life expectancy in Nigeria. International *Journal of Scientific and Research Publications*, *7*(7), 336-340.
Omay, T. (2015). Fractional frequency flexible Fourier form to approximate smooth breaks in unit root testing. *Economics Letters*, *134*, 123-126. https://doi.org/10.1016/j.econlet.2015.07.010
Ozgur, O., Yilanci, V., & Kongkuah, M. (2022). Nuclear energy consumption and CO2 emissions in India: Evidence from Fourier ARDL bounds test approach. *Nuclear Engineering and Technology*, *54*(5), 1657-1663. https://doi.org/10.1016/j.net.2021.11.001
Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326. https://doi.org/10.1002/jae.616
Rahman, M. M., & Alam, K. (2022). Life expectancy in the ANZUS-BENELUX countries: The role of renewable energy, environmental pollution, economic growth and good governance. *Renewable Energy*, *190*, 251-260. https://doi.org/10.1016/j.renene.2022.03.135
Rahman, M. M., Rana, R., & Khanam, R. (2022). Determinants of life expectancy in most polluted countries: Exploring the effect of environmental degradation. *PloS One*, *17*(1), e0262802. https://doi.org/10.1371/journal.pone.0262802
Sahani, J., Kumar, P., Debele, S., & Emmanuel, R. (2022). Heat risk of mortality in two different regions of the United Kingdom. *Sustainable Cities and Society*, *80*, 103758. https://doi.org/10.1016/j.scs.2022.103758
Salomon, J. A., Wang, H., Freeman, M. K., Vos, T., Flaxman, A. D., Lopez, A. D., & Murray, C. J. (2012). Healthy life expectancy for 187 countries, 1990–2010: A systematic analysis for the Global Burden Disease Study 2010. *The Lancet*, *380*(9859), 2144-2162. https://doi.org/10.1016/S0140-6736(12)61690-0
Scovronick, N., Sera, F., Acquaotta, F., Garzena, D., Fratianni, S., Wright, C. Y., & Gasparrini, A. (2018). The association between ambient temperature and mortality in South Africa: A time-series analysis. *Environmental Research*, *161*, 229-235. https://doi.org/10.1016/j.envres.2017.11.001
Sewe, M O., Bunker, A., Ingole, V., Egondi, T., Åström, D. O., Hondula, D. M., Rocklöv, J., & Schumann, B. (2018). Estimated effect on temperature on years of life lost: A retrospective time–series of low, middle and high-income regions. *Environmental Health Perspectives*, *126*(1), 1–12. https://doi.org/10.1289/EHP174
Spiers, G.F., Kunonga, T.P., Beyer, F., Craig, D., Hanratty, B., & Jagger, C. (2021). Trends in health expectancies: a systematic review of international evidence. *BMJ Open*, *11*(2021), e045567. https://doi.org/10.1136/bmjopen-2020-045567
Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66*(1-2), 225-250. https://doi.org/10.1016/0304-4076(94)01616-8
Tsimplis, M. N., Woolf, D. K., Osborn, T. J., Wakelin, S., Wolf, J., Flather, R., Shaw, A.G.P., Woodworth, P., Challenor, P., Blackman, D., Pert, F., Yan, Z., & Jevrejeva, S. (2005). Towards a vulnerability assessment of the UK and northern European coasts: The role of regional climate variability. Philosophical Transactions of the Royal Society A: Mathematical, *Physical and Engineering Sciences*, *363*(1831), 1329-1358. https://doi.org/10.1098/rsta.2005.1571
UNDP. (2023). Human Development Report, 2022, https://hdr.undp.org/data-center/human-development-index#/indicies/HDI https://hdr.undp.org/data-center/human-development-index#/indicies/HDI (Accessed on 31 August 2023)
Watts, N., Adger, W. N., Agnolucci, P., Blackstock, J., Byass, P., Cai, W., ... & Costello, A. (2015). Health and climate change: policy responses to protect public health. *The Lancet*, *386*(10006), 1861-1914. https://doi.org/10.1016/S0140-6736(15)60854-6
Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science*, *341*(6145), 508-513. https://doi.org/10.1126/science.1239402

Wolde-Rufael, Y. (2004). Disaggregated industrial energy consumption and GDP: the case of Shanghai, 1952–1999. *Energy Economics*, *26*(1), 69-75. https://doi.org/10.1016/S0140-9883(03)00032-X

World Health Organization (2015), World health statistics 2015, World Health Organization.

Yilanci, V., Bozoklu, S., & Gorus, M. S. (2020). Are BRICS countries pollution havens? Evidence from a Bootstrap ARDL Bounds Testing Approach with a Fourier Function. *Sustainable Cities and Society*, *55*, 102035, 1-12. https://doi.org/10.1016/j.scs.2020.102035

Zapata, H. O., & Rambaldi, A. N. (1997). Monte Carlo evidence on cointegration and causation. *Oxford Bulletin of Economics and Statistics*, *59*(2), 285-298. https://doi.org/10.1111/1468-0084.00065