



Research article

Green investments as drivers of longevity: empirical insights for policy framework design

Elio Borgonovi¹, Mihaela Onofrei^{2,*}, Bogdan Narcis Fîrțescu² and Dana Claudia Cojocaru³

¹ Department of Social & Political Sciences, Bocconi University, Milan, 20136, Italy

² Finance, Money and Public Administration Department, Alexandru Ioan Cuza University, Carol I Boulevard, No. 22, Iași, 700505, Romania

³ Doctoral School of Economics and Business Administration, Alexandru Ioan Cuza University, Carol I Boulevard, No. 22, Iași, 700505, Romania

* **Correspondence:** Email: onofrei@uaic.ro; Tel: +4-023-220-1429.

Abstract: Against the backdrop of intensifying global efforts to combat climate change, green investments have taken on a strategic role in promoting sustainable economic growth, with direct and indirect implications for public health. The novelty of this study lies in exploring a rarely addressed area of research that links green investments to public health outcomes, as measured by life expectancy. Thus, this study has two main objectives: First, in an initial phase, we explore how air quality, lifestyle factors, and economic growth influence life expectancy. Subsequently, the study analyses the effect of greenfield investments, energy efficiency, and gross domestic product (GDP) on environmental degradation (greenhouse gas (GHG) emissions). To achieve this dual-objective approach, we constructed an original panel dataset covering 35 Organisation for Economic Co-operation and Development (OECD) member states for the period 2003–2023. Utilizing non-linear econometric modelling, our findings reveal that greenhouse gas emissions significantly reduce life expectancy. Moreover, our research has shown that green energy used efficiently can act as a critical mitigator of environmental pressure related to the context of greenfield investments and rapid economic expansion. These results underscore the need for targeted health policies that drive economic growth through resilient investments, thus sustaining gains in human longevity. It also helps integrate the evaluation of companies' economic and financial results with the assessment of positive externalities and non-financial results recently introduced in the European directives on integrated reporting.

Keywords: green investment; life expectancy; green technology innovation; energy efficiency; policy implications

JEL Codes: I15, I31, H51, F64

1. Introduction

In the process of expanding companies into international markets, foreign direct investment (FDI) plays a fundamental role due to their multiple advantages, among which we can mention the increase in gross domestic product (GDP), the dynamics of the labour market, trade, and the improvement of living conditions. In the context of intensifying competition, countries are increasingly interested in attracting growing flows of FDI, while at the same time promoting more flexible public policies to convince investors to participate in the process.

As a result of this permissive environment on the part of public officials, global carbon dioxide (CO₂) emissions, the dominant component of greenhouse gas (GHG) emissions, have increased from 10.9 billion tons per year in 1960 to about 36.8 billion tons per year in 2023, the latter being the final year considered in the empirical analysis (Friedlingstein et al., 2026; NOAA, 2024). This upward trajectory continued in the subsequent period, with an increase of approximately 37.4 billion metric tons recorded in 2024 (Global Carbon Budget, 2024), followed by a further increase in 2025 (Global Carbon Budget, 2025). Furthermore, researchers in the field have demonstrated that exposure to air pollutants affects long-term mental health, cognitive ability, and individual productivity (Yang and Yin, 2024). In addition, since the emergence of SARS-CoV-2, the health issue has attracted worldwide interest, and researchers in the field argue that the mental health of the population has worsened even more (Solmi et al., 2024). It is estimated that between 2030–2050, climate change will cause an estimated 250,000 deaths per year, and by 2030 the direct costs of health damage will be between \$2 and \$4 billion per year (World Health Organization, 2023). These figures indicate that the health of ecosystems and populations is in a delicate state and the whole investment design needs to be rethought. As a result, governments worldwide have implemented various analyses and measures in the last few years to reduce the negative impacts of pollution on ecosystems in conjunction with the selection of investment projects.

The impact analysis of FDI depends on the industrial sector, the environmental regulations applied, energy efficiency requirements, as well as companies' commitments to sustainable practices. Requiring environmental impact assessments before projects are authorized is necessary, regardless of governments' decision between brownfield investment versus greenfield investment. While in the first case, the investor comes to develop a former industrial area and faces the constraints of the existing infrastructure, and in the second case, the investor comes with a new project and builds everything from scratch. But, also in the case of greenfield investment, there are negative environmental impacts. The construction of new facilities can lead to deforestation, destruction of natural habitat, and air, water, and soil pollution.

FDI projects, mainly after 2004, have adopted the imperatives of innovation and sustainability, i.e., they have become “green investments”. From a theoretical point of view, green investments make energy production cleaner and reduce energy consumption, but the transition to a less polluting investment model requires large financial efforts in alternative sources of green energy. This new concept with unusual short-term challenges in a multi-polar international context of protectionist

policies and revision of international agreements underpins our approach and aims to propose solutions to harmonize the interests that arise between private and public decision-makers.

Although it is evident that a healthier environment can improve people's health, research that empirically investigates these effects remains scarce. In particular, while green investments are considered an indispensable tool for promoting sustainable development, existing research pays little attention to their role in explaining variations in life expectancy. In this context, there is a need for further empirical research to investigate the interdependencies between public health, environmental quality, and economic development. Such an approach allows for an assessment of the extent to which these indicators lead to improvements in public health or, conversely, may generate negative effects that must be understood in order to make responsible and rational decisions. Given these concerns, this study contributes to the existing literature by filling gaps in two ways. On one hand, it examines the impact of air quality, consumer behaviour, and economic development on life expectancy. On the other hand, this study explores the impact of investments in new projects, energy efficiency, and economic development on environmental degradation. Studying these relationships has important implications for public policy, as it highlights the need for an integrated approach to economic, environmental and social development. We believe that governments' efforts to moderate investment opportunities in green technologies, with their control of GHG emissions and the quality-of-life impacts, are becoming mainstream public policy.

The research questions follow the following logical roadmap:

1. What are the main factors that influence population longevity?
2. How much variability in life expectancy can be explained by ecological factors?
3. What factors drive the intensification of GHG?
4. How much variability of GHG can be explained by greenfield investments?

The paper fits into the two frameworks of health determinants and One Health. The first framework distinguishes four determinants: genetics, lifestyle, environment, and the effectiveness of health care systems. Many studies attribute a weight of 50–60% to environmental factors and between 15–20% to genetics, lifestyle, and the effectiveness of health care systems. With gene therapies, the possibility of influencing genetic factors began in 2017. Gene therapy is an extremely innovative treatment used to treat, prevent, or cure certain conditions, acting through distinct mechanisms (National Human Genome Research Institute, 2026). In this context, gene therapies represent an intervention that acts directly on one of the most important biological determinants, opening up new perspectives for the prevention and treatment of genetically caused conditions. Health education can improve behaviours and lifestyles. Health and management policies can improve the effectiveness and efficiency of health care systems. Sectoral policies that support green investments can improve environmental factors. The One Health framework connects human, animal, and environmental health. By acting on the environment, a virtuous circle of improvement can be activated.

The research is further structured as follows. Section 2 reviews the literature on previous work in the field of health sciences and green technologies. Section 3 presents the methodology used. The description of the data used, and the results obtained from the application of the econometric tests are highlighted in Section 4, while Section 5 presents the conclusions and policy implications.

2. Background literature and hypotheses

2.1. *The role of healthy and resilient ecosystems in increasing life expectancy*

Current research has shown that, in addition to genetic factors and the adoption of a healthy lifestyle, environmental factors also have a significant influence on life expectancy. The World Health Organization (WHO) (2022) emphasizes that air pollution poses a major threat to the entire population, as about 99% of people inhale air containing significant amounts of pollutants that exceed the WHO limits. In this context, public health can no longer be analysed independently of environmental sustainability, as the degradation of ecosystems has negative effects on the quality of life and longevity of the population.

In response to the growing environmental challenges, the scientific literature has produced a substantial body of epidemiological and clinical research examining the association between pollution levels and health indicators. In a panel analysis conducted on a sample of 20 economies characterized by high levels of air pollution, Azimi and Rahman (2024) highlight the implications of exposure to PM_{2.5} (particulate matter) for public health. Using the generalized method of moments (GMM) technique, the authors found that PM_{2.5} concentrations contribute to 3.69 (years) decrease in life expectancy and a 0.294% increase in infant mortality. Zhang et al. (2026) also provide solid empirical evidence that CO₂ emissions have a negative effect on life expectancy in China, with the effects of this relationship manifesting themselves in both the short and long term. Abdul-Rahman et al. (2024) analyse the interaction between air quality and the pathophysiological basis of cardiovascular disease. The authors argue that suspended particulate matter, ozone, and nitrogen dioxide are the main culprits in intensifying the risk of cardiovascular disease. By analysing a sample of 30 Asian economies, Yang et al. (2026) examine the impact of air pollution on life expectancy over the period 2000–2023. Using various econometric approaches, the authors find that higher levels of CO₂ and nitrous oxide (N₂O) emissions contribute to a significant reduction in life expectancy. Similarly, Adebayo et al. (2026) arrive at similar results through a comprehensive analysis of the United States. Overall, most of the studies identified point to the conclusion that exposure to air pollution is a significant risk factor for a wide range of diseases. Therefore, fostering a clean environment is crucial for improving individual well-being, which justifies a stronger emphasis on public health within economic policy making.

The transition to more durable energy systems, the development of green infrastructure, and the development of more stringent policies to reduce emissions are vital elements in building resilient ecosystems with direct benefits for longevity. In this regard, Guo et al. (2025) note that life expectancy in South Asian Association for Regional Cooperation (SAARC) economies is positively influenced by a number of factors, such as urbanization, renewable energy, GDP, and industrialization. At the same time, Shaari et al. (2024) highlight the fact that the adoption of innovative green technologies, along with increased spending on health care, leads to an increase in life expectancy. The explanation lies in the fact that green technologies substantially reduce pollution levels, which ultimately leads to improved public health. On the other hand, health care spending facilitates access to quality medical services and preventive measures. Notably, Omri et al. (2024) emphasize that human health improves with the availability of efficient technologies. However, the widespread adoption of these technologies depends to a large extent on the existence of adequate financing mechanisms. In this context, the green credit policy is a relevant example of environmental regulation aimed at directing capital toward activities with a low impact on ecosystems. A recent study by Hu et al. (2025) on a sample of 1510

publicly traded Chinese companies demonstrates that the role of green credit policy in stimulating green innovation has, on the whole, been quite limited. However, with the integration of artificial intelligence, the effects of this policy are significantly amplified, primarily by reducing agency costs. As a result, by supporting investments in innovative green technologies, green credit policies, supported by artificial intelligence-based technologies, can reduce the negative effects of climate change on the health of the entire population. Wiredu et al. (2025) examine the interaction between economic development, green finance, urbanization, life expectancy, renewable energy, and CO₂ emissions in the Group of Seven (G-7) countries through the lens of Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) theory. The findings show that there is a positive interaction between life expectancy and CO₂ emissions, while economic development, green finance, and renewable energy are negatively correlated with increasing CO₂ emissions.

2.2. The contribution of investments in green technologies to the reduction of GHG emissions

Green investments capitalize on numerous economic opportunities and are the result of innovative business ideas. They take various forms, including investments in infrastructure, waste management, transportation and housing, renewable energy, energy efficiency, and conservation of natural resources. Given these considerations, green investments take on strategic importance in the current context. Channelling capital toward innovative technologies not only helps protect the environment but also creates favourable conditions for long-term human health. Several studies that have analysed green investments at the macroeconomic level and their effects have concluded that greenfield investments impacts the reducing of CO₂ emissions (Liu, 2025; Xu et al., 2025; Yeboah et al., 2025). For example, Yeboah et al. (2025) explore the impact of green finance, specifically environmental taxes and foreign direct investment, on energy efficiency and CO₂ emissions in 19 African countries, covering the period from 2000 to 2020. To obtain robust results, the authors employ various econometric techniques, including the dynamic common correlated effects estimation (DCCE), the GMM, and the method of moments quantile regression (MMQR). Consequently, the empirical findings highlight that environmental taxation plays a fundamental role in supporting the decarbonization process, while foreign direct investment has a more limited impact. Similar results are also reported by Sohail et al. (2026), who draw on a sample consisting of 31 Chinese provinces. By measuring green financing through green bonds, Alamgir and Osińska (2026) show that green financing contributes significantly to environmental performance. Given that attracting greenfield investment has become a strategic priority for policymakers, Zhang et al. (2024) set out to analyse the correlation between nuclear energy, environmental taxation, greenfield investment, and green economy on a sample of 16 Organisation for Economic Co-operation and Development (OECD) member countries. Based on the MMQR, the empirical results highlight that greenfield investments are a key factor in promoting a green economy. Kwilinski et al. (2026) focus on 26 European Union member states in their investigation of the effects of greenfield investments on the development of renewable energy and CO₂ emissions. Using fixed-effects regressions, the authors demonstrate that greenfield investments promote the expansion of renewable energy sources and significantly reduce emissions. Similar results are also obtained by Li et al. (2024), who argue that green finance and green technologies are key elements for achieving the goals of the Paris Agreement on climate change. In addition, some studies also highlight the role of institutional quality in reducing emissions. For example, Hamrouni et al. (2025) focus on emerging and growth-leading

economies (EAGLE), and the results of their autoregressive distributed lag-pooled mean group (ARDL-PMG) regression show that institutional quality directly reduces CO₂ emissions.

Micro-level studies also argue that green investments, in addition to reducing GHG emissions, improve companies' financial performance (Putrika and Ardianto, 2025), stimulate green innovations (Aleksnevičienė et al., 2025), enhance long-term competitiveness (Yang and Zhu, 2024), and contribute to improved environmental, social, and governance (ESG) ratings (Cao et al., 2023; Feng and Wijethilake, 2026). Zhang et al. (2025) for example, examine 1251 publicly traded Chinese companies to investigate the effects of green investments on ESG performance. The results obtained using ordinary least squares (OLS) regression highlight that companies focusing on green investments significantly improve their ESG ratings. Similar results are also obtained by Wang et al. (2025), who focus on a sample of 1300 publicly traded companies. Using robust econometric techniques, such as difference-in-difference (DID), the authors demonstrate that green financing, as measured by pilot policies in the green financial reform and innovation pilot zone, improves companies' ESG ratings.

The literature has evaluated the significance of a set of macroeconomic variables on the level of green investments. Thus, Xie et al. (2026), Liu et al. (2026), and Yildirim (2026) conclude that the level of green investment is influenced by real GDP, long-term interest rates, the relative price of crude oil on international markets, and the carbon tax. Economic activity is increasing demand for energy and leading to changes in the structure of industry and services, as well as company relocation. Better enforcement of environmental regulations leads to higher environmental spending and reduced environmental degradation. Therefore, when investment decisions are taken, great attention should be paid to the innovative character of investments through the contribution of green technologies that leverage nuclear and renewable energies.

Green technologies also have environmental benefits, including increased energy efficiency, green buildings, and sustainable land and waste management, including pollution control. It can be argued that, within the investment community, green technologies are seen as a selection criterion in greenfield investment decision making (Knutsson and Flores, 2022), focused on ensuring energy efficiency. The feasibility of greenfield projects requires investors to ensure all appropriate expenditures, including additional expenses such as project planning and procurement costs. Also, the decision-making process is driven by the environmental regulations imposed on companies. Based on these requirements, greenfield investments will have a responsible character and will ensure the achievement of environmental objectives. The determinant of environmental progress is still a subject of academic debate, given the complex interrelationships between global economic growth and the quality of international relations.

Analysed studies have emphasized two directions: the importance of greenfield investments in promoting sustainable business models, green technologies and creating new jobs, and, in opposition, the negative environmental impacts. In this context, Zeraibi et al. (2023) aim to shed light on the role of greenfield investments, economic complexity, and financial inclusion on environmental quality and renewable energy in BRICS countries (Brazil, India, South Africa, China, and Russia). Using pooled mean group (PMG), the paper highlights that greenfield investments, urbanization, and economic complexity decrease the promotion of renewable energy while contributing to environmental degradation.

3. Data and empirical method

3.1. Data

We use a panel dataset covering 35 member states of OECD from 2003 to 2023. Countries were selected to include both developed and emerging economies, all featuring attractive investment climates and active green transition strategies (OECD, 2022).

In accordance with the first objective of this paper, we chose *LE* as the dependent variable, as it is frequently used in studies on longevity (Idalfahim and Elouardirhi, 2026; Wiredu et al., 2025), as summarized in column 5, titled “Relevant studies”, of Table 1. In line with the literature, different factors explain the life expectancy, such as *GHG*, *HEALTH*, *ALC*, *VEG*, and *GDP*, being included as independent variables. Regarding the second research objective, *GHG* emissions are used as an indicator of environmental degradation. *GF* are used as an independent variable, along with *NRG* and *GDP*. Unlike other studies in the literature, which use budget spent on renewable energy research and development as a proxy for green investments (Luong and Nguyen, 2024), in this paper we opt for the value of announced greenfield FDI projects, as it is a direct proxy for the intensification of economic activity and the expansion of productive capacities.

The description of the variables included in the models, the data sources, and economic/econometric logic are presented in Table 1.

Table 1. Description of variables.

Nature	Variables	Codes	Source	Rationale	Relevant studies
Dependent variable	Life expectancy at birth, total (years)	LE	The World Bank	It reflects the general level of health and well-being of the population, which is influenced by various factors such as the health care system, social policies, and standard of living.	Idalfahim and Elouardirhi (2026), Wiredu et al. (2025)
Independent variable for LE (see Table 4), Explained variable (see Table 5)	Greenhouse Gas Emissions (tonnes of carbon dioxide-equivalents)	GHG	EPA	It reflects the degree of deterioration of the environment because of various activities that have negative consequences on the quality of life.	Luong and Nguyen (2024)
Independent variable	Current health expenditure (% of GDP)	HEALTH	The World Bank	Reflects a macro-economic view of healthcare investment in relation to the economic size of a country. The level of investment thus influences the quality of health services.	Vărzaru (2025)

Continued on next page

Nature	Variables	Codes	Source	Rationale	Relevant studies
Independent variable	Value of announced greenfield FDI projects	GF	UNCTAD	Reflects the volume of FDI in new, innovative projects.	Zhang et al. (2024), Zeraibi et al. (2023)
Independent variable	Alcohol consumption (litres per person)	ALC	OECD	Reflects consumption behaviour and health implications.	Le et al. (2026)
Independent variable	Vegetable consumption (kg per capita per year)	VEG	Our World In Data	Reflects the quality of one's diet and its implications for health.	Hu (2024)
Independent variable	Energy efficiency (per capita energy consumption from renewables (kWh-equivalent))	NRG	Energy Institute	Illustrates the transition to renewable energy sources.	Zeraibi et al. (2023)
Independent variable	GDP growth (annual %)	GDP	The World Bank	Reflects economic dynamics.	Luong and Nguyen (2024)
Instrumental variable for GDP	Government Effectiveness: Estimate	GOV_EF	The World Bank	A higher score reflects the effectiveness of the implementation of public policies in each economy.	Nica et al. (2023)
Instrumental variable for GDP	Domestic credit to private sector by banks (% of GDP)	FIN_DEV	The World Bank	Financial development indicator.	Nica et al. (2023)
Instrumental variable for GDP	Unemployment, total (% of total labour force) (modelled ILO estimate)	UNEMP	The World Bank	Reflects the state of the labour market and the capacity to create new jobs, including green job opportunities.	Lasisi et al. (2024)

Source: created by authors based on specialized literature.

We have chosen the present methodology on the following considerate: Variables are stationary in levels; the fixed and/or random effects may be biased if the endogeneity is present; the stationary variables may contain cross-sectional factors; and some of the economic variables (e.g.: GDP or GHG emissions) are treated in the literature as lagged dependent. More specifically, the choice of methodology is justified by the following aspects:

- Fixed-effects (FE) and instrumental variable (IV) estimators are used first because they are the standard benchmark in the panel literature on life expectancy and emissions, and because health expenditure and GDP are plausibly endogenous to life expectancy, which the FE-IV specification (two-stage least squares (2SLS) regression analysis, Equations 2–3) is designed to address.

- The cross-sectional dependence (CD) test (Pesaran, 2015) and the cross-sectional dependence exponent are then used because OECD economies are exposed to common shocks (global financial cycles, energy-price shocks, the COVID-19 pandemic) that generate cross-sectional dependence, which standard FE/IV estimators assume away and which, if ignored, would bias the standard errors and potentially the coefficients.
- The DCCE mean-group (DCCE-MG) estimator (Chudik and Pesaran, 2015; Pesaran, 2015) is therefore used as the main specification because it allows for heterogeneous slopes across countries and explicitly filters out unobserved common factors, and the ARDL/error-correction variant is added to separate short-run from long-run effects.

The methodology is presented as follows.

3.2. Methodology and tests

Considering a standard linear model in panel data with $\alpha_{it} = \alpha$, $\beta_{it} = \beta$, and error term $\mu_i + \epsilon_{it}$, controlling for specific individual omitted variables (*FE or random effects*) can be estimated as in (1); see Croissant and Millo (2008).

$$y_{it} = \alpha + \beta^T x_{it} + \mu_i + \epsilon_{it}. \quad (1)$$

In the presence of some endogenous variables, instrumental variables can be used as in (2).

$$\tilde{y}_{it} = \tilde{Z}_{it} + \tilde{v}_{it}, \quad (2)$$

where $\tilde{y}_{it}$ is the explained variable, Y_{it} is $1 \times g_2$ vector of observations on g_2 endogenous variables, X_{1it} is a $1 \times k_1$ vector, $Z_{it} = [Y_{it} X_{1it}]$, and γ, β , and δ are vector of coefficients. The centre of the model is the *within transformation*, calculated as $\tilde{w}_{it} = w_{it} - \bar{w}_i + \bar{w}$, where $\bar{w}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} w_{it}$ and $\bar{w} =$

$$\frac{1}{N} \sum_{i=1}^n \sum_{t=1}^{T_i} w_{it}.$$

In case of the endogeneity, $\hat{\beta}_{IV}$ coefficients are calculated as in (3); see Baum et al. (2003).

$$\hat{\beta}_{IV} = \{X'Z(Z'Z)^{-1}Z'X\}^{-1}X'Z(Z'Z)^{-1}Z'y = (X'P_ZX)^{-1}X'P_Zy. \quad (3)$$

In a panel data (time) series, one can control for the dependence across cross-sectional units and common factors (interactive FE, as in Ditzén (2022)). Panel time series permit to run “separate regressions for each group” (see Pesaran et al. (1999)). The dynamic panel model with heterogeneous slopes and interactive FE is presented in (4).

$$\begin{aligned} y_{i,t} &= \lambda_i y_{i,t-1} + \beta_i x_{i,t} + u_{i,t}, \\ x_{i,t} &= \gamma_{x,1,i} f_{1,t} + \gamma_{x,2,i} f_{2,t} + \xi_{i,t}, \\ u_{i,t} &= \gamma_{u,1,i} f_{1,t} + \gamma_{u,3,i} f_{3,t} + \epsilon_{i,t}, \end{aligned} \quad (4)$$

where $y_{i,t}$ and $x_{i,t}$ are observed values, $\gamma_{u,k,i} f_{k,t}$ are the common unobserved factors, $\xi_{i,t}$ and $\epsilon_{i,t}$ are both white noise, $\lambda_i \sim \|D(\lambda, \sigma_\lambda^2)$ and $\beta_i \sim \|D(\beta, \sigma_\beta^2)$ are heterogeneous slopes, and unit specific and time FE can be integrated in the interactive FE.

The approximation of the common factors as proposed in Chudik and Pesaran (2015) can be written as in (5).

$$y_{i,t} = \alpha_i + \lambda_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{l=0}^{p_T} (\psi_{l,x,i} \bar{x}_{t-l} + \psi_{l,y,i} \bar{y}_{t-l}) + \epsilon_{i,t}, \quad (5)$$

where $\bar{y}_t = 1/N \sum_{i=1}^N y_{i,t}$, $\bar{x}_t = 1/N \sum_{i=1}^N x_{i,t}$, and $p_T = \sqrt[3]{T}$.

The mean group (MG) estimator can be calculated as $\hat{\beta}_{MG} = \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i$ as in Pesaran and Smith (1995), Pesaran et al. (1999), and Chudik and Pesaran (2019).

We first check for the presence of non-stationarity in data. For testing the stationarity in panels (Equation (6)), usual panel unit root tests are used, such as Breitung and Das (2005), Harris and Tzavalis (1999), Im et al. (2003), Levin et al. (2002), and Fisher type (Choi, 2001).

The tested null hypothesis is the unit root presence in all panels, H_0 : *all panels contain a unit root* (most tests) or H_0 : *all panels are (trend) stationary* (as the Hadri Lagrange multiplier test); see Hadri (2000). The value of ρ_i is checked on (6).

$$Y_{it} = \alpha_{it} + \rho_i Y_{i,t-1} + \mu_t. \quad (6)$$

For the endogeneity case, to test the relevance of instruments and overidentifying restrictions in IV, usually the Sargan test is used (see Baum et al. (2003)).

To determine the presence of cross-sectional factors, we use the methodology proposed by Bai and Ng (2002), Onatski (2010), Ahn and Horenstein (2013), and Gagliardini et al. (2019) and implemented by Ditzen and Reese (2023). If common factors are encountered in the independent variables, strong cross-sectional dependence may appear (analytically explained in Ditzen (2022)).

In a dynamic panel model where slopes are heterogeneous and interactive FE appears (as in (7)), the common factors are $f_{1,t}$ and $f_{2,t}$. Cross-section dependence is present when coefficients are not equal to zero, as in (7).

$$y_{i,t} = \lambda_i y_{i,t-1} + \beta_i (\gamma_{x,1,i} f_{1,t} + \gamma_{x,2,i} f_{2,t} + \xi_{i,t}) + \gamma_{u,1,i} f_{1,t} + \gamma_{u,3,i} f_{3,t} + \epsilon_{i,t}. \quad (7)$$

Econometrical literature propose a test for weak cross-section dependence (see Pesaran (2015)), the CD-test with the null hypothesis H_0 : *weak dependence* vs. alternative H_1 : *strong dependence* (further developments are treated in econometric literature by Fan et al. (2015), Pesaran (2021), Xie and Pesaran (2022), and Juodis and Reese (2022)).

We began by identifying the main factors that influence population longevity. Thus, we estimate the impact on the life expectancy of the following proxies, using the general model as in (8):

- air quality, with proxy GHG emissions ($GHG_{i,t}$);
- public policy effects, with proxy current public health expenditures ($HEALTH_{i,t}$);
- alcohol consumption with same proxy in logarithmic values ($\log_ALC_{i,t}$);
- vegetables consumption with same proxy in logarithmic values ($\log_VEG_{i,t}$);
- economic development, with gross domestic product used as proxy ($GDP_{i,t}$).

To control for the possible presence of endogenous variables, the $GDP_{i,t}$ is 2SLS instrumented by the following variables: government efficiency, financial development, and unemployment.

Since air quality influences the quality and duration of life, the second objective of the paper is derived: What are the influence factors on air quality (using the $GHG_{i,t}$ as proxy, considered as the dependent variable this time; the model being presented in Equation (9)). In this second approach, the greenfield investment GF is analysed, along with the following variables:

- first lag of GHG emissions ($l1.GHG$);
- investments, using as proxy the greenfield investments, in logarithmic values ($\log_GF_{i,t}$);
- energy efficiency, with the same proxy, in logarithmic values ($\log_NRG_{i,t}$);
- economic development, with gross domestic products used as proxy ($GDP_{i,t}$).

As in the first group of models, we suspect the endogeneity, for example, between the greenfield investments ($\log_GF_{i,t}$) and GDP, so the latest is instrumented using the same variables in the first group: government efficiency, financial development, and unemployment.

$$LE_{i,t} = \beta_{0,i} + \beta_{1,i}GHG_{i,t} + \beta_{2,i}HEALTH_{i,t} + \beta_{3,i}\log_ALC_{i,t} + \beta_{4,i}\log_VEG_{i,t} + \beta_{5,i}GDP_{i,t} + \mu_i + \epsilon_{i,t}, \quad (8)$$

$$GHG_{i,t} = \beta_{0,i} + \beta_{1,i}l1.GHG_{i,t} + \beta_{2,i}\log_GF_{i,t} + \beta_{3,i}\log_NRG_{i,t} + \beta_{4,i}GDP_{i,t} + \mu_i + \epsilon_{i,t}. \quad (9)$$

The tests statistics and empirical results are presented and explained in the next section.

4. Empirical results and discussion

4.1. Preliminary tests

The characteristics of the data is presented in Table 2, suggesting a large variability among the selected variables (diversified economic and geopolitical situation of the countries under analysis).

The table presents the series statistics in the order of the models: Series used in the first set of the models are presented until the first line (LE , ..., GDP); the variables used as instruments for GDP are shown in the next part (GOV_EF , ..., $UNEMP$); series used for the second set of models are presented as followed ($\log_GF$, $\log_NRG$); and the initial un-logged values are presented in the final section of the table.

As Table 2 shows, the raw greenfield investment and energy variables are strongly right-skewed and leptokurtic (GF : skewness 3.26, kurtosis 14.96; NRG : skewness 3.94, kurtosis 19.59), far from the normal-distribution benchmarks of 0 and 3. After the log transformation, $\log_GF$ and $\log_NRG$ have skewness of -0.39 and -0.22 and kurtosis of 2.61 and 3.88, values much closer to normality and consistent with the stationarity results reported in Table 3.

Alcohol and vegetable consumption were transformed on the same log scale for specification consistency within the lifestyle block of regressors and to allow all coefficients to be read as semi-elasticities: In a level-log specification, a coefficient β on a logged regressor indicates that a 1% change in that variable is associated with an approximate $\beta/100$ -unit change in the dependent variable (life expectancy or GHG emissions, both measured in levels). We will add a sentence to Section 3.2 making this rationale and coefficient interpretation explicit.

Table 2. Summary statistics.

Variables	Mean	SD	Min	Max	Skew	Kurt	N
LE	78.9033	3.4163	69.5460	83.8317	−0.8264	2.8064	840
GHG	11.6974	5.8506	4.8519	34.0630	1.5890	5.6482	840
HEALTH	8.4500	2.0976	4.7806	16.1992	0.9427	4.9637	840
log_ALC	2.1822	0.3334	0.9933	2.6532	−1.5974	5.8325	840
log_VEG	4.7250	0.3520	3.6617	5.4959	−0.3690	3.5834	840
GDP	2.3761	3.1739	−8.6246	10.5660	−0.6793	5.0361	840
GOV_EF	1.2359	0.5790	−0.2219	2.2103	−0.5172	2.4770	840
FIN_DEV	88.2274	40.8826	13.4442	190.1544	0.3318	2.3588	840
UNEMP	7.3170	3.9193	2.3450	22.0580	1.5022	5.4446	840
log_GF	8.3103	1.9154	3.5951	11.9544	−0.3936	2.6060	840
log_NRG	8.3330	1.4735	3.7776	11.8964	−0.2201	3.8818	840
ALC_cons_t	9.2932	2.4913	2.7000	14.2000	−0.6142	3.1042	840
VEG_cons_cap	119.6471	41.2086	38.9270	243.6800	0.7944	3.8219	840
GF	15726.2641	27411.5218	36.4200	155497.7646	3.2629	14.9646	840
NRG	11892.6452	24153.1629	43.7113	146732.1250	3.9394	19.5927	840

Source: author's calculation.

Regarding the variables, we can conclude that GOV_EF has the lowest mean (1.2359) and, at the same time, the lowest standard deviation (0.5790), while FIN_DEV has the highest mean (88.2274) and standard deviation (40.8826). The minimum value of the variable of life expectancy is 69.5460 (Korea, 2003), while the maximum value recorded is 83.8317 (Spain, 2019), with a mean of 78.90 years and a high standard deviation of 3.41. As an indirect indicator of environmental degradation, GHG emissions record a mean of 11.69 tons of CO₂ equivalent, with a standard deviation value of 5.85, with values ranging from 4.85 (Colombia, 2005) to 34.06 (Australia, 2012), suggesting different implications of governments in emission reduction strategies. The variable log_GF has a mean value of 8.30, and the standard deviation in this context is 1.93. This variable also varies between a minimum of 2.41 and a maximum of 11.95. According to the results, all variables show increasing effects in the sample period. Empirical results are available in the next section.

The unit root test results are presented in Table 3.

For the Im-Pesaran-Shin unit-root test, the null H_0 : *all panels contain unit roots* is strongly rejected at 0.05 confidence level (the Z-t-tilde-bar statistic presented on column 2 of the table has a p-value of 0.000*** for all the implied variables).

Table 3. Unit root tests results.

Variables	r(zttildebar)	r(P)	r(L)	r(Z)	r(Pm)
LE	-3.9734 ***	112.9291 ***	-4.2237 ***	-4.4827 ***	3.6282 ***
d.LE	-10.9078 ***	697.1339 ***	-30.8201 ***	-19.2565 ***	53.0025 ***
HEALTH	-4.3701 ***	129.0677 ***	-5.0209 ***	-5.0472 ***	4.9921 ***
d.HEALTH	-12.9412 ***	528.9024 ***	-24.7003 ***	-18.3507 ***	38.7843 ***
GHG	-2.0952 **	140.2524 ***	-4.4366 ***	-2.4138 ***	5.9374 ***
d.GHG	-11.8082 ***	582.0973 ***	-26.8402 ***	-18.3507 ***	43.2801 ***
log_ALC	-4.0412 ***	131.4081 ***	-4.6702 ***	-4.5297 ***	5.1899 ***
d.log_ALC	-13.5357 ***	697.9108 ***	-32.5679 ***	-21.4157 ***	53.0682 ***
log_VEG	-5.0699 ***	172.9454 ***	-6.9187 ***	-5.9510 ***	8.7005 ***
d.log_VEG	-16.7523 ***	1117.9199 ***	-52.2371 ***	-29.7985 ***	88.5654 ***

Source: author's calculation.

Regarding the Fisher-type unit-root tests (based on Phillips-Perron tests), the inverse chi-squared (70) P statistic has p-values that strongly reject the null hypothesis at the 0.05 significance level (column 3). The inverse logit (L) Fisher-type unit-root test* (column 4) also strongly rejects the null, since all p-values are close to zero. Similar result applies to Z statistics (column 5). The modified inverse chi-squared (Pm) statistic (column 6) further confirms the rejection of the null hypothesis. This indicates that our series are stationary in both levels and first differences. Consequently, we can use the variables in levels, and the proposed methodology is appropriately chosen.

Finally, we have tested the cross-sectional dependence, which occurs when errors across different cross-sectional units (e.g., countries, firms, individuals) are correlated, which can cause issues in inference and lead to biased estimates if ignored (the initial results available on demand confirm the presence of strong cross-sectional): $GHG_{i,t}$, $\log_GF_{i,t}$, $\log_NRG_{i,t}$, and $GDP_{i,t}$ have values for α that are above the threshold (the α exponent measures the degree of cross-sectional dependence in the panel dataset, with the following outcome: $\alpha < 0.5$ means weak or no cross-sectional dependence; $0.5 \leq \alpha \leq 1$ means strong cross-sectional dependence; and $\alpha = 1$ means perfect cross-sectional dependence). We can conclude that cross-sectional dependence is present and all variables have $\alpha \geq 0.5$, meaning they exhibit strong dependence across cross-sections (countries). A particular case is the GDP that has $\alpha = 1.006$, suggesting near-perfect cross-sectional dependence: GDP is highly correlated across countries, so the proposed methodology is correctly chosen.

4.2. Regression results

The results for the first set of models as in Equation (8) that analyses the influence on the total life expectancy are presented in Table 4.

The first model (1) on the first column, named fe , is controlling for the country heterogeneity (as in 2), these factors being incorporated in the fixed effects term μ_i , while other factors are in the error term ϵ_{it} . The μ_i is used to control for time-invariant country characteristics (e.g., factors like GDP growth, which are not explicitly included in the model: country's economic, long-standing institutions, historical factors).

For the second model (column 2), named *fe-iv*, beside the time-invariant control, we debate the exogeneity of the considered independent variables ($GDP_{i,t}$ may not be purely independent to other variables, e.g., health expenditures and GHG emissions, but the exclusion of GDP from the model is not a solution, since higher life expectancy values are mainly encountered in developed countries (high GDP)).

Table 4. Determinant factors on total life expectancy.

Variables	(1) fe	(2) fe-iv	(3) dcce-mg-nocr	(4) dcce-mg-cr
GHG	−0.1443*** (0.0240)	−0.1311*** (0.0271)	−0.4571* (0.2714)	−0.2081 (0.1544)
HEALTH	0.5384*** (0.0511)	0.7583*** (0.0883)	0.2256 (0.2719)	0.0129 (0.1200)
log_ALC	−3.2054*** (0.5056)	−3.3553*** (0.5658)	−3.4107** (1.3559)	−1.8180 (1.1963)
ldog_VEG	1.9114*** (0.2259)	1.5179*** (0.2794)	0.9676 (1.2300)	0.5151 (0.5979)
GDP	−0.0302** (0.0132)	0.1567*** (0.0592)	0.0783 (0.0686)	0.0151 (0.0544)
Constant	74.0781*** (1.5247)			
Observations	840	840	840	840
R-Squared	0.4416	0.3008	0.3854	0.4815
Number of countries	35	35		
Number of groups			35	35

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Source: author's calculation.

In this case, the GDP is 2SLS instrumented (as in Equation (10)) by government efficiency, financial development, and unemployment.

$$GDP_{i,t}P = \beta_{0,i} + \beta_{1,i}GOV_EF_{it} + \beta_{2,i}FIN_DEV_{it} + \beta_{3,i}UNEMP_{it} + \epsilon_{i,t}, \quad (10)$$

where $GDP_{i,t}P$ represents the predicted values of $GDP_{i,t}$.

The third model (column 3), named *dcce-mg-nocr* uses the MG estimator proposed by Pesaran (2015), Pesaran (2021), and Pesaran et al. (1999) and implemented by Ditzén (2018) but without the common factors using cross-section averages. The fourth model (column 4), named *dcce-mg-cr*, also controls cross-section dependence.

Woychik et al. (2022) have signalled the alarming nature of climate change, highlighting its negative impact on population health through exacerbation of cardiovascular and respiratory diseases, spread of infectious diseases, and food insecurity. In this context, reducing GHG emissions and thus global warming, as set out in the Paris Agreement, is a major public health objective. For our models, the influence of air quality is negative, as expected. The impact is between 0.14 and 0.45 (the coefficients are negative; see first row). An increase in GHG emissions with one unit decreases the life expectancy by 0.45 years, on average, ceteris paribus (see model 3). On the first three models, the statistical significance is at least at 0.1 percent level. We can conclude that air quality negatively

influences life expectancy, so these findings are becoming an essential base for analysing the influencing factors on air quality. The results are fully consistent with studies in the existing literature indicating that GHG emissions pose a threat to human health (Adebayo et al., 2026; Azimi and Rahman, 2024; Yang et al., 2026; Zhang et al., 2026), as they release pollutants such as carbon monoxide and nitrogen oxides into the atmosphere, which significantly degrade air quality and contribute to the onset or worsening of respiratory and cardiovascular conditions.

Another factor that influences life expectancy is the amount of health expenditure, the results showing that the impact is positive, as expected (see second row). The results are statistically significant (first models), the influence being estimated between 0.01 and 0.75. An increase by one unit in financing the health policies (expenditures) increases the life expectancy by 0.75 years, on average, *ceteris paribus* (the coefficient from second model *fe-iv* is used). According to the literature, health is the central pillar of human capital and a vital factor in ensuring a sustainable trajectory for global economies: Investing in health should be seen as an economic imperative, as it contributes to the creation of high-performing human capital capable of ensuring long-term economic sustainability. These empirical findings lend credibility to existing research, such as that by Ridwan et al. (2026), Zhang et al. (2026), and Alghannam and Alharbi (2026), which conclude that health spending has a significant positive effect on life expectancy.

The consequence of alcohol consumption is negative and statistically significant at least at 5% level. A 1% increase in alcohol consumption is associated with a decrease in life expectancy of approximately 0.03 years ($\beta/100$), *ceteris paribus*, being in line with Jiesisibieke and Schooling (2024) and Trias-Llimós and Spijker (2022). Alcohol is considered a major risk factor for liver disease (Roerecke et al., 2019), cardiovascular disease (Le et al., 2026) and various types of cancer, causing an estimated 2.6 million deaths in 2019, according to the WHO (2024).

Conversely, in line with trends identified in the literature, vegetable consumption has a positive impact on life expectancy. An increase with 1% in vegetables consumption increase changes the life expectancy by approximately 0.064, with similar findings being reported by Fadnes et al. (2024) and Hu (2024). Even if the influence of GDP is not statistically significant (as the control variable), the impact is positive on instrumented models, as expected, posing that in developed countries, life expectancy is higher (in line with Lasisi et al. (2024) and Țarcă et al. (2024), which demonstrates that the use of IVs is the correct choice). The underidentification test (Anderson canonical correlation Lagrange Multiplier (LM) statistic) supports the initial supposition of endogeneity (the comprehensive results are available on demand). The Sargan overidentification test statistic is 4.652, with a chi-squared p-value of 0.0977, so our instruments are likely exogenous (i.e., uncorrelated with the error term).

The next results analysis shows the influence on GHG emissions and is presented in the following table (see Table 5). We also quantify the long-run error-correction term and MG coefficients (lag dependent variables models). The error-correction term is reported, the MG estimates being calculated by the implementation proposed by Ditzen (2018) and the model 9 being estimated using non-cross-sectional dependence, long-run, and ARDL options.

Table 5. Determinant factors on GHG emissions.

Variables	(5) fe	(6) fe-iv	(7) dcce-mg- nocr	(8) dcce-mg-cr	(9) dcce-cs-ardl- nocr	(10) dcce-cs-ardl- cr
<i>l.GHG</i>			0.6273*** (0.0464)	0.3121*** (0.0674)	0.6273*** (0.0464)	0.3121*** (0.0674)
<i>log_GF</i>	0.0828 (0.0943)	0.0719 (0.1047)	0.0484 (0.1698)	0.0148 (0.0913)	0.0484 (0.1698)	0.0148 (0.0913)
<i>log_NRG</i>	−0.9500*** (0.0967)	−0.7359*** (0.1182)	−1.0478** (0.4265)	−0.1775 (0.3552)	−1.0478** (0.4265)	−0.1775 (0.3552)
<i>GDP</i>	0.0112 (0.0204)	0.2923*** (0.0689)	0.2554* (0.1382)	0.0413 (0.0500)	0.2554* (0.1382)	0.0413 (0.0500)
<i>lr_GHG</i>					−0.3727*** (0.0464)	−0.6879*** (0.0674)
CONSTANT	18.8985*** (1.0826)					
Observations	840	840	805	805	805	805
R-squared	0.1121	−0.0980	0.6651	0.4014	0.6651	0.4014
Number of countries	35	35				
Number of groups			35	35	35	35

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Source: author's calculation.

For model 6 (*fe-iv*) the tests confirm the necessity of the IVs' usage. For models 6 to 9, the GDP_{it} values are 2SLS instrumented by the following variables: government efficiency, financial development, and unemployment.

The first lag of the dependent variable $l.GHG_{i,t}$ is positive and statistically significant in all models, meaning that current GHG levels are positively influenced by the past ones (the coefficients are between 0.3 and 0.6).

The greenfield investments in logarithmic values ($log_GF_{i,t}$) suggests a positive effects on $GHG_{i,t}$ in the economies analysed but not statistically significant (the new investments are not always ecological friendly ones or use latest green technologies). This finding aligns with the results of Zeraibi et al. (2023) and Bashir et al. (2024), which show that greenfield investments may pose a barrier to the transition to renewable energy, confirming the necessity of public intervention by subsidies or taxation. Furthermore, our results are consistent with those reported by Raza et al. (2024), who find that greenfield investments increase CO₂ emissions in low-income, middle-income, and even high-income countries. The energy efficiency (in logarithm) – $log_NRG_{i,t}$ – has a negative influence on GHG , as expected. The coefficients are estimated to be between 0.17 and 1, meaning that an *increase* in one unit of energy efficiency is reducing the GHG emissions by approximately 0.0392 ($\ln(1.04)$) units of GHG , on average, ceteris paribus. In the current climate, improving energy efficiency is proving to be

a cost-effective solution for reducing GHG emissions, our findings being in line with Amin et al. (2025), Tithi (2026), and Dai et al. (2025), who emphasize the importance of this indicator in promoting sustainable development.

The error correction term (ECT) on models 9 and 10 suggests that there is a long-term relationship (ECT is negative and statistically significant, meaning that approximately 37% to 68% of the gap between the actual value and the equilibrium value is corrected in each year). Related to the $GDP_{i,t}$ influence, the impact is positive and statistically significant in most of the models, as expected (as stated above, in the models 6 to 10, the GDP variable is instrumented (in highly developed economies, the levels of GHG are higher, as expected)).

The cross-sectional dependence has improved for estimated predicted residuals after using the suggested methodology (Ditzen (2018)): The weak cross-sectional dependence on predicted residuals confirms the correct choice for the proposed methodology (all results are available on demand).

5. Conclusions and policy implications

This study aims to investigate the interdependencies between public health, environmental sustainability, and economic development using a sample of OECD member states covering the period 2003–2023. The results confirm a negative and significant relationship between GHG emissions and life expectancy, with increasing emissions resulting in a reduction of the population longevity. This can be explained by the degradation of air quality, which increases the incidence of cardiovascular and respiratory diseases while accelerating the decarbonization agenda. In order to reduce emissions, policymakers and regulators should do more to promote the development of renewable energy generation capacity, the modernization of power grids, the acceleration of electrification, and the expansion of energy storage solutions, as these measures not only facilitate the achievement of decarbonization goals but also reduce the population's exposure to air pollutants resulting from the burning of fossil fuels. Furthermore, policymakers should develop more effective systems for monitoring, reporting, and verifying (MRV) emissions. Continuous monitoring of emissions, particularly in high-carbon sectors, allows for the rapid identification of major sources of pollution and the assessment of the effectiveness of implemented reduction measures. Empirical findings obtained through the application of a rigorous methodology support the view that environmental and public health policies must be designed within an integrated framework to strengthen communities' resilience to emerging environmental and health risks.

The results also highlight that current health expenditures have a positive contribution to the increase in life expectancy, being relevant for policymakers and offering a robust evidence-based foundation for designing effective public policies. A strategic allocation focused on prevention, accessibility, and use of digitalization can help mitigate social health inequalities and enhance life expectancy. Moreover, green investment can contribute to increasing life expectancy in good health, which has a double positive effect: On the one hand, it reduces the cost of care for chronicity, and on the other hand, it maintains people who can collaborate to health service delivery as volunteers or patient associations. Our findings underscore the need for a coordinated public policy at the central level to incorporate economic, educational, and environmental determinants into long-term development strategies. This observation takes on particular significance in the context of OECD countries, where fiscal pressures over the past few decades have led to budgetary austerity measures in many countries, which have had a particularly severe impact on the health sector.

Although greenfield investments expand productive capacity and employment, our findings indicate that they elevate GHG emissions, highlighting the essential requirement for adopting advanced clean technologies. In this context, policymakers should strengthen the climate assessment criteria applicable to these projects prior to their approval and implementation. To this end, ex-ante assessments should place greater emphasis on the impact on GHG emissions, energy efficiency, and the compatibility of investments with decarbonization goals. At the same time, the granting of fiscal and financial incentives could be made contingent on the climate performance of projects, thereby steering investment flows toward low-emission activities. The efficient use of alternative forms of green energy brings with it numerous benefits, including GHG emission reductions and cost savings at micro- and macro-economic levels, contributing to the achievement of the Sustainable Development Goals. The correlation between GDP and GHG emissions is traditionally positive since the economic expansion is usually accompanied by an increase in industrial activities and energy production from conventional sources. Our findings confirm that public health policies should be reconsidered to address the use of green investments and non-pollutant energy alternatives, supporting environmental quality and population health.

6. Limitations and future prospects

Although this paper addresses a topic of utmost importance in the current context and offers new perspectives to the specialized literature in the field, it is not without limitations, which may, at the same time, serve as new directions for future research. The first limitation relates to the time frame of the analysis, specifically the period 2003–2023, a choice determined by the limited availability of data for the variables included in the model. Although this period spans more than two decades, allowing us to capture significant changes in green investment and the evolution of environmental and health indicators in OECD economies, extending the time horizon, as new data series become available, could provide a more comprehensive perspective on the long-term relationships between variables. A second limitation is that our study focuses exclusively on OECD countries. Although this sample has the advantage of a high level of economic development and well-functioning health care systems, the results cannot be automatically extrapolated to other regions. In this regard, future research could expand the sample by including emerging economies or low- and middle-income countries to assess whether the identified relationships hold in different economic and institutional contexts. Another limitation concerns the choice of indicators used to measure environmental degradation. In this study, environmental degradation is captured through GHG emissions, a relevant indicator for assessing pressures on the environment. However, environmental degradation could also be assessed using other indicators, such as concentrations of fine particulate matter (PM_{2.5} and PM₁₀) or composite environmental performance indices, which could lead to a more nuanced understanding of the mechanisms through which green investments influence public health.

Author contributions

The authors declare to have contributed equally to the manuscript. All authors have read and approved the final manuscript.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

The authors wish to note that no external funding was received for this study.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

The data used in this study are publicly available and can be accessed through their official databases (see Table 1).

References

- Abdul-Rahman T, Roy P, Bliss ZSB, et al. (2024) The impact of air quality on cardiovascular health: A state of the art review. *Curr Probl Cardiol* 49: 102174. <https://doi.org/10.1016/j.cpcardiol.2023.102174>
- Adebayo TS, Nwosu LC, Alhassan GN, et al. (2026) Effects of health expenditure, death rate, and infant mortality rate on life expectancy: A case study of the United States. *Energy Environ* 37: 2312–2339. <https://doi.org/10.1177/0958305X241281804>
- Ahn SC, Horenstein AR (2013) Eigenvalue Ratio Test for the Number of Factors. *Econometrica* 81: 1203–1227. <https://doi.org/10.3982/ECTA8968>
- Alamgir M, Osińska M (2026) Green bonds, climate resilience, and environmental performance: A global panel analysis of sustainable finance effectiveness. *Energy Policy* 216: 115363. <https://doi.org/10.1016/j.enpol.2026.115363>
- Aleknevičienė V, Kazilionienė A, Bendoraitytė A (2025) Does the green bond premium exist in the secondary market? Evidence from Nordic countries. *Equilibrium* 20: 327–355. <https://doi.org/10.24136/eq.3389>
- Alghannam R, Alharbi A (2026) Assessing the impact of government healthcare expenditure and life expectancy on economic growth in Saudi Arabia: An econometric time-series study (2000–2023). *Health Econ Rev* 16: 13. <https://doi.org/10.1186/s13561-026-00720-4>
- Amin N, Sharif A, Shabbir MS, et al. (2025) Evaluating the impact of natural resource rents, R&D expenditures, green finance and energy efficiency on carbon emissions in BRICS economies: Greening the path to carbon neutrality in the post-COP 27 era. *Technol Soc* 81: 102826. <https://doi.org/10.1016/j.techsoc.2025.102826>
- Azimi MN, Rahman MM (2024) Unveiling the health consequences of air pollution in the world's most polluted nations. *Sci Rep* 14: 9856. <https://doi.org/10.1038/s41598-024-60786-0>
- Bai J, Ng S (2002) Determining the Number of Factors in Approximate Factor Models. *Econometrica* 70: 19–221. <https://doi.org/10.1111/1468-0262.00273>

- Bashir MF, Inglesi-Lotz R, Razi U, et al. (2024) Economic complexity, greenfield investments, and energy innovation: Policy implications for sustainable development goals in newly industrialised economies. *Environ Sci Pollut Res* 31: 36013–36027. <https://doi.org/10.1007/s11356-024-33433-4>
- Baum CF, Schaffer ME, Stillman S (2003). Instrumental variables and GMM: Estimation and testing. *The Stata J* 3: 1–31. <https://doi.org/10.1177/1536867X0300300101>
- Breitung J, Das S (2005) Panel unit root tests under cross-sectional dependence. *Stat Neerl* 59: 414–433. <https://doi.org/10.1111/j.1467-9574.2005.00299.x>
- Cao M, Duan K, Ibrahim H (2023) Green investments and their impact on ESG ratings: An evidence from China. *Econ Lett* 232: 111365. <https://doi.org/10.1016/j.econlet.2023.111365>
- Choi I (2001) Unit root tests for panel data. *J Int Money Finance* 20: 249–272. [https://doi.org/10.1016/S0261-5606\(00\)00048-6](https://doi.org/10.1016/S0261-5606(00)00048-6)
- Chudik A, Pesaran MH (2015) Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *J Econom* 188: 393–420. <https://doi.org/10.1016/j.jeconom.2015.03.007>
- Chudik A, Pesaran MH (2019) Mean group estimation in presence of weakly cross-correlated estimators. *Econ Lett* 175: 101–105. <https://doi.org/10.1016/j.econlet.2018.12.036>
- Croissant Y, Millo G (2008) Panel data econometrics in R: The plm package. *J Stat Softw* 27: 1–43. <https://doi.org/10.18637/jss.v027.i02>
- Dai J, Mehmood U, Nassani AA (2025) Empowering sustainability through energy efficiency, green innovations, and the sharing economy: Insights from G7 economies. *Energy* 318: 134768. <https://doi.org/10.1016/j.energy.2025.134768>
- Ditzen J (2018) Estimating dynamic common-correlated effects in stata. *Stata J* 18: 585–617. <https://doi.org/10.1177/1536867X1801800306>
- Ditzen J (2022) Illuminating the factor and dependence structure in large panel models. *London Stata Conference 2022*. Available from: <https://ideas.repec.org/p/boc/lsug22/18.html>.
- Ditzen J, Reese S (2023) xtnumfac: A battery of estimators for the number of common factors in time series and panel-data models. *Stata J* 23: 438–454. <https://doi.org/10.1177/1536867X231175305>
- Fadnes LT, Javadi Arjmand E, Økland J-M, et al. (2024) Life expectancy gains from dietary modifications: A comparative modeling study in 7 countries. *Am J Clin Nutr* 120: 170–177. <https://doi.org/10.1016/j.ajcnut.2024.04.028>
- Fan J, Liao Y, Yao J (2015) Power enhancement in high-dimensional cross-sectional tests. *Econometrica* 83: 1497–1541. <https://doi.org/10.3982/ECTA12749>
- Feng Z, Wijethilake C (2026) The impact of green innovation and green finance on corporate ESG performance. *Bus Strategy Environ*. <https://doi.org/10.1002/bse.71050>
- Friedlingstein P, Le Quéré C, O’Sullivan M, et al. (2026) Emerging climate impact on carbon sinks in a consolidated carbon budget. *Nature* 649: 98–103. <https://doi.org/10.1038/s41586-025-09802-5>
- Gagliardini P, Ossola E, Scaillet O (2019) A diagnostic criterion for approximate factor structure. *J Econom* 212: 503–521. <https://doi.org/10.1016/j.jeconom.2019.06.001>
- Global Carbon Budget (2024) Fossil fuel CO₂ emissions increase again in 2024. *Global Carbon Budget*. Available from: <https://globalcarbonbudget.org>.
- Global Carbon Budget (2025) Fossil fuel CO₂ emissions hit record high in 2025. *Global Carbon Budget*. Available from: <https://globalcarbonbudget.org>.

- Guo A, Ullah O, Zeb A, et al. (2025) Unveiling health dynamics: Exploring the impact of CO₂ emissions, urbanization, and renewable energy on life expectancy and infant mortality in SAARC countries (1990–2022). *Nat Resour Forum* 49: 1795–1822. <https://doi.org/10.1111/1477-8947.12460>
- Hadri K (2000) Testing for stationarity in heterogeneous panel data. *Econom J* 3: 148–161. <https://doi.org/10.1111/1368-423X.00043>
- Hamrouni D, Hasni R, Ouerghi I (2025) The moderating effect of institutional quality on the relationship between structural change and CO₂ emissions in emerging economies. *Environ Sustain Indic* 27: 100817. <https://doi.org/10.1016/j.indic.2025.100817>
- Harris R, Tzavalis E (1999) Inference for unit roots in dynamic panels where the time dimension is fixed. *J Econom* 91: 201–226. [https://doi.org/10.1016/S0304-4076\(98\)00076-1](https://doi.org/10.1016/S0304-4076(98)00076-1)
- Hu FB (2024) Diet strategies for promoting healthy aging and longevity: An epidemiological perspective. *J Intern Med* 295: 508–531. <https://doi.org/10.1111/joim.13728>
- Hu Z, Zhang J, Chang CP (2025) AI and green credit: A new catalyst for green innovation in Chinese enterprises. *Oeconomia Copernicana* 16: 1447–1489. <https://doi.org/10.24136/oc.3020>
- Idalfahim M, Elouardirhi S (2026) Impact of carbon dioxide emissions on life expectancy in Morocco: An ARDL model approach. *World Dev Sustain* 8: 100305. <https://doi.org/10.1016/j.wds.2026.100305>
- Im KS, Pesaran MH, Shin Y (2003) Testing for unit roots in heterogeneous panels. *J Econom* 115: 53–74. [https://doi.org/10.1016/S0304-4076\(03\)00092-7](https://doi.org/10.1016/S0304-4076(03)00092-7)
- Jiesisibieke ZL, Schooling CM (2024) Impact of Alcohol Consumption on Lifespan: A Mendelian randomization study in Europeans. *Sci Rep* 14: 25321. <https://doi.org/10.1038/s41598-024-73333-8>
- Juodis A, Reese S (2022) The incidental parameters problem in testing for remaining cross-section correlation. *J Bus Econ Stat* 40: 1191–1203. <https://doi.org/10.1080/07350015.2021.1906687>
- Knutsson P, Flores PI (2022) Trends, investor types and drivers of renewable energy FDI. *OECD Work Pap Int Invest* 2022. <https://doi.org/10.1787/4390289d-en>
- Kwilinski A, Lyulyov O, Pimonenko T (2026) Pathways to EU decarbonization: The role of green investment and R&D activity. *Sustain Sci*. <https://doi.org/10.1007/s11625-026-01852-6>
- Lasisi TT, Eweade BS, Eluwole KK (2024) Analyzing the interaction among tourism, life expectancy, and unemployment in Japan: Insights from cointegration and conditional causality approach. *Int J Tourism Res* 26: e2736. <https://doi.org/10.1002/jtr.2736>
- Le NT, Nguyen HL, Le LT, et al. (2026) Waterpipe smoking and risk of cardiovascular disease mortality: Findings from a Prospective Cohort Study. *Am J Prev Cardiol*, 101516. <https://doi.org/10.1016/j.ajpc.2026.101516>
- Levin A, Lin CF, James Chu CS (2002) Unit root tests in panel data: Asymptotic and finite-sample properties. *J Econom* 108: 1–24. [https://doi.org/10.1016/S0304-4076\(01\)00098-7](https://doi.org/10.1016/S0304-4076(01)00098-7)
- Li T, Yue XG, Qin M, et al. (2024) Towards Paris Climate Agreement goals: The essential role of green finance and green technology. *Energy Econ* 129: 107273. <https://doi.org/10.1016/j.eneco.2023.107273>
- Liu J, Ye J, Chen J, et al. (2026) Shipping transition under green energy supply risks: Three-dimensional mechanism analysis. *Marit En* 179: 44–77. <https://doi.org/10.1680/jmaen.25.01917>
- Liu Y (2025) Whether fintech, natural resources, green finance and environmental tax affect CO₂ emissions in China? A step towards green initiatives. *Energy* 320: 135181. <https://doi.org/10.1016/j.energy.2025.135181>

- Luong TA, Nguyen MH (2024) Aging in the Air: The impact of carbon emissions on health-related quality of life. *TSE Working Paper*, 24–1549. <https://doi.org/10.2139/ssrn.4879284>
- National Human Genome Research Institute (2026) *Gene Therapy*. Available from: <https://www.genome.gov/genetics-glossary/Gene-Therapy>.
- Nica E, Poliakova A, Popescu GH, et al. (2023) The impact of financial development, health expenditure, CO₂ emissions, institutional quality, and energy Mix on life expectancy in Eastern Europe: CS-ARDL and quantile regression Approaches. *Heliyon* 9: e21084. <https://doi.org/10.1016/j.heliyon.2023.e21084>
- NOAA (2024) No sign of greenhouse gases increases slowing in 2023. *NOAA Research*. Available from: <https://research.noaa.gov/no-sign-of-greenhouse-gases-increases-slowing-in-2023/>.
- OECD (2022) The geography of foreign investment in OECD member countries: How investment promotion agencies support regional development. *OECD Bus Finance Policy Pap*. Available from: <https://doi.org/10.1787/1f293a25-en>.
- Omri A, kahouli B, Kahia M (2024) Environmental sustainability and health outcomes: Do ICT diffusion and technological innovation matter? *Int Rev Econ Finance* 89: 1–11. <https://doi.org/10.1016/j.iref.2023.09.007>
- Onatski A (2010) Determining the number of factors from empirical distribution of eigenvalues. *Rev Econ Stat* 92: 1004–1016. https://doi.org/10.1162/REST_a_00043
- Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. *Econom Rev* 34: 1089–1117. <https://doi.org/10.1080/07474938.2014.956623>
- Pesaran MH (2021) General diagnostic tests for cross-sectional dependence in panels. *Empir Econ* 60: 13–50. <https://doi.org/10.1007/s00181-020-01875-7>
- Pesaran MH, Shin Y, Smith RP (1999) Pooled mean group estimation of dynamic heterogeneous panels. *J Am Stat Assoc* 94: 621. <https://doi.org/10.2307/2670182>
- Pesaran MH, Smith R (1995) Estimating long-run relationships from dynamic heterogeneous panels. *J Econom* 68: 79–113. [https://doi.org/10.1016/0304-4076\(94\)01644-F](https://doi.org/10.1016/0304-4076(94)01644-F)
- Putrika U, Ardianto (2025) How green investment affects stock returns: Exploring the role of financial performance. *J Account Sci* 9: 62–78. <https://doi.org/10.21070/jas.v9i1.1938>
- Raza A, Azam K, Khan AUI, et al. (2024) Balancing growth and sustainability: The impact of Greenfield investment on trade adjusted carbon emissions. *Sustain Futures* 8: 100253. <https://doi.org/10.1016/j.sftr.2024.100253>
- Ridwan M, Antor ZA, Akther A, et al. (2026) Heterogeneous associations of health expenditure, environmental pollution, and economic growth on life expectancy in BRICS economies. *Front Public Health* 14: 1767163. <https://doi.org/10.3389/fpubh.2026.1767163>
- Roerecke M, Vafaei A, Hasan OS, et al. (2019) Alcohol consumption and risk of liver cirrhosis: A systematic review and meta-analysis. *Am J Gastroenterol* 114: 1574–1586. <https://doi.org/10.14309/ajg.0000000000000340>
- Shaari MS, Majekodunmi TB, Sulong A, et al. (2024) Examining the interplay between green technology, CO₂ emissions, and life expectancy in the asean-5 countries: Insights from the panel FMOLS and DOLS approaches. *Discover Sustainability* 5: 456. <https://doi.org/10.1007/s43621-024-00706-4>
- Sohail HM, Haron NF, Bhat MA, et al. (2026) Heterogeneous impact of green finance on decarbonization: Evidence from GMM and machine learning approaches. *J Clim Finance* 15: 100086. <https://doi.org/10.1016/j.jclimf.2026.100086>

- Solmi M, Thompson T, Estradé A, et al. (2024) Global and risk-group stratified well-being and mental health during the COVID-19 pandemic in adults: Results from the international COH-FIT Study. *Psychiatry Res* 342: 115972. <https://doi.org/10.1016/j.psychres.2024.115972>
- Tithi SI (2026) Towards sustainable development goals: an ardl analysis of energy efficiency, finance, and technology in mitigating CO₂ emissions in the united states. *Syst Anal* 4: 13–26. <https://doi.org/10.31181/sa41202667>
- Trias-Llimós S, Spijker JJA (2022) Educational differences in alcohol-related mortality and their impact on life expectancy and lifespan variation in Spain (2016–2018): A cross-sectional analysis using multiple causes of death. *BMJ Open* 12: e053205. <https://doi.org/10.1136/bmjopen-2021-053205>
- Țarcă V, Țarcă E, Moscalu M (2024) Social and economic determinants of life expectancy at birth in Eastern Europe. *Healthcare* 12: 11. <https://doi.org/10.3390/healthcare12111148>
- Vărzaru AA. (2025). Assessing the relationships of expenditure and health outcomes in healthcare systems: a system design approach. *Healthcare* 13: 352. <https://doi.org/10.3390/healthcare13040352>
- Wang HJ, Zheng MQ, Wang HY, et al. (2025) The impact of green finance on ESG: Evidence from the Chinese enterprises. *Oeconomia Copernicana* 16: 557–592. <https://doi.org/10.24136/oc.3534>
- Wiredu J, Yang Q, Lu T, et al. (2025) Delving into environmental pollution mitigation: Does green finance, economic development, renewable energy resource, life expectancy, and urbanization matter? *Environ Dev Sustain* 27: 1–30. <https://doi.org/10.1007/s10668-024-05934-2>
- World Health Organization (2022) Billions of people still breathe unhealthy air: New WHO data. Available from: <https://www.who.int/news/item/04-04-2022-billions-of-people-still-breathe-unhealthy-air-new-who-data>.
- World Health Organization (2023) Climate change. Available from: <https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health>.
- World Health Organization (2024) Alcohol. Available from: <https://www.who.int/news-room/fact-sheets/detail/alcohol>.
- Woychik RP, Bianchi DW, Gibbons GH, et al. (2022) The NIH climate change and health initiative and strategic framework: Addressing the threat of climate change to health. *Lancet* 400: 1831–1833. [https://doi.org/10.1016/S0140-6736\(22\)02163-8](https://doi.org/10.1016/S0140-6736(22)02163-8)
- Xie Y, Pesaran MH (2022) A bias-corrected cd test for error cross-sectional dependence in panel data models with latent factors. *SSRN Electronic J*, 4198155. <https://doi.org/10.2139/ssrn.4198155>
- Xie Z, Liu W, Tao R, et al. (2026) Driving green investment through innovation and regulation: The role of R&D and pollution control in China. *J Innov Knowl* 12: 100909. <https://doi.org/10.1016/j.jik.2025.100909>
- Xu Y, Wu X, Adam NA, et al. (2025) Decarbonizing growth: Nuclear energy, Green investments, and CO₂ emissions in BRICS economies. *Ann Nucl Energy* 224: 111746. <https://doi.org/10.1016/j.anucene.2025.111746>
- Yang B, Hassan FA, Ahmad W, et al. (2026) Impact of air pollution on life expectancy in Asian developing countries: Does renewable energy adoption matter? *Front Public Health* 14: 1724402. <https://doi.org/10.3389/fpubh.2026.1724402>

- Yang J, Yin W (2024) How air pollution affects corporate total factor productivity? *PLOS ONE* 19: e0304079. <https://doi.org/10.1371/journal.pone.0304079>
- Yang MJ, Zhu N (2024) Online public opinion attention, digital transformation, and green investment: A deep learning model based on artificial intelligence. *J Environ Manage* 371: 123294. <https://doi.org/10.1016/j.jenvman.2024.123294>
- Yeboah KE, Feng B, Jamatutu SA, et al. (2025) Impact of green financing on energy efficiency and CO₂ emissions in Africa: The role of environmental tax and FDI. *J Clean Prod* 521: 146258. <https://doi.org/10.1016/j.jclepro.2025.146258>
- Yildirim H (2026) Green finance and investment. *Green Econ. Financ. Clim. Justice*, 5–70. https://doi.org/10.1007/978-3-032-17588-5_4
- Zeraibi A, Jahanger A, Sunday Adebayo T, et al. (2023) Greenfield investments, economic complexity, and financial inclusion-environmental quality nexus in BRICS Countries: Does renewable energy transition matter? *Gondwana Res* 117: 139–154. <https://doi.org/10.1016/j.gr.2022.12.020>
- Zhang H, Shao Q, Uddin I, et al. (2026) Do environmental degradation, ICT, health expenditure, and institutional quality affect life expectancy? *Am J Mens Health* 20: 15579883261420408. <https://doi.org/10.1177/15579883261420408>
- Zhang M, Zhang X, Song Y (2025) Do green investments really make companies “green”? Empirical evidence from corporate ESG ratings. *Environ Dev Sustain*. <https://doi.org/10.1007/s10668-025-06133-3>
- Zhang Y, Hassan ST, Khan S (2024) Towards achieving status of green economy in OECD countries: Articulating the role of nuclear energy, greenfield investment and environmental taxation. *Nucl Eng Technol* 56: 4494–4501. <https://doi.org/10.1016/j.net.2024.06.012>



AIMS Press

© 2026 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0>)