THE IMPACT OF CLEAN ENERGY RESEARCH AND DEVELOPMENT, HEALTH EXPENDITURE, AND ECONOMIC GROWTH ON ENVIRONMENTAL QUALITY

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Abstract. This study investigates the impact of clean energy technologies, health expenditure, and economic growth on environmental quality using the Fourier Engle-Granger cointegration method for the United States in the 1974–2022 period. The Fourier approach successfully identifies gradual structural shifts and nonlinear dynamics in long-run relations, which are frequent in macroeconomic and environmental time series but are typically overlooked by standard approaches. The findings show that clean energy research and development investment—specifically in energy efficiency, renewable resources, and nuclear technologies—and health expenditures significantly positively impact environmental quality. However, economic growth has a negative impact environmental quality in the United States. These results highlight the necessity of integrating environmental objectives into energy and health policy and prioritizing investment in sustainable technologies to achieve ecological sustainability in the long term.
Keywords: *load capacity factor, energy technologies, energy efficiency, sustainability, Fourier cointegration*

Introduction

The attainment of net-zero emissions necessitates substantial and sustained research and development (R&D) efforts in clean energy technologies. The United States, as a leading global economy and one of the world's largest energy consumers, occupies a unique position as both a significant emitter of greenhouse gases and a pioneer in clean energy innovation. In 2023, the United States was largest investor International Energy Agency (IEA) member nation to invest in clean energy R&D. This dual role renders the United States an especially valuable case for examining the long-term impacts of clean energy investments on environmental quality. Accordingly, the United States context offers critical insights into the complex interplay between economic growth, technological advancement, and environmental sustainability.

Environmental innovation aims to enhance environmental quality and resource efficiency. The relationship between economic growth and environmental pollution is

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often represented by the Environmental Kuznets Curve (EKC) hypothesis in an inverted U-shaped form. However, the relationship remains complex and an area of ongoing controversy. Environmental pollution also impacts public health, raising the burden of health expenditures. Although health infrastructure investment and public health programs might indirectly improve environmental quality, there is limited and inconclusive empirical evidence on the direct influence of health expenditures on overall ecological indicators, including the load capacity factor (LCF) (Apergis et al., 2018; Zaidi and Saidi, 2018).

The formulation of sustainable growth policies involves the coordination of environmental policy, energy policy, and health policy, which are in line with the Sustainable Development Goals. Addressing a significant gap in the literature, this study examines the impact of clean energy technologies—classified as efficiency, nuclear, renewable, and fossil R&D—along with with health expenditure and economic growth on environmental quality in the United States, measured by the LCF. With yearly data from 1974 to 2022, this article employs the Fourier Engle-Granger (EG) cointegration test with structural breaks and nonlinear dynamics. It estimates long-run coefficients via the Fully Modified Ordinary Least Squares (FMOLS) method.

While widely studied, the EKC's inverted-U relationship requires re-examination through disaggregated technologies and LCF's comprehensive framing. Our investigation tests three theoretically grounded hypotheses: H_1: Clean energy technologies improve environmental quality. Disaggregated clean energy R&D (particularly nuclear and renewables) improves LCF beyond aggregate measures, extending the EKC framework to technology-specific effects. The U.S. economy shows a significant increase in R&D expenditures in clean energy technologies within the framework of sustainable environmental policies. According to IEA data, the United States ranks first in clean energy R&D expenditures, which are expected to affect environmental quality positively. H_2: Health expenditures improve environmental quality. Health expenditures indirectly enhance environmental quality through a) pollution-reducing medical technologies and b) health-aware policymaking mechanisms overlooked in current EKC literature. Health expenditures treat diseases and include environmentally sound infrastructure, public health policies, and various energy-saving health technologies. These expenditures can reduce the carbon footprint by raising environmental awareness and thus positively impact ecological quality. H_3: Economic growth reduces environmental quality. United States' economic growth remains coupled with environmental degradation, contradicting the EKC's predicted decoupling phase. As the EKC hypothesis states, economic growth increases environmental pollution to a certain threshold. There are various underlying reasons for this. For example, economic growth directly increases industrialization, energy-intensive consumption, and fossil fuel use, which hurt environmental quality. Since industry, transportation, and intensive consumption are the primary sources of growth in the United States, economic growth reduces ecological quality.

While existing research has established broad relationships between energy investments and environmental outcomes, two critical gaps remain. First, most studies treat clean energy R&D as a monolithic category, ignoring crucial differences between nuclear, renewable, and efficiency technologies. Second, conventional metrics like carbon dioxide (CO_2) emissions fail to capture ecological capacity—a gap our LCF approach resolves. LCF's biocapacity/ecological footprint ratio provides unique insights that emission-based metrics cannot. Our LCF approach builds on Pata et al. (2023) while addressing Zaidi and Saidi's (2018) call for better integrated health-environment metrics.

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Three contributions of this research stand out most: i) it focuses on the United States as both a large emitter and an innovator, ii) it employs the LCF as a general measure of environmental quality, and iii) it disaggregates clean energy R&D into different types, providing new insights into the specific impacts of each technology type. Applying the Fourier approach further enhances the robustness of the empirical results.

The research is organized as follows: the first section includes an overview of the existing literature related to energy, healthcare expenditure, economy and environment. Afterwards, the research methodology is presented. The third section is results and discussions. The last section is related to concluding remarks.

Theoretical background

The United States has a dual role as a leading clean energy innovator and one of the most prominent global emitters, which makes it particularly interesting for analysis. To build on this, several works focus on the specific regions and technologies related to clean energy R&D and its environmental impacts in the United States. For example, Raihan et al. (2022) and Pata (2021) provide baseline assessments regarding the relationship between investment in clean technology and environmental factors. Kartal (2024) goes further to show that the impact of R&D spending differs strikingly in different parts of the United States, while the U.S. Environmental Protection Agency (2023) brings attention to carbon reduction trends at the state level. Importantly, IEA (2024) reports that patent applications for clean technologies surged by 12% annually since 2020 compared to the European Union (EU) and China.

Further, fuel-specific R&D activities influence environmental outcomes differently: Kartal et al. (2023) find that particular renewable energy expenditures lead to heightened carbon emissions regionally, whereas nuclear investments tend to lower emissions. This finding highlights how significant technology can be in shaping environmental results. Based on United Kingdom research, Caglar's warning (2023) suggests those conclusions cannot be applied straightforwardly to America due to differences in institutions and policies. In America, policymakers have emphasized "just transitions," or achieving clean energy goals while fairly distributing environmental and economic opportunities among regions and social demographics (Carley and Konisky, 2020).

Beyond the United States, studies from developing countries focus on the relationship between economic development, energy consumption, urban expansion, and environmental degradation (Yıldız, 2019). There is a popular notion called "decoupling", which believes that technology advances and proper policies can unlink economic growth from environmental damage. This "planetary boundaries" approach (Rockström et al., 2009) argues equally for maintaining ecological limits while developing further. Moreover, there are also institutional factors. Carley (2011) demonstrates how state-level renewable portfolio standard in the United States have significantly increased renewable energy production. Government stimulus programs increase adoption of clean technologies as well (Johnstone et al., 2020). However, the impact of health expenditures on the environment remains murky—even contested—showing both strong and weak effects globally (Apergis et al., 2018; Zaidi and Saidi, 2018; Alola, 2019). More recent research indicates that health expenditures may enhance environmental protection indirectly by raising awareness of pollution prevention for associated illnesses (Ganda, 2021; Triki et al., 2023).

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Global assessments provide important context: the latest report from the Intergovernmental Panel on Climate Change (2023) found that the pace of the United States' energy transition is 18% slower than that of the EU, particularly in nuclear and wind energy, while official data from the U.S. Energy Information Administration (2023) show that the health expenditure-environmental quality relationship is 1.3 times stronger in the United States than in Germany and Japan. Carley and Konisky's (2020) 'just transition' study highlights how the United States emphasis on social justice differs from Europe's technology-focused approach, while Yang and Khan (2022) find that China's state-supported R&D model delivers 40% faster growth in renewable energy than the United States' private sector-dominated system. Organisation for Economic Co-operation and Development's (OECD) (2023) comparative analysis finds that the United States lags in environmental health outcomes despite its healthcare expenditure as a share of gross domestic product (GDP) being 2.1 times higher than that of the Nordic countries.

Recent advancements have transformed our approach to studying the interplay of economics, society, and the environment. For instance, the Fourier cointegration technique can identify gradual changes and cycles within data that previous techniques would overlook (Enders and Lee, 2012). It does have its drawbacks. Its sensitivity to frequency selection and tendency to over fit small sample sizes means robustness checks (Yilanci, 2019) are essential. Employing the Dynamic Least Squares (DOLS) and Canonical Cointegrated Regression (CCR) tests is common in confirming stable relationships in environmental econometrics (Park, 1992; Stock and Watson, 1993). Even with these enhancements, most researchers do not analyze the separate impacts of various clean energy R&D activities, health spending, and economic growth on key environmental metrics such as LCF for the United States. There remains a gap in seeking the integration and decomposition of these factors using sophisticated time series techniques. This research seeks to address that through applying Fourier cointegration analysis, uncovering the impact of clean energy R&D investments alongside healthcare expenditures and economic growth on United States' environmental quality over extended periods.

Research methodology

Data

This study utilizes annual data for the United States covering 1974–2022. All variables are transformed into their natural logarithms to obtain elasticity coefficients. Description of variables is summarized in the *Table 1*.

In the literature, ecological footprint data has been used in many studies as an indicator of environmental quality. However, the ecological footprint only reflects the environmental degradation caused by human demand for natural resources and neglects nature's ability to meet environmental requirements, i.e., biocapacity. An indicator that reflects both the supply and demand sides of nature can enable a better analysis of environmental quality (Pata and Samour, 2022). The LCF variable, first proposed by Siche et al. (2010) and further developed in Pata (2021), is a more comparable indicator of environmental quality because it considers both the demand and supply sides of the environment. This study references the work of Pata et al. (2023) and uses the LCF variable as an indicator of environmental quality. The LCF, the dependent variable, is calculated as the ratio of biocapacity to ecological footprint. An LCF value greater than 1 indicates environmental sustainability, while less than 1 signals unsustainability. A

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value equal to 1 represents the sustainability threshold (Pata et al., 2023). *Fig. 1* shows the United States' LCF trend during the study period, which has generally declined since the 1970s.

Table 1. *Description of variables*

Variable	Symbol	Unit	Source
Load Capacity Factor	LCF	Biocapacity/Ecological Footprint	Global Footprint Network
Energy Efficiency	ERDD	Public Budget 2024 Prices, USD	IEA, Energy Technology RD&D Budgets
Fossil Fuels	FRDD	Public Budget 2024 Prices, USD	IEA, Energy Technology RD&D Budgets
Renewable Energy Sources	RRDD	Public Budget 2024 Prices, USD	IEA, Energy Technology RD&D Budgets
Nuclear Fission and Fusion	NRDD	Public Budget 2024 Prices, USD	IEA, Energy Technology RD&D Budgets
Total Budget	TRDD	Public Budget 2024 Prices, USD	IEA, Energy Technology RD&D Budgets
Health Expenditures	HEX	% GDP	World Health Organisation (WHO)
Economic Growth	PCGDP	2015 constant prices, USD	World Bank, World Development Indicators

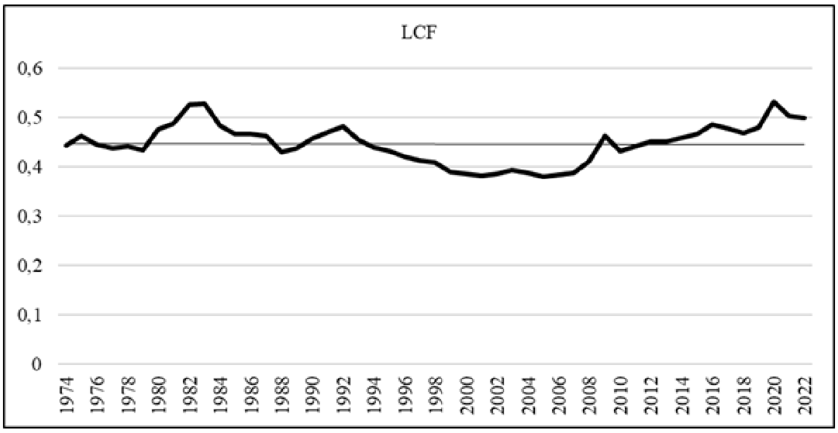

Figure 1. *United States' LCF Values for the Period 1974-2022*

R&D and demonstration (RDD) investments reflected in *Fig. 2* are utilized for clean energy technology categories in the United States' LCF Values for the Period 1974-2022 and serve as optimum indicators in this study for environmental innovation. The R&D expenditure as a share of total U.S. expenditures has been rising steadily since the early 2000s, and the United States holds the highest R&D budget of any IEA member. This increased funding has focused mainly on energy efficiency and renewable resources, with a decline in nuclear and fossil fuel R&D. The temporary spike in funding between 2008 and 2010, followed by a decrease, resulted from the Global Financial Crisis, increased domestic production of energy, and substantial improvements in energy efficiency, especially concerning vehicle fuel economy (Nadel et al., 2015; Ben Youssef, 2020). Further, the Inflation Reduction Act of 2022 has competitively positioned the country, financially, to upscale low-emission technologies significantly.

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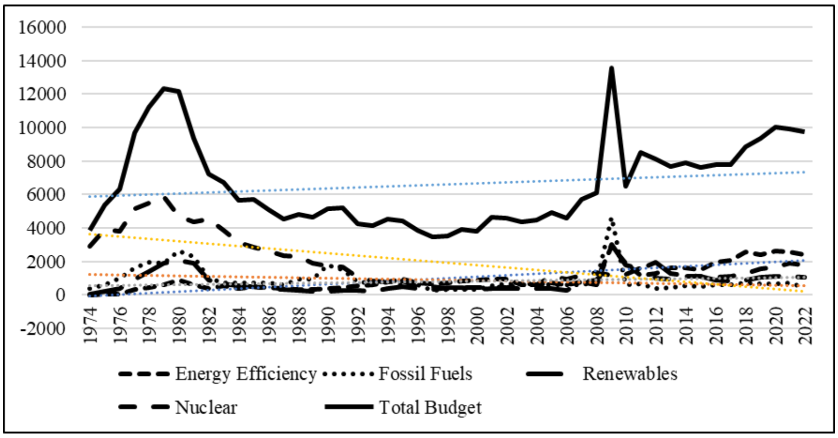

Figure 2. *United States' Clean Energy Technologies Sub-Indicators and Total RRD Budget for the Period 1974-2022 (USD)*

As demonstrated in *Figure 2*, public RDD expenditures by subcategory and total budget have markedly evolved from 1974 to 2022. The data reveal a significant shift in the United States energy innovation priorities toward sustainable technologies, highlighting the dynamic structure of clean energy investments over time.

United States' health expenditures for the period 1974-2022 demonstrate in *Figure 3*. Health expenditures (HEX) are measured as a percentage of GDP. The United States allocates a significantly higher share of its GDP to health than other high-income countries, with expenditures rising from approximately 7% in the mid-1970s to over 16% in 2022 (OECD, 2022; WHO, 2023). This trend reflects demographic, technological, and policy changes over time.

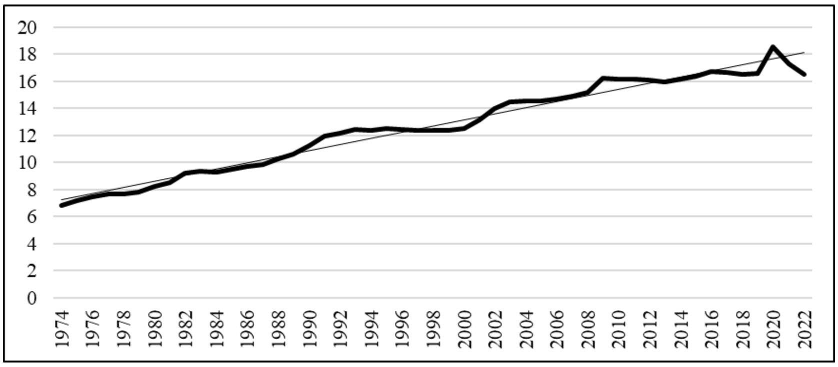

Figure 3. *United States' Health Expenditures for the Period 1974-2022 (% GDP)*

The study includes GDP per capita as a control variable. This variable has shown a steady increase throughout the study period and a brief decrease during the COVID-19 pandemic. *Figure 4* demonstrates the real GDP per capita change in the United States from 1974 to 2022.

The figure shows that there has been a steady increase in per capita income in general, except for short-term fluctuations such as the COVID-19 pandemic. This long-term economic growth provides an important background for analyzing the study's relationship between economic growth and environmental quality. The figure visually reveals the

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macroeconomic environment in which changes in environmental and health indicators occur.

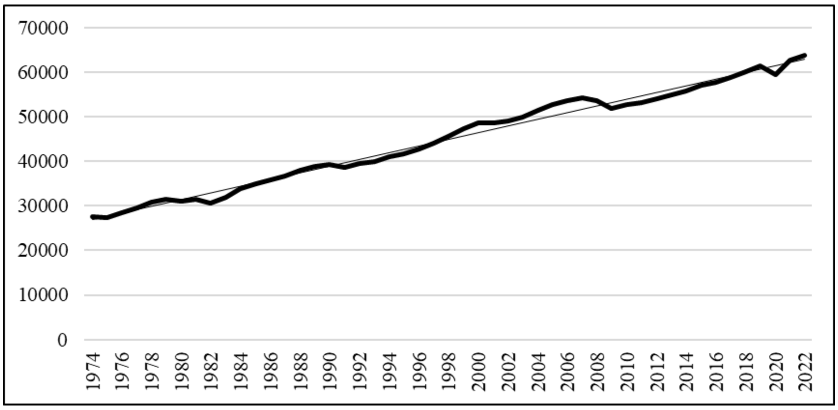

Figure 4. *United States' GDP per Capita for the Period 1974-2022 (USD)*

Model and hypotheses

Five different models are developed based on the empirical literature. The LCF variable is used as the dependent variable in all models. Each model includes one clean energy RDD sub-indicator, health expenditures, and GDP per capita as independent variables. This approach avoids multicollinearity and allows for the identification of the most effective innovation type for environmental quality. The general model specification is as *Eq. 1*:

$$\ln LCF_t=\alpha_0+\alpha_1\ln X_t+\alpha_2\ln HEX_t+\alpha_3\ln PCGDP_t+\varepsilon_t \quad \text{(Eq.1)}$$

where: ln is logarithm; X represents each RDD indicator (ERDD, FRDD, RRDD, NRDD, TRDD); t is time; ε is error term.

The models created in the study are as in *Equations 2-6*:

$$\text{Model 1: } \ln LCF_t=\beta_0+\beta_1\ln ERDD_t+\beta_2\ln HEX_t+\beta_3\ln PCGDP_t+\varepsilon_{1t} \quad \text{(Eq.2)}$$

$$\text{Model 2: } \ln LCF_t=\gamma_0+\gamma_1\ln FRDD_t+\ln HEX_t+\gamma_3\ln PCGDP_t+\varepsilon_{2t} \quad \text{(Eq.3)}$$

$$\text{Model 3: } \ln LCF_t=\delta_0+\delta_1\ln RRDD_t+\delta_2\ln HEX_t+\delta_3\ln PCGDP_t+\varepsilon_{3t} \quad \text{(Eq.4)}$$

$$\text{Model 4: } \ln LCF_t=\theta_0+\theta_1\ln NRDD_t+\theta_2\ln HEX_t+\theta_3\ln PCGDP_t+\varepsilon_{4t} \quad \text{(Eq.5)}$$

$$\text{Model 5: } \ln LCF_t=\mu_0+\mu_1\ln TRDD_t+\mu_2\ln HEX_t+\mu_3\ln PCGDP_t+\varepsilon_{5t} \quad \text{(Eq.6)}$$

where: β_0,γ_0,θ_0, δ_0 and μ_0 are constant terms; $\beta_{1\text{-}3}$,$\gamma_{1\text{-}3}$,$\delta_{1\text{-}3}$,$\theta_{1\text{-}3}$, and μ_{1-3} are long-run coefficients; and $\varepsilon_{1\text{-}5t}$ is error term.

The hypotheses tested in the study are as follows:

- H_1: Clean energy technologies improve environmental quality.
- H_2: Health expenditures improve environmental quality.
- H_3: Economic growth reduces environmental quality.

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Method

The Fourier approach is preferred in this study because it allows for modelling smooth structural breaks and nonlinear trends in the data without requiring prior knowledge of the number or timing of such breaks. This method is particularly suitable for analyzing complex interactions in environmental economics, as it captures gradual structural shifts (e.g., policy changes in the 2000s) without pre-specifying break dates (Enders and Lee, 2012). For a summary of the methodological advantages and limitations of the Fourier approach, Unit root tests were applied to test the variables' stationarity in the first stage of the econometric analysis. According to the series' stationarity, the cointegration test will be used, and the coefficients in the models will be estimated.

Most unit root tests use dummy variables to allow for structural breaks and therefore have some drawbacks, such as detecting only sharp breaks and predetermining the number of structural breaks. In addition to not allowing structural changes, the wrong number of structural breaks can lead to erroneous results (Yilanci et al., 2019, 2020). Based on Becker et al. (2006), and Enders and Lee (2012) developed the Fourier approach. An essential feature of this approach is that there is no need to know the break dates, the exact number of breaks, and/or the exact shape of the breaks in advance. Moreover, the Fourier approximation can reduce the need to estimate many parameters and hence can be applied as a test with large size and power characteristics (Enders and Lee, 2012).

A simple form of the Dickey-Fuller (DF) type test is to allow the deterministic term to be a time-dependent function denoted by d(t) in *Eq. 7*:

$$y_t = d(t) + \rho y_{t-1} + \gamma . t + \varepsilon_t \tag{Eq.7}$$

where: ε_t is stationary disturbance with variance σ_ε^2; d(t) is a deterministic function of t.

Enders and Lee (2012) propose a Fourier approach for the calculation of the $d(t)$ term as in *Eq. 8*:

$$\Delta y_t = \alpha_0 + \delta_1 \Delta \sin(2\pi kt/T) + \delta_2 \Delta \cos(2\pi kt/T) + u_t \tag{Eq.8}$$

where: k is number of specific frequencies; T is number of observations; sin and cos are trigonometric terms.

In the Fourier Augmented DF (FADF) approach, k allows the frequency value to be between 1 and 5. If all coefficients of the trigonometric terms in *Eq. 8* are not statistically significant, a DF unit root test is required since a linear process will occur. In the first stage of unit root tests, the frequency number k is estimated, and the model with the smallest residual squares is selected. In the second stage, FADF test statistics are calculated using the appropriate model, and the unit root hypothesis is tested by comparing it with critical values.

Following the work of Perron (1989), who modelled structural breaks using dummy variables, Beckers et al. (2006) developed a new cointegration test using the Fourier function. These tests were extended by Yilanci (2019) to test for a cointegration relationship that allows for unknown forms of breaks. The Fourier EG cointegration test equation is as in *Eq. 9*:

$$y_{1t} = \alpha_0 + \gamma_1 \sin(2\pi kt/T) + \gamma_2 \cos(2\pi kt/T) + \beta' y_{2t} + u_t \tag{Eq.9}$$

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To test the null hypothesis of no cointegration, the ADF unit root test is applied to the residuals of *Eq. 9*. The ADF unit root test equation is estimated as in *Eq. 10*:

$$\Delta\hat{u}_t=\rho\hat{u}_{t-1}+\sum_{i=1}^{p}\gamma_i\,\hat{u}_{t-i}+\varepsilon_t \qquad \text{(Eq.10)}$$

where: ε_t~i.i.d. $(0,\sigma^2)$.

The Fourier EG cointegration test is calculated as in *Eq. 11*:

$$\tau_{FEG}=\frac{\hat{\rho}}{se(\hat{\rho})} \qquad \text{(Eq.11)}$$

where: $\hat{\rho}$ is the OLS estimator of ρ; $se(\hat{\rho})$ is the standard errors of $\hat{\rho}$.

In Yilanci's (2019) study, critical values for the Fourier EG cointegration test were obtained through simulations considering different numbers of regressors (n=1, 2, 3) and frequency values (k=1, 2, 3, 4, 5). The main advantage of the Fourier approach is its ability to capture smooth structural breaks and cyclical patterns in the data without requiring prior knowledge of the number or timing of breaks (Enders and Lee, 2012). This flexibility increases the robustness of cointegration analysis in the presence of complex, real-world dynamics. However, the method is sensitive to the choice of frequency parameter and may be prone to overfitting, especially in small samples. Therefore, robustness checks and careful model selection are essential (Yilanci, 2019).

Results and discussion

Results

The FADF and ADF unit root tests were applied to test the series' stationarity. There are two reasons for using these tests together. First, macroeconomic variables may exhibit various structural breaks of unknown number and form. The FADF unit root test is a test that takes structural breaks and changes into account and allows for smooth breaks. Second, using the conventional ADF test together with the stationarity tests that take structural changes into account, i.e., applying the FADF unit root test together, will increase the reliability of the test results (Tsong et al., 2016; Naimoğlu, 2022). The primary purpose of applying these tests is to determine the stationarity level of the series before proceeding to the cointegration test. The findings of the FADF and ADF unit root tests are presented in *Table 2*.

Table 2. *FADF and ADF unit root test results*

Variables	Min SSR	F statistic	k	FADF	ADF statistic	p-value
lnLCF	0.069265	1.905252	1	$-3.773754^{(*)\,(5)}$	-1.397605	0.5758
lnERDD	3.520746	17.54741^{**}	1	$-5.174619^{(***)\,(2)}$		
lnFRDD	8.715157	6.915694^{*}	5	$-3.428981^{(**)\,(0)}$		
lnRRDD	5.081131	6.349627	1	$-4.277493^{(**)\,(3)}$	-2.317356	0.1709
lnNRDD	1.546508	0.724956	1	$-3.390393^{\,(6)}$	-1.121971	0.6997
lnTRDD	1.232558	2.619783	1	$-4.695497^{(***)\,(3)}$	-1.343841	0.6014
lnPCGDP	0.015695	0.882005	5	$-1.550053^{\,(1)}$	-1.262182	0.6396
lnHE	0.035548	6.315149	5	$-2.932291^{(**)\,(0)}$	-3.047692	0.6580

***, **, and * indicates 1%, 5%, and 10% significance level, respectively; SSR – sum of squared residuals

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First, whether the trigonometric terms are statistically significant in the FADF unit root test is tested. For this purpose, the values obtained are compared with the table's critical values in Enders and Lee (2012). Accordingly, since the F-statistic values calculated for all variables, except that lnERDD and lnFRDD are smaller than the critical table value, the trigonometric terms are statistically insignificant. Therefore, the conventional ADF unit root test results are valid for these values. However, the F-statistic value calculated for lnERDD is statistically significant at the 5% level, and the F-statistic value calculated for lnFRDD is statistically significant at the 1% level compared to the critical table values. Therefore, FADF unit root test results are valid for these variables. Both FADF and ADF unit root test results show that all variables are stationary in difference, i.e., $I(1)$. This finding allows us to investigate the possible long-run cointegration relationship between the variables.

The results of the Fourier EG cointegration test developed by Yılancı (2019) are presented in *Table 3*. In all models, it is determined that the most appropriate frequency value for Min SSR is 1. In all models where the test statistic obtained for the proper frequency is greater than the critical values, the null hypothesis expressed as $H_0\text{: }no\ cointegration$ is rejected at a 5% significance level. Moreover, it is observed that there is a cointegrated relationship between the variables in the long run, and the independent variables together affect the dependent variable.

Table 3. *Fourier EG cointegration test results*

Models	Test statistic	k	Min SSR
Model 1	-5.392195**	1	0.018549
Model 2	-5.283829**	1	0.018469
Model 3	-5.411704**	1	0.018514
Model 4	-5.572866**	1	0.018346
Model 5	-5.349652**	1	0.018495

**, indicates 5% significance level; the critical table values of the Fourier EG cointegration test obtained from Yılancı (2019) are 1%=-5.596, 5%=-4.957, and 10%=-4.640

After determining the long-run relationships with the Fourier EG cointegration test, the FMOLS estimator developed by Phillips and Hansen (1990) was used to determine the severity and direction of the effect of the independent variables on the dependent variable. The Phillips and Hansen (1990) study stated that when there is endogeneity in the regressors, the instruments alone are insufficient to eliminate the bias effects asymptotically. The modified estimators form the basis of the so-called fully modified Wald tests. These are Wald statistics for testing general linear hypotheses about the coefficients in a cointegrated regression. The results obtained with the Fourier-based FMOLS estimator are presented in *Table 4*.

The findings in *Table 4* can be summarized as follows: *i) Clean Energy Technologies RDD Expenditures:* When the results for both the sub-indicators of clean energy technologies and the total budget are analyzed, it is seen that all variables have a statistically significant and positive effect on environmental quality. This finding shows that investments in clean energy improve ecological quality, albeit at different levels. Among the RDD investments, the sub-indicator that affects LCF the most is the nuclear fission and fusion indicator. *ii) Health Expenditures:* Health expenditures have a statistically significant and positive effect on environmental quality in all models. A 1%

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increase in health expenditures is associated with a 0.56% to 0.88% improvement in LCF. This result aligns with previous studies (e.g., Pata, 2021; Ganda, 2021), though the literature remains mixed. *iii) Economic Growth (GDP per Capita):* Across all models, GDP per capita has a statistically significant adverse effect on environmental quality, supporting the EKC hypothesis for the United States context (Yang and Khan, 2022; Raihan et al., 2022; Kartal et al., 2023).

Table 4. *FMOLS estimation results*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
lnERDD	$0.0915^{(***)}$ (0.0016)				
lnFRDD		$0.0675^{(***)}$ (0.0135)			
lnRRDD			$0.0864^{(***)}$ (0.000)		
lnNRDD				$0.1266^{(***)}$ (0.000)	
lnTRDD					0.1916^{***} (0.000)
lnHEX	$0.5615^{(***)}$ (0.0107)	$0.5221^{(**)}$ (0.0221)	$0.7810^{(***)}$ (0.0002)	$0.7446^{(***)}$ (0.000)	0.8791^{***} (0.000)
lnPCGDP	$-0.9713^{(***)}$ (0.0002)	$-0.6023^{(**)}$ (0.0206)	$-1.0390^{(***)}$ (0.000)	$-0.6346^{(***)}$ (0.000)	$-1.0906^{(***)}$ (0.000)
Constant term	12.1730 (0.2717)	$8.4824^{(***)}$ (0.0004)	$12.392^{(***)}$ (0.000)	$7.7915^{(***)}$ (0.000)	$11.5775^{(***)}$ (0.000)
SS	$-0.0367^{(**)}$ (0.0463)	$-0.0314^{(*)}$ (0.0996)	$-0.0643^{(***)}$ (0.0008)	$-0.0196^{(*)}$ (0.0663)	$-0.0538^{(***)}$ (0.0002)
CC	$0.0209^{(***)}$ (0.000)	-0.0274 (0.1364)	0.0175 (0.2778)	$-0.0347^{(***)}$ (0.0011)	-0.0084 (0.4735)
Jarque-Bera	0.5652	1.4186	0.1742	0.0054	0.9396
Prob.	0.7537	0.4919	0.9165	0.9972	0.6251
Adj. R^2	0.24	0.11	0.34	0.64	0.53

***, **, and * indicates 1%, 5%, and 10% significance level, respectively

The DOLS method, developed by Stock and Watson (1993), and the CCR method, developed by Park (1992), are used to test the consistency of FMOLS estimation results. The most important reason for preferring these methods is that they allow the interpretation of long-run cointegration coefficients. While the FMOLS estimator eliminates endogeneity and autocorrelation problems by using a nonparametric approach, the DOLS estimator eliminates these problems by using a parametric approach and lags and priors of explanatory variables (Dogan and Seker, 2016). Fourier-based DOLS estimation results are presented in *Table 5*.

The DOLS method allows the inclusion of estimated lagged values in the model and considers the first differences of the independent variables. The CCR method, on the other hand, is an efficient estimation method that allows the chi-square test to be performed asymptotically. FMOLS and CCR approaches provide asymptotic fit by investigating the correlation effect (Erdoğan et al., 2018; Pattak et al., 2023).

The CCR estimation results developed by Park (1992) are presented in *Table 6*. According to the DOLS method, when GDP per capita increases by 1%, LCF decreases between 0.57% and 0.97%, while when health expenditures increase by 1%, LCF increases by 0.43% and 0.74%. Fourier-based CCR estimation results are presented in *Table 6*. Similarly, according to the CCR method, when GDP per capita increases by 1%, LCF decreases between 0.60% and 1.14%, while when health expenditures increase by

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1%, LCF increases between 0.52% and 0.87%. When the DOLS and CCR estimation results are evaluated with the FMOLS method, the findings obtained for all models are consistent. According to the findings of all empirical analyses that there is a negative relationship between per capita GDP and LCF, while there is a positive relationship between all other variables and LCF.

Table 5. *DOLS estimation results*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
lnERDD	0.048** (0.0293)				
lnFRDD		0.0423* (0.0981)			
lnRRDD			0.0671*** (0.0004)		
lnNRDD				0.1164*** (0.000)	
lnTRDD					0.166*** (0.0000)
lnHEX	0.4329** (0.0560)	0.4879** (0.0337)	0.6142*** (0.0031)	0.7401*** (0.0000)	0.7309*** (0.0001)
lnPCGDP	-0.7115** (0.0056)	-0.5763** (0.0294)	-0.8353*** (0.0006)	-0.6583*** (0.0002)	-0.9192*** (0.0000)
Constant term	9.9974*** (0.000)	8.4492*** (0.000)	10.7506*** (0.000)	8.1268*** (0.000)	10.3348*** (0.000)
SS	-0.0279 (0.1416)	-0.0261 (0.1785)	-0.0522*** (0.0074)	-0.0209* (0.0902)	-0.0467*** (0.0022)
CC	0.0065 (0.7385)	-0.0222 (0.2152)	0.0114 (0.4967)	-0.0331*** (0.0051)	-0.0087 (0.4912)
Jarque-Bera	0.5273	0.2805	0.0335	0.1048	0.5480
Prob.	0.7682	0.8691	0.9833	0.9489	0.7603
Adj. R^2	0.16	0.12	0.30	0.64	0.53

***, **, and * indicates 1%, 5%, and 10% significance level, respectively

Table 6. *CCR estimation results*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
lnERDD	0.0713*** (0.0013)				
lnFRDD		0.0654*** (0.0107)			
lnRRDD			0.0831*** (0.0000)		
lnNRDD				0.1273*** (0.0000)	
lnTRDD					0.1907*** (0.0000)
lnHEX	0.5357** (0.0211)	0.5203** (0.0270)	0.7575*** (0.0004)	0.7296*** (0.0000)	0.8716*** (0.0000)
lnPCGDP	-0.8928*** (0.0008)	-0.6068** (0.0264)	-1.01480*** (0.0001)	-0.6147*** (0.0001)	-1.0843*** (0.0000)
Constant term	11.5337*** (0.000)	8.5488*** (0.000)	12.2141*** (0.000)	7.6122*** (0.000)	11.5371*** (0.000)
SS	-0.0342* (0.0614)	-0.0314 (0.1009)	-0.0629*** (0.0009)	-0.0193* (0.0719)	-0.0537*** (0.0002)
CC	0.0175 (0.3671)	-0.0265 (0.1416)	0.0178 (0.2839)	-0.0338*** (0.0013)	-0.0079 (0.5027)
Jarque-Bera	0.4942	1.4891	0.1336	0.0122	0.8911
Prob.	0.7811	0.4749	0.9353	0.9938	0.6404
Adj. R^2	0.22	0.11	0.34	0.65	0.53

***, **, and * indicates 1%, 5%, and 10% significance level, respectively

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Discussion

Nuclear fission and fusion are the most important clean energy technologies for improving environmental quality. Fusion, in particular, is considered one of the most environmentally friendly energy sources due to its potential for almost zero CO_2 or other harmful emissions and the absence of hazardous radioactive waste typical of fission reactors (Ball, 2023; IEA, 2024; U.S. Department of Energy, 2025).

Of course, all health problems require significant spending to ensure a healthy life. That is why it is so important for governments to keep environmental quality in check and reduce health issues that could affect human capital development (Alimi et al., 2020). In this light, the finding that health expenditures in the United States help improve environmental quality is quite significant. The United States spends more per person on health than almost any other country.

The FMOLS results indicate that a 1% increase in health expenditures leads to a 0.56%–0.88% improvement in LCF, consistent with Pata (2021) but higher than Ganda (2021). Clean energy R&D, especially in energy efficiency, renewables, and advanced nuclear technologies such as fusion, has a significant positive effect on environmental quality, supporting the findings of Ahmed et al. (2021) and Kartal et al. (2023). In contrast, fossil fuel R&D negatively affects LCF, aligning with the theoretical expectations and previous literature.

These results suggest that health expenditures and targeted clean energy R&D investments are practical tools for improving environmental quality. The findings also highlight the importance of policy coordination, as the positive effects of health spending and clean energy R&D are maximized when implemented together. Furthermore, the negative relationship identified between economic growth and environmental quality underlines the necessity of integrating sustainability parameters into growth strategies and strengthening environmental regulations, so that economic development can proceed without further environmental degradation, in line with the EKC hypothesis (Yang and Khan, 2022; Raihan et al., 2022; Kartal et al., 2023).

Conclusion

The present research illustrates that emphasizing R&D in clean energy, alongside expenditures on health, is crucial for enhancing environmental quality within the United States. According to the FMOLS, DOLS, and CCR estimation results, all hypotheses forming the basis of the study are valid. Clean energy technologies and health expenditures increase environmental quality while reducing economic growth. The empirical findings indicate that investments directed towards nuclear and renewable energy R&D exhibit approximately double the elasticity regarding the LCF compared to R&D for fossil fuels. These results justify a strategic redistribution of public R&D funding. Particularly, the diversion of R&D spending from fossil fuels to renewable energy in a ratio of at least 3:1 would ensure the highest beneficial effects on environmental quality, as observed through the coefficients considered. Such a shift in spending also aligns with the goals of the Inflation Reduction Act of 2022, under which historic incentives and funding have been provided to speed up the adoption of clean energy technologies and lower carbon emissions in the United States. The interaction between our findings and the trajectory of Inflation Reduction Act policy highlights the need to protect and reinforce such fiscal policies, primarily by incorporating environmental sustainability standards into health sector investments.

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Besides, the beneficial impact of health spending on environmental quality implies that policies that encourage "green hospitals," enhance energy efficiency, and implement sustainable waste management practices in the health sector can bring about substantial co-benefits for public health and environmental sustainability. Policymakers should thus ensure that health budgets officially include environmental performance metrics and facilitate the adoption of low-carbon technologies.

The consistent negative relationship between economic growth and environmental quality, as indicated by the high negative coefficients corresponding to per capita GDP, brings to the forefront the imperative of decoupling economic development from environmental degradation. This can be done by introducing sustainability parameters into growth policies, improving environmental regulations, and more intensive public awareness campaigns for responsible production and consumption.

There are limitations to this study that must be recognized. The present study limits itself to the period of 1974-2022 and does not, therefore, include any effect of policy change or technological improvements that may have taken place after this period. The results are also particular to the United States' situation and may not be directly relevant to other nations with alternate institutional arrangements or energy mixes.

Furthermore, though the LCF offers a broad assessment of environmental quality, it may not capture all aspects of ecological well-being, including water quality metrics, soil erosion, or biodiversity loss. Future research could resolve these limitations by expanding the analysis to more nations, including other current data, or using other environmental indicators. In summary, the findings of this study support a policy agenda of shifting R&D investments from fossil fuels to nuclear energy and renewables, investing in the health sector for environmental gains, and aligning national strategy with milestones such as the Inflation Reduction Act. throughout, the United States can achieve remarkable progress toward long-run ecological and public health objectives.

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