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RESEARCH ARTICLE

In-depth analysis of the effect of decomposed growth on the environment: A global perspective

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Abstract

The traditional Environmental Kuznets Curve (EKC) theory, which establishes a relationship between economic growth and a select number of pollutants, does not fully capture the broad and nuanced impacts on environmental qualityThis research examines the implications of decomposed economic growth by considering the separate contributions of scale, composition, and technique effects on environmental health and ecosystem vitality. The research spans 121 countries from 2001-2019, using robust statistical methods, including Driscoll-Kraay standard error, fully modified ordinary least squares, and panel quantile estimation techniques. The study reveals complex relationships that depend on countries' income levels. A predominantly positive and non-linear relationship between the scale effect and environmental health is observed for the full sample of countries and for low-income countries. The scale effect also shows a non-linear and predominantly positive relationship with ecosystem vitality in lower-middle-income, upper-middle-income, and high-income countries. The association between the composition effect and environmental health is inverted U-shaped in lower-middle-income countries, while it is mostly negative and non-linear in low-income and high-income countries. For ecosystem vitality, the composition effect shows a negative, non-linear relationship in all sampled countries, but a positive, non-linear relationship in higher-income countries. The relationship between the technology effect and environmental health is largely positive and non-linear in all sampled countries, lower-middle-income countries, upper-middle-income countries, and higher-income countries. However, the relationship is negative in lower-middle-income countries. These results have important policy implications. Governments are encouraged to adopt renewable, sustainable, and low-carbon technologies to address the scale effect. In addition, the formulation and enforcement of stringent environmental regulations for polluting industries is crucial, given the significant impact of the composition effect.

Keywords Decomposed growth · Environment · In-depth analysis · Panel mean · Panel quantile · Global perspective

Introduction

In environmental economics, the Environmental Kuznets Curve (EKC) hypothesis proposes a U-shaped relationship between economic activity and environmental degradation. According to this perspective, as an economy expands, environmental quality deteriorates until a certain economic threshold is reached, after which the environment begins to improve (Grossman and Krueger 1993; Panayotou 1993; Halkos and Managi 2016; Halkos and Managi 2017; Beyene and Kotosz 2020; Beyene 2022).

Traditional EKC studies have primarily examined the relationship between economic growth and limited pollutant categories. However, this approach has been criticized for its narrow focus, which reduces complex environmental quality to a few pollution indicators. Critics argue that focusing exclusively on specific pollutants cannot provide a holistic understanding of the relationship between economic activities and broader environmental indicators such as environmental health (EH) and ecosystem vitality (EV) (Beyene 2022).

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The reductionist nature of the EKC hypothesis also has other consequences. A focus on broad environmental indicators may overlook the complex interactions among variables. Many empirical studies have relied on the EKC framework to analyze the impact of economic activity on the environment, but such a narrow view can distort the real picture (Panayotou 1997; Tenaw 2021; Beyene 2022), potentially leading to misguided policy recommendations (Panayotou 1997). Therefore, a more systematic and logically coherent approach is needed to understand which components of economic growth affect environmental quality and how to mitigate their negative impacts (Arrow et al. 1996; Kaufmann et al. 1998).

A handful of empirical studies have examined the decomposed EKC hypothesis. Among them, only a few, such as Sadat (2016), Keho (2017), Allard et al. (2018), Zhou et al. (2018), Nkengfack et al. (2019), and Beyene (2022), have used quantile regression. Moreover, most of these studies have been narrow in scope, focusing on a single country or province within a country. Except for Zhou et al. (2018), Ansari and Khan (2021), and Beyene (2022), most of these studies did not use essential panel econometric tests prior to their estimation, which could lead to erroneous results and flawed methodology.

Recent studies on the environmental impact of decomposed growth include those by Ansari and Khan (2021), Tenaw (2021), and Beyene (2022). Tenaw's (2021) study was limited to Ethiopia and did not consider nonlinear scale effects, and except for Beyene (2022), the others used specific metrics to measure the environment. Although Beyene (2022) included the decomposed EKC, a broad indicator of environmental quality, panel mean and panel quantile, basic econometric tests, and many sampled countries, the number of low-income countries in the sample were limited to four. This focus on broad environmental measures may overlook the specific causes and the detailed relationships between variables. Furthermore, Beyene (2022) did not examine the effect of disaggregated growth on the components of environmental quality and their categories[1], leaving a gap for future studies.

This study aims to fill this gap by investigating the effects of decomposed growth on both environmental health and ecosystem vitality and their components, including air quality, sanitation and drinking water, heavy metals, biodiversity and habitat, ecosystem services, fisheries, climate change, pollutant emissions, agriculture, and water resources. Our research broadens the scope of the EKC hypothesis by examining the impact of decomposed growth on both broad and specific environmental indicators, providing more nuanced interpretations and policy recommendations.

Our approach is distinctive in that we focus on the global distribution patterns of countries grouped by income level rather than by geographic location, ensuring a more inclusive approach that includes countries at different stages of economic development. In addition, we adjust the environmental quality measures from the Yale Center for Environmental Law and Policy (YCELP) (2020) to the most recent year's weights, which allows for a larger sample of countries, up-to-date environmental measures, and the resolution of missing data issues.

This study also makes a theoretical contribution by extending the scope of the EKC hypothesis from pollution to environmental quality indicators, providing a U-shaped theoretical background. Methodologically, we consider preliminary diagnosis and basic panel econometric tests, and our execution, statistical methods, and design are comprehensive and rigorous, ensuring the reliability of the results and providing evidence-based policy recommendations. Thus, this study offers both a novel perspective and valuable contributions to the existing literature on EKC theory.

This paper is structured in several sections to provide a comprehensive analysis. The next section discusses the literature related to the topic. The third section explains the detailed methodology of the study with justifications. The fourth section provides the study results. The study also offers a discussion and, finally, the conclusion.

Literature review

Theoretical framework

The EKC was first proposed by Grossman and Krueger in 1991b. Based on Kuznets' 1955 theory of income inequality, this hypothesis suggests an inverted U-shaped relationship between economic activity and environmental degradation. In the early stages of economic growth, environmental degradation accelerates. However, once a certain point of economic development is passed, further growth reduces environmental degradation (Panayotou 1993; Grossman and Krueger 1993; Halkos and Managi 2016; Halkos and Managi 2017).

This study takes a novel approach to the conventional EKC hypothesis, proposing a U-shaped relationship between environmental quality and economic growth instead. This innovative perspective is visualized by the dashed line in Fig. 1, which serves as the conceptual and theoretical framework of the investigation.

In this figure, the solid line represents the traditional EKC, while the dashed line symbolizes a reimagined version of the EKC that focuses on environmental quality, not just pollution.

[1] EH components (air quality, Sanitation & drinking water, and heavy metals) and EV components (biodiversity & habitat, ecosystem services, fisheries, climate change, pollution emissions, agriculture, and water resources).

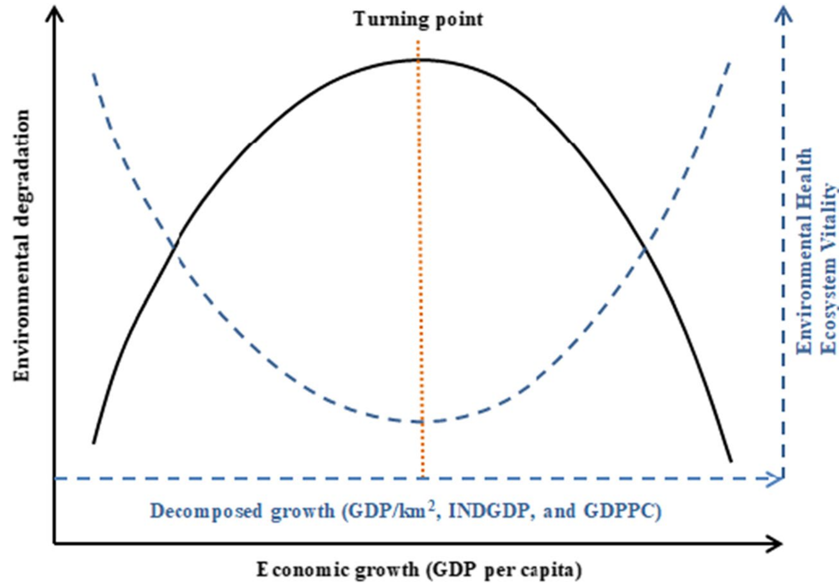

Fig. 1. The traditional and modified environmental Kuznets curve. (Source: Adapted from the theoretical frameworks of Beyene and Kotosz 2020 and Beyene 2022).

The environmental Kuznets curve is shaped by three interrelated structural effects associated with economic activity: the scale effect, the composition effect, and the technical effect (Grossman and Krueger 1991a; Panayotou 1993; Copeland and Taylor 2004). Summarizing these relationships, Brock and Taylor (2005), Jobert and Karanfil (2012), Bakehe (2018), and Nkengfack et al. (2019) propose that:

$$\textit{Pollutant levels} = \textit{Scale effect} + \sum \textit{Composition effect} + \sum \textit{Technique effect} \tag{1}$$

where pollutant levels represent aggregate emissions, scale effect captures the effect of changes in production quantity, and composition and technique effects denote structural and technological changes in the production process, respectively. The symbols in front of the composition and technique effects indicate their relationship with the share of industry and service products (for the composition effect) and energy efficiency and total energy use (for the technique effect) in a country.

Building on this, our study rewrites equation (1) as

$$\textit{Pollutant levels} = \textit{Scale effect} \pm \sum \textit{Composition effect} \pm \sum \textit{Technique effect} \tag{2}$$

Furthermore, this study adopts Environmental Health (EH) and Ecosystem Vitality (EV) as dependent variables instead of pollutant levels, thus transforming equation (2) to:

$$1/\textit{Pollutant levels} = 1/\left(\textit{Scale effect} \pm \sum \textit{Composition effect} \pm \sum \textit{Technique effect}\right) \tag{3}$$

The scale effect in this equation is the effect of a unit change in the quantity of output on environmental health and EV, assuming that the composition and technology effects remain constant. The composition effect refers to the structural shift in production from agriculture to industry or industry to services and its effect on environmental health and ecosystem vitality. The technique effect reflects how technological advances in production can improve environmental health and ecosystem vitality.

Husnain et al. (2021) expand on the original EKC theory by emphasizing that the relationship between environmental degradation and economic growth is not purely deterministic. Instead, it is influenced by a variety of factors. The EKC assumes an inverted U-shaped relationship, where initial economic growth leads to environmental degradation, but subsequent growth beyond a certain threshold leads to environmental improvement. This relationship depends on the scale, composition, and technique effects, which describe the impact of economic activities on the environment.

The scale effect represents the impact of increased economic activity or production on the environment. With more production comes more emissions, leading to more pollution and environmental degradation.

The composition effect concerns transitioning from an agrarian economy to an industrial economy and then to a service-based economy. An agrarian economy tends to have less environmental impact than an industrial economy, which is typically resource intensive and leads to significant pollution. However, transitioning from an industrial to a service-based economy often reduces environmental impacts because service industries are less polluting than heavy industries.

The technique effect refers to technological advancement and its environmental impact. Initially, the use of technology can lead to more efficient use of resources and less pollution per unit of output. However, at a certain point, increased efficiency can lead to an overall increase in consumption - a phenomenon known as the rebound effect - which can negate the initial environmental benefits of technological progress.

Husnain et al. (2021) argue that the relationship between economic growth and environmental degradation can be influenced by other factors, such as policy regulations, population density, and societal values, adding nuance to the EKC. In particular, strategic policy interventions and technological developments can push economies toward sustainable growth, thereby shifting the curve downward. This evolution of EKC theory posits that through conscious effort and strategic intervention, economic growth can be accompanied by environmental improvement, deviating from the conventional EKC narrative.

The findings of Husnain et al. (2021) further strengthen our theoretical framework. They argue that the relationship between economic growth and environmental degradation is not always deterministic. Instead, it is nuanced and depends on various factors such as the level of technology, policy regulations, population density, and societal values. They suggest that strategic policy interventions can decisively shift economies toward sustainable growth. Thus, our theoretical framework, which integrates the insights of Husnain et al. (2021), incorporates the influence of policy interventions and technological progress.

Thus, our study provides a more comprehensive picture and proposes a U-shaped curve, suggesting that environmental quality may initially decline with economic growth, increase after a certain threshold is crossed, and continue to improve as the economy grows, driven by policy and technological development.

The relationship between structural effects and the environment

The complex and multidimensional nature of the relationship between economic growth and environmental degradation presents a challenge to empirical investigation, as highlighted by Everett et al. (2010). To navigate this intricate nexus, researchers have delineated three distinct but interrelated factors that shape this relationship: the scale effect, the composition effect, and the technique effect.

The scale effect represents the basic concept that expanding economies harm the environment. As a nation's production and consumption activities grow, environmental degradation follows (Everett et al., 2010). This consequence results from the increased resource extraction, waste generation, and emissions associated with escalating economic activities.

Moving along the spectrum of economic development, the composition effect captures the environmental impact of shifts in the structural composition of an economy. As elaborated by Ekins (2000), as an economy shifts from an agricultural base to a manufacturing base, there is usually a concomitant increase in environmental degradation due to the industrial processes involved. Conversely, as an economy matures and transitions from a manufacturing base to a service-oriented one, it often experiences a decline in environmental degradation because service industries generally have a lower environmental impact than manufacturing industries.

The technique effect, on the other hand, highlights the role of technological innovation in mediating the environmental impacts of economic activities. Technological progress can reduce environmental degradation by improving energy and operational efficiency, as Everett et al. (2010) noted. However, counterarguments suggest that technological progress could inadvertently lead to increased environmental damage. For example, such damage could occur if improved technology leads to an overall increase in energy consumption or triggers the emergence of new industries with significant energy requirements.

Overall, the structural relationship between economic growth and environmental degradation is complex and multifaceted. This complexity arises from the interplay of scale, composition, and technique effects, each of which contributes differently and dynamically to environmental outcomes in the context of economic growth. Consequently, understanding this interplay is critical to developing effective strategies for balancing the dual imperatives of economic growth and environmental sustainability.

Empirical literature

Numerous studies have used different methodologies to examine different indicators of environmental degradation. Among the earlier studies, Panayotou (1997) examined the effect of decomposed economic growth on carbon dioxide (CO_2) emissions. Using fixed effects (FE) and random effects (RE) models, a positive relationship was found between scale and composition effects and sulfur dioxide (SO_2) emissions across 30 countries. In contrast, Antweiler et al. (2001) found that composition effects reduced SO_2 emissions, contradicting Panayotou's findings. This discourse was extended by Allard et al. (2018), who confirmed the existence of an N-shaped EKC across all income groups, except for upper-middle-income countries.

The influence of decomposed economic growth on different types of pollution was investigated by Tsurumi and Managi (2010) using semiparametric generalized additive models. They found that only SO_2 emissions were reduced by the technological effect, while CO_2 and energy consumption remained unaffected. These results were consistent with those of Ling et al. (2015) and Sadat (2016), who applied autoregressive distributed lag (ARDL) models and found a reduction in CO_2 emissions in Malaysia due to the technological effect.

In a Canada-specific study, Mohapatra et al. (2016) found that while the scale effect increased pollution, the technical effect counteracted it. Interestingly, the scale effect appeared to dominate the technique effect. In a broader context, Zhou et al. (2018) identified an inverted U-shaped EKC for five developing and four developed countries, with Keho (2017) confirming the EKC at all quantiles for sub-Saharan Africa (SSA), the United States, and Europe.

Examining the effects of decomposed growth on deforestation, Bakehe (2018) found that scale, composition, and technical effects all contributed to increased deforestation in the Central African subregion. Conversely, Jena (2018) revealed both positive and negative effects of scale and technique on pollutants in major industrial states in India.

The discourse on the EKC hypothesis has continued in recent studies, such as Nkengfack et al. (2019) and Ansari and Khan (2021). Both studies found an increase in CO_2 emissions due to scale and composition effects, while technological improvements led to their reduction. In addition, studies by Tenaw (2021) and Beyene (2022) highlighted the impact of decomposed growth on different types of emissions and environmental quality. They used ARDL and quantile regression techniques and found that while scale effects increased emissions, the impact of composition and technique effects varied by type of emissions and environmental quality.

Beyond the scope of disaggregated and quantile studies, several studies, including Apergis and Ozturk (2015), Jebli et al. (2016), Haider et al. (2020), Huang et al. (2020), Huang et al. (2021), Li et al. (2021), Husnain et al. (2022), and Haider et al. (2022), examined the EKC hypothesis in different contexts. These studies confirmed the EKC hypothesis, albeit with certain limitations, such as a focus on singular pollution indicators, limited sample sizes, or lack of consideration of decomposed GDP.

In a specific study, Apergis and Ozturk (2015) tested the EKC hypothesis in 14 Asian countries from 1990 to 2011. Using the Generalized Method of Moments (GMM) methodology in a multivariate framework, they found a statistically significant inverted U-shaped relationship between emissions and per capita income. Their research highlighted the importance of income and policies in influencing the income-emissions relationship.

The study by Husnain et al. (2022) examined the energy-environment Kuznets curve (EEKC) for 144 countries from 1990 to 2017. They found a non-linear positive relationship between economic growth, total energy, and non-renewable energy consumption. The EEKC hypothesis was supported for upper-middle-income countries, but results varied for lower-income quantiles due to their heterogeneity. The study highlighted the influence of income distribution, urbanization and population growth on energy consumption.

In the Canadian context, Haider et al. (2022) observed the relationship between economic growth and nitrous oxide emissions, and their results confirmed the EKC hypothesis. The tipping point of GDP per capita for total N_2O emissions was identified at $41,718. Their results reflected a positive and significant effect of agricultural land use on total N_2O emissions, although its effect on agricultural-related N_2O emissions was negative but insignificant. Besides, Haider et al. (2020) investigated the EKC using panel data from 1980 to 2012 for developed and developing nations on N_2O emissions from agriculture, economic development, agricultural land use, and exports. The findings support the EKC by demonstrating that N_2O emissions and economic development are co-integrated in both panels. Furthermore, agricultural land usage has a largely favorable impact on N_2O emissions.

Ben Jebli et al. (2016) tested the EKC hypothesis for a panel of 25 OECD countries from 1980 to 2010. They found bi-directional causality between several factors, including renewable and non-renewable energy consumption and trade. Their results supported the inverted U-shaped EKC hypothesis and suggested that increased trade and renewable energy use can reduce CO_2 emissions in OECD countries.

In addition, Wang et al. (2023a, 2023b) analyzed the EKC by considering income inequality as a threshold variable and the effect of trade openness, human capital, renewable energy, and natural resource rent on carbon emissions. However, they did not consider decomposed growth, focused on specific pollution indicators, and did not use quantile regression.

Furthermore, Huang et al. (2020) examined the impact of technological development on carbon emissions using Malmquist-Luenberger index with a spatial dynamic model for Chinese provinces from 2000 to 2016. The findings reveal that neither technical advancement nor its components have considerably decreased carbon emissions. The spatial dynamic model, on the other hand, shows that technological improvement in nearby regions substantially lowers emissions, implying efficiency changes have a greater impact than technical changes. In addition, Huang et al. (2021) used Driscoll and Kraay (1998), fixed effects with instrumental variables, and difference GMM to examine the influence of energy patents on China's carbon emissions. Human capital and energy patents from businesses and scientific institutions have a good impact on lowering carbon emissions, whereas those from higher education institutions have a greater impact. However, they did not apply quantile regression, focused on particular pollution indicators, and employed conventional estimation techniques.

Despite the substantial body of research examining the relationship between economic growth and environmental degradation, there are still gaps in the empirical literature. In particular, there is a lack of studies that use a quantile regression approach to examine the relationship between decomposed economic growth and environmental degradation. This study attempts to fill this gap by examining this relationship across different income quantiles, thus providing a more detailed perspective on the EKC hypothesis.

The tendency to analyze the effects of economic growth by focusing on a single type of pollution also neglects the multifaceted nature of environmental degradation.

This study aims to fill this gap by considering multiple indicators of environmental degradation, thus providing a more comprehensive analysis. In addition, studies often focus on individual countries or small groups of countries, which may limit the understanding of the global relationship between economic growth and environmental degradation. This study aims to include a broader sample of countries at different income levels to provide a more globally relevant perspective.

Although there is a wealth of research on the relationship between economic growth and environmental degradation, significant gaps remain. By using a quantile regression approach, incorporating multiple types of environmental degradation, and expanding the sample of countries, this study aims to enrich the understanding of the complex relationship between economic growth and environmental degradation.

Methodology of the study

Data type, sources, and sampled countries

The study employs secondary panel data from international organizations (see Table 1).

Model Specification

In this study, we adopt a model inspired by Panayotou (1997), Nkengfack et al. (2019), and Beyene (2022), with modifications to suit our specific objectives. We consider both broad and specific indicators of environmental quality, using environmental health and ecosystem vitality as our dependent variables. To address these two aspects of environmental quality, the study specifies the following functions:

$$EH = f\left(GDP/km^2, SqGDP/km^2, INDGDP, SqINDGDP, GDPPC, SqGDPPC, POPG, TO, FD \right) \tag{4}$$

$$EV = f\left(GDP/km^2, SqGDP/km^2, INDGDP, SqINDGDP, GDPPC, SqGDPPC, POPG, TO, FD \right) \tag{5}$$

Where:

- GDP/km^2 and $SqGDP/km^2$ are the Gross Domestic Product and its square per square kilometer, respectively.
- INDGDP and SqINDGDP are the industrial share of GDP and its square, respectively.
- GDPPC and SqGDPPC are gross domestic product per capita and its square, respectively.
- POPG is the annual population growth rate.
- TO and FD are trade openness and financial development, respectively.

POPG is included as a control variable since population growth, directly and indirectly, affects environmental health and ecosystem vitality. The effects of population growth are manifold, including increased consumption of natural resources, increased waste and pollution, and influence on economic policies and development practices (Marquette 1997).

TO is critical for isolating the effects of our key independent variables because it refers to a country's economic exposure to international trade, which has complex environmental implications. These include scale effects, composition effects, and technology effects, all of which can lead to environmental degradation (Frankel 2009; Nasir et al. 2018).

FD is included for its potential positive and negative impacts on environmental health and ecosystem vitality. It can channel resources into cleaner technologies and green industries and enforce better environmental regulations. Conversely, it can also lead to the expansion of polluting industries if investments prioritize short-term economic gains over long-term sustainability (Bui 2020; Nasir et al. 2019).

These functions use panel mean estimation, which provides information on the mean of coefficients rather than the conditional distribution of endogenous variables. However, this approach can lead to biased results and policy implications (Cade and Noon 2003). Therefore, we also use the quantile technique introduced by Koenker and Basset (1978)

Table 1 Variables used, their measurement, and data sources

Variables	measurement	Sources
EH and EV	Refers to proxies for the quality of the environmental measured in an index (0 to 100).	YCELP
GDP/km^2	GDP per square km, which is calculated as GDP (constant 2010 US$) divided by land area (sq. km), is a proxy for the scale effect	WDI
SqGDP/km^2	The square of GDP/km^2 measured a scale effect	
INDGDP	Industry share in GDP is a proxy for the composition effect	
SqINDGDP	The square of INGDP is a proxy for the composition effect	
GDPPC	GDP per capita (constant 2010 US$) is a proxy for the technique effect	
SqGDPPC	The square of GDPPC measures the technique's effect	
POPG	Annual population growth (%)	
TO	Trade openness calculated as trade (% of GDP)	
FD	Financial development is measured as banks' domestic credit to the private sector (% GDP)	

Sampled countries

LICs (low-income countries): Burkina Faso, Burundi, Chad, Dem. Rep. Congo, Guinea, Guinea-Bissau, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Sudan, Togo, and Uganda.

LMICs (lower-middle-income countries): Angola, Algeria, Bangladesh, Belize, Benin, Bhutan, Bolivia, Cabo Verde, Cambodia, Cameroon, Comoros, Republic of Congo, Cote d'Ivoire, Egypt, El Salvador, Eswatini, Ghana, Haiti, Honduras, India, Indonesia, Kenya, Kyrgyz Republic, Micronesia, Fed. Sts., Mongolia, Morocco, Nepal, Nicaragua, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, Tanzania, Ukraine, Vietnam, and Zambia.

UMICs (upper-middle-income countries): Albania, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Fiji, Gabon, Georgia, Guatemala, Jamaica, Jordan, Kazakhstan, Malaysia, Mauritius, Mexico, Moldova, Namibia, North Macedonia, Panama, Paraguay, Peru, Romania, Russian Federation, Serbia, South Africa, Thailand, Tonga, and Turkey.

HICs (high-income countries): Antigua and Barbuda, Australia, Austria, Bahamas, The, Belgium, Brunei Darussalam, Chile, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Israel, Italy, Japan, Korea, Rep., Luxembourg, Netherlands, Norway, Oman, Poland, Seychelles, Singapore, Spain, Sweden, United Arab Emirates, United Kingdom, United States, and Uruguay.

Source: Authors Construction

and refined by Koenker and Machado (1999) and Koenker and Hallock (2001). This approach specifies the conditional quantile of an endogenous variable (y_i) given the exogenous variables (x_i) as follows:

$$Q_{y_{it}}\left(\tau/x_{it}\right) = x_{it}^{\tau}\beta_{\tau} \tag{6}$$

Subsequently, the panel quantile models of this study are written as follows:

$$\begin{aligned} QEH_{i,j}\left(\tau|X_{i,j}\right) = {} & \alpha_{1,\tau}GDP/km^2_{i,\tau} + \alpha_{2,\tau}SqGDP/km^2{}_{i,\tau} + \alpha_{3,\tau}INDGDP_{i,\tau} \\ & + \alpha_{4,\tau}SqINDGDP_{i,\tau} + \alpha_{5,\tau}GDPPC_{i,\tau} + \alpha_{6,\tau}SqGDPPC_{i,\tau} \\ & + \alpha_{7,\tau}POPG_{i,\tau} + \alpha_{8,\tau}TO_{i,\tau} + \alpha_{9,\tau}FD_{i,\tau} \end{aligned} \tag{7}$$

$$\begin{aligned} QEV_{i,j}\left(\tau|X_{i,j}\right) = {} & \alpha_{1,\tau}GDP/km^2_{i,\tau} + \alpha_{2,\tau}SqGDP/km^2{}_{i,\tau} + \alpha_{3,\tau}INDGDP_{i,\tau} \\ & + \alpha_{4,\tau}SqINDGDP_{i,\tau} + \alpha_{5,\tau}GDPPC_{i,\tau} + \alpha_{6,\tau}SqGDPPC_{i,\tau} \\ & + \alpha_{7,\tau}POPG_{i,\tau} + \alpha_{8,\tau}TO_{i,\tau} + \alpha_{9,\tau}FD_{i,\tau} \end{aligned} \tag{8}$$

where i refers to cross-section while j indicates time ($i=1, 2, \ldots, n.,\quad j=1, 2, \ldots m_i$). By including these control variables (POPG, TO, and FD), we control for different socioeconomic factors across countries and adjust for time-varying biases.

Fundamental panel econometric tests

Cross-sectional dependence

Panel data models are prone to having a high cross-sectional dependency (CD) in the errors. Despite the fact that the influence of CD in estimating depends on several factors, the effect of CD in dynamic panel estimators is more severe than in static models (De Hoyos and Sarafidis 2006). Furthermore, Pesaran (2006) points out that economic events (shocks) can influence all countries. These events always introduce cross-sectional interdependencies between the cross-sectional unit, its regressors, and the error terms. As a result, ignoring the CD in panel data leads to misleading estimates and results (De Hoyos and Sarafidis 2006; Pesaran 2007). Breusch and Pagan's (1980) LM test, Pesaran's (2021) scaled LM test, Pesaran (2021) CD test, and Baltagi et al. (2012) bias-corrected scaled LM test is commonly used CD tests (Tugcu and Tiwari 2016). Friedman (1937) and Frees (1995, 2004) also CD tests (see De Hoyos and Sarafidis 2006). Friedman (1937), Frees (1995), and Pesaran (2021) are among the available CD tests used in this study. This is because these tests can be used with both a big N and a large T. Furthermore, Free's CD test is capable of overcoming the inconsistent signals that come with correlation.

Panel unit root test

In the literature, Im et al. (2003), Maddala and Wu (1999), Choi (2001), Levin et al. (2002), Breitung (2000), and Hadri (2000) are examples of first-generation panel unit root tests: However, Bai and Ng (2004), Chang (2002, 2004), Choi (2002), Phillips and Sul (2003), Harris and Sollis (2003), Smith et al. (2004), Moon and Perron (2004), Cerrato and Sarantis (2007) are second-generation tests.

Because they presume cross-sectional independence, the first-generation panel unit root tests have been questioned (O'Connell 1998; Hurlin and Mignon 2005; Baltagi 2008; Chudik and Pesaran 2015). Since macroeconomic time series shows a strong cross-sectional correlation among nations in a panel (Baltagi 2008), co-movements of economies are frequently found in most macroeconomic applications of unit root tests. Nonetheless, this hypothesis is restrictive and incorrect (Hurlin and Mignon 2005). In panel data applications, the cross-sectional correlation of errors is more likely to be the rule than the exception (Chudik and Pesaran 2015). Furthermore, using first-generation unit root tests while there is a CD in a model can cause significant size distortions (O'Connell 1998). This, in turn, results in the null hypothesis (H0) of nonstationary being rejected (Pesaran 2007; Eberhardt and Presbitero 2015). As a result, Pesaran (2007) suggested second-generation panel unit root tests that consider CD.

Due to the CD test results, this study uses both the first (Levin et al. 2002; Im et al. 2003; Fisher-ADF type) and second (Pesaran's (2007)) generation unit root test. The use of first-generation tests is justified because they are widely available in EViews and Stata. Unlike other unit root tests that enable CDs, such as Bai and Ng (2004), Moon and Perron (2004), and Phillips and Sul (2003), Pesaran's (2007) is that it is straightforward and clear. It is also robust in unobserved time-series heteroscedasticity (Hashiguchi and Hamori 2010). Moon and Perron (2004), Choi (2006), and Pesaran (2007) all require large N and T in theory, but Pesaran (2007) is particularly robust in small sample sizes (Albulescu et al. 2016).

Cointegration test

The cointegration test is also one of the panel data econometric tests. However, the type of test is determined by the CD results. Pedroni (1999, 2004), Kao (1999), and Fisher-type are the most common Engle-Granger-based cointegration tests that can be employed when no CD exists. Besides, they are commonly used and available in EViews and Stata. Compared to the others (Kao and Fisher), the Pedroni residual-based test has the benefit of accounting for variability through specified parameters (Beyene and Kotosz 2020). However, when the model has a large number of explanatory factors, it may be unable to produce results. The Kao and Fisher types of cointegrations are proposed in this circumstance. Unlike the Pedroni test, the Kao cointegration test uses two numbers to determine the long-run relationship (t-statistics and probability). The Fisher type of combined

Johansen test is the type of panel cointegration test. The Kao cointegration test, on the other hand, is more comprehensive than the Fisher type. Thus, this study employs Levin et al. (2002), Im et al. (2003), and Fisher-ADF type unit root tests for low-income countries and high-income countries in the ecosystem vitality model.

When there is CD, the most commonly used panel cointegartion tests are: Westerlund (2007), Westerlund and Edgerton (2007), Westerlund and Edgerton (2008), Groen and Kleibergen (2003), Westerlund (2008) Durbin-Hausman test, Gengenbach et al. (2016), and Banerjee and Carrion-i-Silvestre (2017). Most of them, except for a few, are not programmed in Stata or EViews. Therefore, except for low-income countries and high-income countries in the ecosystem vitality model, this study uses Banerjee and Carrion-i-(2017) Silvestre's cointegration test. However, Westerlund's (2007) cointegration test was employed for low-income countries and high-income countries.

Regression techniques

This study uses panel mean regressions (Driscoll and Kraay 1998) standard error (DKSE) and fully modified ordinary least squares (FMOLS)) and panel quantile approaches. Several dynamic estimation techniques, such as pooled mean group, mean group, and Fully modified ordinary least squares, do not apply while CD exists. However, in this study, the maximum number of iterations exceeded in mean group, and the iterations could not converge under pooled mean group. Therefore, the study uses Fully modified ordinary least squares for low-income countries and high-income countries in the ecosystem vitality model. The rationale for using fully modified ordinary least squares is that it takes care of small samples and endogeneity bias. Further, it uses the white heteroskedastic standard errors. Even though the CD is allowed by several panel estimation techniques, most of them, such as cross-sectional ARDL, cross-sectional distributed lag, common correlated effects pooled, and common correlated effects mean group estimators, require many observations across groups and periods. Stata and EViews did not code the continuously updated fully modified and continuously updated bias-corrected estimators. Others, such as feasible generalized least squares and seemingly unrelated regression, require a larger number of years (T) than countries (N) to be feasible (Hoechle 2007; Breitung and Pesaran 2008). The Driscoll and Kraay (1998) standard error estimate, on the other hand, necessitates a larger N than T (Hoechle 2007). As a result, the Driscoll and Kraay (1998) standard error regression is used in this study based on the CD, cointegration test, Stata and EViews availability, and comparing N to T. However, employing the Hausman test before Driscoll and Kraay (1998) standard error calculations, this study chose a more efficient model amongst fixed effect and random effect.

Generally, this study considered and improved the methodological aspects. For instance, it calculated the environmental health and ecosystem vitality using the formula proposed by YCELP; this can be regarded as an innovation of the study. Besides, the execution of this study improved since it performed sufficient technical rigor in the method, allowing confidence in the results. Specifically, it used appropriate data collection and replicated analysis methods and employed appropriate and justified statistical tests and analysis techniques. Moreover, it has good data quality, documented (reported) the results in detail and interpreted them meaningfully, and clearly understood and described the limitations of the research.

Moreover, the study provided detailed statistical methods appropriate and justified for the research objective and data being analysed. Specifically, its dataset is relatively up-to-date and relevant to the topic, conducted appropriate tests for basic assumptions in the error terms, presented the results clearly and understandably, clearly defined the unit of measurement, reported descriptive statistics, and basic regression results with other statistics.

This study's design also indicates an improvement since it employed an appropriate approach (including controls and analysis protocols) for the objective. By adding research questions and clearly defining the objective and several statistical analyses in the method section, it became evident that the study design was appropriate. Specifically, it has a clear objective, data collection method, and reliable, valid, and quality data. In addition, it considered potential control variables and their potential to affect the study results. Finally, even though humans and animals did not participate in this study, the study considered ethical issues.

Results

Preliminary diagnosis

Descriptive statistics and correlation analysis

Table 2 shows the overall mean of environmental health is 42.98, ranging between 10.045 and 99.267. Similarly, the mean value of ecosystem vitality is 43.33 and ranges between 12.47717 and 76.43098, which shows a high variation. Moreover, GDP/km^2, INDGDP, and GDPPC have a mean of 4589203, 26.72456, and 12530.07, respectively. When we observe the Skewness and Kurtosis of the variables of the models, all variables are positively skewed and kurtosis. Table 2 also shows except for the correlation between environmental health with GDPPC and FD, the degree of relationship between variables are below the threshold or rule of thumb (0.7) for a greater association (Allard et al. 2018), indicating the absence of a multicollinearity problem.

Table 2 Descriptive statistics and correlation analysis

Descriptive statistics							Correlation analysis							
Variable	Mean	SD	Min	Max	Sk	Ku	1	2	3	4	5	6	7	8
1	42.98787	24.21484	10.04454	99.26658	0.7263304	2.400841	1	0.649	0.206	-0.0746	0.8445	-0.4148	0.2607	0.7513
2	43.32738	11.97348	12.47717	76.43098	0.4245984	2.636068		1	0.0346	-0.0764	0.531	-0.4493	0.0586	0.4169
3	4589203	3.27E+07	2529.649	4.92E+08	11.69672	146.0767			1	-0.0176	0.2629	0.0045	0.5313	0.181
4	26.72456	10.84466	3.150196	74.11302	1.351333	5.71187				1	-0.0497	0.1587	0.0735	-0.0782
5	12530.07	17700.72	278.3194	105454.7	2.119457	7.835925					1	-0.1441	0.3405	0.637
6	1.394002	1.345095	-3.84767	15.17725	1.89966	17.87018						1	-0.0624	-0.2965
7	83.66932	48.83709	1.218845	437.3267	2.735213	15.478							1	0.2523
8	48.98721	40.81089	0	304.5751	1.506686	5.971976								1

EH=1, EV=2, GDP/km^2=3, INDGDP =4, GDPPC=5, POPG=6, TO=7, FD=8, Sk= Skewness, Ku=Kurtosis, SD= standard deviation

Source: The authors used Stata 15

Detecting influential observations and outliers

Cooks D is an indicator of high leverage and residuals (Cook, 1977). The impact is high when D exceeds 4/N, (N=number of observations). A D > 1 implies a significant outlier problem. The Cooks D result of this study confirms the absence of outliers' problem (see supplementary file 4).

Normality, multicollinearity, serial correlation, and heteroskedasticity tests

The results in Table 3 indicate that the normality test's probability value is above 0.01, implying the residuals are normally distributed. On the other hand, the heteroskedasticity results show that the probability value of the chi-square statistic is less than 0.01. Therefore, the H0 of constant variance can be rejected at a 1% level of significance. In other words, the modified Wald test for Groupwise heteroskedasticity rejects the H0 of Groupwise homoskedasticity that is observed by the probability value of 0.0000. This implies the presence of heteroskedasticity in the residuals. Similarly, the ecosystem vitality model suffers from serial correlation since the probability value of 0.0000 rejects the H0 of no first-order serial correlation, indicating the presence of autocorrelation. Finally, the multicollinearity test reveals that the models have no problem since the variance inflation factors values are below 5.

Basic panel econometric tests

This section discusses the basic panel econometric tests; however, the table results are not presented here in the interest of space. Under the environmental health model, the CD test confirms that all groups reject the H0 of cross-sectional independence at a 1% significance level. Similarly, except for low-income countries and high-income countries, two CD tests strongly rejected the H0 under the ecosystem vitality model. As a result, in all other groupings of nations, except for low-income countries and high-income countries in the ecosystem vitality model, there is CD among the variables (countries or error terms). Furthermore, except for low-income countries and high-income countries in the ecosystem vitality model, this study employs Pesaran's (2007) stationarity test. The results show that all variables are stationary at the level, first difference, or second difference, implying there is a unit root. However, in the ecosystem vitality model, Levin et al. (2002), Im et al. (2003), and Fisher-ADF type unit root tests are used for low-income countries and high-income countries. The findings show that all variables are stationary at a 1% level of significance. Hence, we can proceed to the long-run relationship (cointegration) test.

Table 3 Normality, heteroskedasticity, multicollinearity, serial correlation

Tests		EH model	EV model
Normality test	Joint test for Normality on e:	chi2(2) = 4.12 Prob > chi2 = 0.1278	chi2(2)= 6.62 Prob > chi2= 0.0365
	Joint test for Normality on u:	chi2(2) =3.44 Prob > chi2 = 0.1786	chi2(2) = 4.79 Prob> chi2= 0.0913
Modified Wald test for groupwise heteroskedasticity		chi2(121)=62994.81 Prob>chi2=0.0000	chi2(121)=33602.2 Prob>chi2=0.000
Serial correlation		F(1,120)=8782.651 F(1,120)=1106.37	Prob > F=0.0000 Prob > F=0.0000
Multicollinearity/Variable		VIF	
FD		1.82	1.82
GDPPC		1.81	1.81
TO		1.51	1.51
GDP/km^2		1.42	1.42
POPG		1.13	1.13
INDGDP		1.04	1.04
	Mean VIF	1.45	1.45

Source: The authors used Stata 15

Because of the existence of CD, except for low-income countries and high-income countries in the ecosystem vitality model, this study uses Banerjee and Carrion-i-(2017) Silvestre's cointegration test for the target and all variables of the model. However, for low-income countries and high-income countries in the ecosystem vitality model, the study uses Kao's (1999) cointegration test since there is no CD. The results reveal that the H0 of no long-run relationship is rejected at 1%.

DKSE, FMOLS, and panel quantile results of EH and EV models

Our study seeks to thoroughly corroborate the findings of Beyene (2022), a recent paper that uses a decomposed EKC while considering broad environmental quality indicators, basic econometric tests, and a large sample of countries. We use three methods: Driscoll and Kraay (1998) standard error, fully modified ordinary least squares, and panel quantile regression. The resulting data are presented in Tables 4 and 5, showing associations between decomposed growth and both environmental health and ecosystem vitality.

The study extensively uses Driscoll and Kraay (1998) standard error regression across all country groups, except for lower-income countries and higher-income countries, within the ecosystem vitality model. For these exceptions, we use Fully modified ordinary least squares due to limitations in the application of panel ARDL. Prior to Driscoll and Kraay (1998) standard error regression, we conducted the Hausman test to ensure the selection of the most efficient model between fixed effects and random effects.

Our results indicate complex relationships between the variables studied. For example, the scale effect, represented by gross domestic product per square kilometer, shows a positive, non-linear relationship with environmental health in total sampled countries and low-income countries up to certain inflection points at 338855000 and 622857 GDP/km^2, respectively. After these thresholds, the relationship becomes negative. However, it's important to note that this relationship does not follow a standard inverted U-shape, as most observations in different periods fall below these inflection points, indicating a predominantly positive and non-linear relationship.

The relationship between the scale effect and ecosystem vitality varies across different categories of countries. In lower-middle-income countries, upper-middle-income countries and high-income countries, the relationship is positive and non-linear, derived from different environmental categories such as biodiversity and habitat, climate change, pollution emissions and agriculture. In contrast, the relationship is negative in low-income countries and insignificant in total sampled countries. Notably, these results contrast with those of Beyene (2022), who found a negative and non-linear relationship between the scale effect and the Environmental Performance Index (EPI) in high-income countries, but no significant relationship in upper-middle-income countries.

The composition effect, measured by the industry share in the gross domestic product (INDGDP), significantly influences both environmental health and ecosystem vitality. In the context of environmental health, it reduces the value in low-income countries, lower-middle-income countries and high-income countries, while showing an increase in the quadratic term of INDGDP. The relationship between INDGDP and environmental health is inverted U-shaped in lower-middle-income countries, but predominantly negative and non-linear in low-income countries and high-income

Table 4 DKSE^{+} and FMOLS^{++} results

Variables	TSCs		LICs		LMICs	
	EH^{+}	EV^{+}	EH^{+}	EV^{++}	EH^{+}	EV^{+}
GDP/km^2	2.25e-07***	1.33e-07	0.00004***	0.01***	1.17e-06**	0.00001**
SqGDP/km	-3.32e-16***	-3.24e-16	-3.50e-11**	-3.92E-07***	1.28e-13***	-1.21e-12**
INDGDP	-0.238***	-0.636***	-0.18***	-0.011	0.104***	-0.663*
SqINDGDP	0.0015	0.0044**	0.0038***	0.0096	-0.002***	0.007
GDPPC	0.0014***	0.0005***	-0.0025	0.106	0.005***	-0.016***
SqGDPPC	-9.60e-09***	-1.77e-09	1.75e-06***	-0.000226	-3.39e-07**	2.34e-06***
POPG	-0.364**	-1.015***	-0.1087	-15.238***	0.591***	-3.142***
TO	0.026***	0.03***	0.0176***	-0.036*	0.015	0.0047
FD	0.0528***	-0.00199	-0.0112	-0.477***	0.0072**	0.0167*
CONS	30.234***	50.541***	18.645***	-	11.636***	70.278***
	UMICs		HICs			
	EH^{+}	EV^{+}	EH^{+}	EV^{++}		
GDP/km^2	-1.05e-06	0.00002***	6.77e-08*	-0.0013***		
SqGDP/km^2	2.84e-15	-1.80e-12 ***	-7.62e-17	1.86E-09***		
INDGDP	-0.27**	-0.416**	-0.782***	-5.274***		
SqINDGDP	0.002	0.0014	0.006***	0.151***		
GDPPC	0.0034***	-0.0035**	0.0007***	0.0399***		
SqGDPPC	-1.00e-07***	1.42e-07***	-3.63e-09***	-1.58E-06***		
POPG	-0.382	-0.471	-0.224**	1.0012*		
TO	-0.012***	0.08***	0.074***	0.0059		
FD	0.044**	-0.027	0.022	0.0296		
CONS	29.458***	53.623***	62.601***	-		

*, significant at 10%, **, significant at 5%, ***, significant at 1% level. Values in the table are coefficients.
Source: The authors used Stata 15 (for DKSE) and EViews 10 (for FMOLS) results

countries. For ecosystem vitality, however, the relationship is negative and non-linear in total sampled countries, but predominantly positive and non-linear in high-income countries.

The technique effect, represented by gross domestic product per capita (GDPPC), shows complex patterns for environmental health and ecosystem vitality. For environmental health, it shows an increase in all groups except low-income countries, with a predominantly positive and non-linear association. For ecosystem vitality, GDPPC shows a predominantly negative and non-linear relationship in Lower-middle-income countries, confirming Beyene's (2022) findings of unclear pathways between GDPPC and EPI in lower-middle-income countries, upper-middle-income countries, and high-income countries.

We employed panel quantile regression, whose results reflect similar complex relationships to provide a more nuanced view. The scale effect and environmental health show a predominantly positive and non-linear relationship in low-income countries, upper-middle-income countries, and high-income countries, while the scale effect and ecosystem vitality show a predominantly negative and non-linear relationship in Lower-middle-income countries. Similar complicated patterns are observed between INDGDP and environmental health as well as GDPPC and environmental health and ecosystem vitality.

Unlike traditional EKC studies, our study reverses the perspective by focusing on environmental quality indicators instead of environmental pollution. As a result, our results differ from previous findings, making comparisons difficult. Nevertheless, we can observe consistencies between our results and those of other studies such as Antweiler et al. (2001), Bakehe (2018), and Panayotou (1997), especially regarding the impact of GDP/km^2, INDGDP, and GDPPC on environmental indicators.

In sum, our results underscore the complexity of the relationships between scale, composition, and technique effects and environmental health and ecosystem vitality, revealing intricate patterns of interaction across different economic contexts. These findings underscore the need for nuanced and tailored environmental policies to achieve desired outcomes in different national settings.

DKSE and panel quantile results for the categories of EH

In this section, the Driscoll and Kraay (1998) standard error and panel quantile results present the impact of decomposed

Table 5 Panel quantile results

Variables	TSCs		LICs		LMICs	
	EH	EV	EH	EV	EH	EV
GDP/km^2	-1.45e-08	1.61e-07**	4.24e-05***	5.25e-06	2.90e-06***	-3.85e-06***
SqGDP/km^2	-4.86e-17	-4.94e-16***	-5.28e-11***	8.30e-12	-3.70e-14	4.54e-13**
INDGDP	0.341***	0.433***	0.035	0.18	0.465***	0.497***
SqINDGDP	-0.0061***	-0.0068***	0.0025	-0.0016	-0.0089***	-0.007***
GDPPC	0.002***	0.0008***	-0.0016	-0.032***	0.002	0.001
SqGDPPC	-1.50e-08***	-6.91e-09***	1.62e-06*	1.39e-05***	1.97e-07	2.80e-07
POPG	-3.674***	-2.967***	1.91***	-2.506**	-2.527***	-1.078
TO	0.017**	-0.017*	-0.0039	0.0045	0.092***	-0.036***
FD	0.078***	-0.031***	0.0696*	0.049	0.036*	-0.094***
CONS	21.759***	37.561***	8.344***	49.692***	9.882**	35.199***
	UMICs		HICs			
GDP/km^2	6.20e-06***	3.34e-07	2.23e-07***	8.19e-08		
SqGDP/km^2	-8.18e-13***	-3.88e-13	-4.43e-16***	-3.67e-16**		
INDGDP	0.304	0.13	-0.079	0.913***		
SqINDGDP	-0.0078	-0.0012	0.00014	-0.015***		
GDPPC	0.0028***	0.0022***	0.0012***	0.0007***		
SqGDPPC	-9.14e-08***	-9.88e-08**	-6.44e-09***	-5.80e-09***		
POPG	-2.121***	-2.144***	-2.691***	-5.165***		
TO	0.036**	0.0029	-0.082***	0.024		
FD	0.038**	-0.104***	0.0514***	0.025**		
CONS	19.848***	38.506***	52.305***	28.289***		

*, significant at 10%, **, significant at 5%, ***, significant at 1% level. Values in the table are coefficients. A bootstrap of 500 was used to acquire the quantile results. EH and EV are the dependent variables.

Source: The authors used EViews 10

growth on the environmental health categories. To facilitate space efficiency, this and the following sections focus on the results of the target variables. The Hausman test is used to select the most appropriate model between fixed effect and random effect before running the Driscoll and Kraay standard error regression. Due to the different treatments of low-income countries and high-income countries in the ecosystem vitality model, fully modified ordinary least squares is used for estimation.

Driscoll and Kraay (1998) standard error results show predominantly positive, non-linear relationships between all environmental health categories and scale and technique effects. A notable exception is the predominantly negative, non-linear relationship between the composition effect and air quality in total sampled countries. As noted in the previous section, these results potentially underpin the predominantly positive, non-linear relationship between GDP/km^2 (GDPPC) and environmental health. A positive, non-linear relationship is observed between GDP/km^2 and sanitation & drinking water (heavy metals) in low-income countries, as all observations across periods are below the inflection point. This could explain the predominantly positive, non-linear relationship shown in Table 4. However, the relationship between INDGDP and sanitation and drinking water (heavy metals) is the opposite. The association between INDGDP and air quality is predominantly positive and non-linear, possibly explaining the predominantly positive, non-linear relationship in Table 4. The relationship between GDPPC and air quality (or heavy metals) is mostly (completely) negative and non-linear, as shown in Table 6.

For Lower-middle-income countries, where 64.58% of observations are above the tipping point, the relationship between INDGDP and sanitation & drinking water is predominantly negative and non-linear (Table 6). Given that other environmental health components do not have a clear relationship with INDGDP, this could lead to the inverted U-shaped association between INDGDP and environmental health in Table 4. However, the association between GDPPC and sanitation & drinking water (or heavy metals) is mostly (entirely) positive and non-linear. Interestingly, a U-shaped association is found between GDPPC and air quality. This could explain the predominantly (entirely) positive, non-linear association between GDPPC and environmental health in Lower-middle-income countries, as shown in Table 4.

In the Upper-middle-income countries, there is a predominantly negative, non-linear association between GDP/km^2 and air quality (Table 6). Since the weight of

Table 6 DKSE and panel quantile results

Variables /Categories	TSCs					
	Air quality		Sanitation & drinking water		Heavy metals	
	DKSE	Panel quantile	DKSE	Panel quantile	DKSE	Panel quantile
GDP/km^2	3.49e-07***	-7.20e-08***	7.51e-08**	3.17e-08	4.12e-07***	-1.00e-07
SqGDP/km^2	-5.03e-16***	9.77e-17**	-1.28e-16***	-2.00e-16	-5.88e-16***	1.37e-16
INDGDP	-0.474***	0.216***	0.034	0.381***	-0.296***	0.255**
SqINDGDP	0.0038**	-0.0064***	-0.0012	-0.0032**	0.0013	-0.0056***
GDPPC	0.0014***	0.0017***	0.0016***	0.0021***	0.0015***	0.0015***
SqGDPPC	-7.05e-09***	-1.20e-08***	-1.42e-08***	-1.70e-08***	-7.86e-09***	-1.04e-08***
			LICs			
GDP/km^2	0.000011	2.24e-05***	0.000077***	6.30e-05***	0.00013***	8.62e-05***
SqGDP/km^2	2.02e-11	-2.58e-11	-9.20e-11***	-7.82e-11***	-1.46e-10***	-1.03e-10***
INDGDP	0.108**	0.29**	-0.559***	-0.41	-0.175***	-0.55*
SqINDGDP	-0.0017*	-0.0041	0.011***	0.014***	0.0037***	0.015**
GDPPC	-0.016***	-0.017***	0.015***	0.017***	-0.0099***	0.021731***
SqGDPPC	3.94e-06 ***	4.15e-06***	-1.13e-06	-2.17e-06*	4.35e-06***	-1.43e-05***
			LMICs			
GDP/km^2	2.58e-07	6.71e-07	2.13e-06***	3.50e-06**	2.15e-06***	-2.56e-06*
SqGDP/km^2	2.95e-13***	9.30e-14	-3.62e-14	1.17e-14	-8.24e-15	3.21e-13*
INDGDP	-0.022	0.124	0.256***	0.614***	0.182	-0.095
SqINDGDP	0.000697	-0.004*	-0.0054***	-0.012***	-0.0033**	-0.0028
GDPPC	-0.0045***	-0.0005	0.019***	0.002	0.0077***	0.013***
SqGDPPC	1.11e-06 ***	5.42e-07	-2.16e-06***	4.93e-07	-7.43e-07**	-2.12e-06***
			UMICs			
GDP/km^2	-6.52e-06*	8.92e-06***	3.70e-06	5.99e-06***	-7.04e-06	-4.77e-06
SqGDP/km^2	5.68e-13**	-1.37e-12***	-5.64e-13**	-8.11e-13***	7.26e-13**	1.01e-12*
INDGDP	-0.215	-0.068	-0.338***	0.562***	-0.466***	-0.294
SqINDGDP	0.0012	-0.005	0.0033***	-0.007**	0.003**	0.0016
GDPPC	0.0034***	0.0017**	0.0043***	0.0033***	0.0027***	0.0018**
SqGDPPC	-7.40e-08 ***	-2.39e-09	-1.63e-07***	-1.38e-07**	-2.84e-08	-4.27e-08
			HICs			
GDP/km^2	9.51e-08*	3.80e-08	3.75e-08**	2.03e-07***	1.03e-07	-4.60e-08
SqGDP/km^2	-1.08e-16	-7.81e-17	-4.29e-17	-4.69e-16***	-1.02e-16	2.97e-17
INDGDP	-1.1996***	-0.079	-0.328***	-0.085	-1.023***	0.916***
SqINDGDP	0.0094***	-0.0009	0.0024***	0.00095	0.0066**	-0.013***
GDPPC	0.00089***	0.0013***	0.0004***	0.0013***	0.001***	0.0011***
SqGDPPC	-4.00e-09***	-7.81e-09***	-3.54e-09***	-8.91e-09***	-4.37e-09***	-7.25e-09***

*, significant at 10%, **, significant at 5%, ***, significant at 1% level. Values in the table are coefficients. A bootstrap of 500 was used to acquire the quantile results. The dependent variables are categories of EH.

Source: The authors used Stata 15 (for DKSE) and EViews 10 (for quantile)

the significant variable air quality (0.5*40%) is almost equal to the sum of the insignificant variables sanitation & drinking water and heavy metals (0.45*40%), they cancel each other out. This could explain the insignificant relationship between GDP/km^2 and environmental health shown in Table 4. The relationship between INDGDP and sanitation & drinking water (or heavy metals) is mainly (entirely) negative and non-linear, which could lead to the insignificant relationship between INDGDP and environmental health in Table 4. Conversely, GDPPC has a mainly (fully) positive, non-linear relationship with sanitation & drinking water and air quality, which could explain the positive, non-linear association between GDPPC and environmental health in Table 4.

In the high-income countries, the association between INDGDP and all environmental health categories is mostly (or entirely) negative and non-linear (Table 6). This may explain the predominantly negative and non-linear association between

INDGDP and environmental health in Table 4. However, the association between GDPPC and all environmental health components is mostly (entirely) positive and non-linear, which may explain the mostly (entirely) positive, non-linear association between GDPPC and environmental health in Table 4.

Quantile results indicate a predominantly negative, non-linear relationship between GDP/km^2 and air quality in total sampled countries (Table 6), possibly leading to the insignificant relationship between GDP/km^2 and environmental health in Table 5. The relationship between INDGDP and environmental health categories is mixed, suggesting a non-linear and mainly negative relationship between INDGDP and air quality, while INDGDP and heavy metals show an almost inverted U-shape in total sampled countries. This may explain why INDGDP and environmental health have a non-linear and predominantly positive relationship in Table 5. The panel quantile result mirrors the panel mean result, indicating a predominantly positive and non-linear association between GDP/km^{2}and sanitation and drinking water (heavy metals) in low-income countries. This could explain the non-linear and predominantly (fully) positive association between GDP/km^{2}and environmental health in Table 5. However, the relationship between INDGDP and heavy metals is U-shaped. In low-income countries, the relationship between GDPPC and air quality is non-linear and mostly negative, GDPPC and sanitation and drinking water (positive and non-linear), and GDPPC and heavy metals (non-linear and mostly positive). These mixed results could explain the insignificant relationship between GDPPC and environmental health observed in Table 5.

Quantile results confirm a non-linear and predominantly negative association between GDP/km^2 and heavy metals in Lower-middle-income countries (Table 6). As the share of heavy metals is insignificant, this may explain the insignificant relationship between GDP/km^2 and environmental health in Table 5. On the other hand, INDGDP shows an inverted U-shaped relationship with sanitation & drinking water (as seen in Table 5), while GDPPC and heavy metals show a non-linear and mainly positive relationship. In Upper-middle-income countries, a non-linear and predominantly positive relationship is observed between GDP/km^2 and air quality (sanitation & drinking water), which may explain the predominantly (fully) positive, non-linear relationship between GDP/km^2 and environmental health in Table 5. A similar positive and non-linear relationship is observed between GDPPC and sanitation & drinking water.

Similar to the panel mean, the quantile results show a predominantly positive and non-linear association between GDPPC and all environmental health categories in high-income countries. However, in contrast to the panel mean, there is a non-linear and predominantly positive relationship between GDP/km^2 & sanitation & drinking water and INDGDP & heavy metals (Table 6).

DKSE and FMOLS results for the categories of EV

In total sampled countries, the scale effect shows a positive and non-linear relationship with ESC, fisheries, and pollution emissions, as shown in Table 7. However, this relationship is not reflected in the relationship between scale effect and ecosystem vitality in Table 4 because of the overwhelming weight of other ecosystem vitality components, which is greater than the sum of ESC, fisheries, and pollution emissions ((0.1+0.1+0.05)*60%). On the other hand, the composition effect interacts negatively and non-linearly with climate change, accounting for a large portion (0.4*60%) of the category, likely leading to the negative, non-linear relationship between INDGDP and ecosystem vitality shown in Table 4. The technique effect, on the other hand, shows a positive, non-linear relationship with Biodiversity & Habitat and Agriculture, but a negative, non-linear relationship with Fisheries.

In low-income countries, GDP/km^2 shows a dominant negative, non-linear relationship with biodiversity and habitat, climate change, and agriculture, as shown in Table 7. Given the significant share of these components, this may explain the negative, non-linear relationship between the scale effect and ecosystem vitality observed in Table 4. INDGDP primarily shows a negative, non-linear relationship with biodiversity and habitat in low-income countries. Since other components of ecosystem vitality account for a larger share than Biodiversity & Habitat, this likely contributes to the insignificant relationship between INDGDP and ecosystem vitality shown in Table 4. In contrast, GDPPC shows mixed results with ecosystem vitality components, which may explain the insignificant relationship between GDPPC and ecosystem vitality in Table 4.

For lower-middle-income countries, the scale effect is positively and non-linearly related to biodiversity & habitat and climate change, but negatively related to ecosystem services and fisheries, as shown in Table 7. Given that the combined weighted share of biodiversity & habitat and climate change ((0.25+0.4)*60%) exceeds that of ecosystem services and fisheries ((0.1+0.1)*60%), this likely justifies the positive, non-linear relationship between the scale effect and ecosystem vitality in Table 4. INDGDP shows a mixed relationship with the ecosystem vitality components, which may explain the insignificant relationship between INDGDP and ecosystem vitality in Table 4. The technique effect primarily shows a negative, non-linear relationship with ecosystem services, climate change, and pollution emissions, but the opposite with agriculture. Given the larger proportion of negatively associated components, this likely explains the negative, non-linear relationship between GDPPC and ecosystem vitality in Table 4.

For upper-middle-income countries, GDP/km^2 is positively and non-linearly related to climate change, pollution emissions, and agriculture but negatively related to fisheries, as shown in Table 7. This is likely to contribute

Table 7 DKSE^{+} and FMOLS^{++} results

Variables /Categories	TSCs^{+}					
	Biodiversity & habitat	Ecosystem services	Fisheries	Climate change	Pollution emissions	Agriculture
GDP/km^2	5.68e-08	5.74e-08***	2.97e-07***	1.20e-07	6.57e-07**	4.46e-08
SqGDP/km^2	-1.20e-16	-9.33e-17***	-3.23e-16**	-4.95e-16	-1.06e-15**	-1.39e-17
INDGDP	-0.368***	0.507**	0.087**	-1.425***	-0.747*	0.085
SqINDGDP	0.0022	-0.00385	-0.00058	0.01019**	0.0068	-0.0027*
GDPPC	0.00191***	-0.00041***	-0.00011**	-0.000045	0.00031	0.00067***
SqGDPPC	-1.55e-08***	9.16e-10	9.24e-10**	6.19e-09**	-1.35e-09	-9.73e-09***
			LICs^{++}			
GDP/km^2	0.006***	0.0044	0.00012	0.019***	0.0081**	0.0041***
SqGDP/km^2	-3.20e-07***	-1.06e-07	-5.81e-09	-7.64e-07***	1.93e-07	-1.04e-07**
INDGDP	-3.71***	5.485**	0.244	0.827	0.129	0.12
SqINDGDP	0.077***	-0.09	-0.0074	0.00025	0.013	-0.0095
GDPPC	-0.621***	2.26***	-0.08	0.109	0.571	-0.57***
SqGDPPC	0.00065***	-0.0026***	5.90e-05	-0.00027	-0.0011	0.00055**
			LMICs^{+}			
GDP/km^2	4.00e-06*	-1.62e-05***	-8.95e-06***	3.25e-05***	1.67e-05	9.48e-07
SqGDP/km^2	-4.69e-13**	1.04e-12***	4.10e-13**	-2.94e-12***	-1.27e-12	1.34e-13
INDGDP	-2.13e-02	-0.6241283**	1.50e-01***	-1.28e+00	-1.84e+00	-5.52e-02
SqINDGDP	-0.0029	1.10e-02***	-1.70e-03**	1.41e-02	2.56e-02	-4.50e-04
GDPPC	-6.26e-04	-8.90e-03***	-9.01e-04	-3.39e-02***	-3.29e-02***	9.21e-03**
SqGDPPC	7.50e-07**	1.77e-06***	3.87e-07	4.40e-06***	5.24e-06***	-1.39e-06***
			UMICs^{+}			
GDP/km^2	3.71e-06	-6.34e-06	-3.22e-06***	4.48e-05***	4.29e-05***	1.29e-05***
SqGDP/km^2	-5.91e-13	1.07e-12**	1.86e-13**	-3.51e-12***	-3.63e-12***	-1.26e-12***
INDGDP	-6.23e-01*	-1.42e-01	3.33e-01***	-1.03e+00**	3.52e+00***	-5.57e-01***
SqINDGDP	7.64e-03**	8.30e-04	-2.65e-03*	4.14e-03	-4.64e-02***	4.81e-03**
GDPPC	5.78e-03***	1.47e-03	-9.05e-05	-1.18e-02***	-1.78e-03	9.22e-05
SqGDPPC	-2.30e-07***	-4.92e-08	-3.20e-09	4.91e-07***	3.11e-08	1.92e-08
			HICs^{++}			
GDP/km^2	-0.0005	-0.00024***	-0.0002**	-0.0023***	-0.004***	-0.0004
SqGDP/km^2	4.45e-11	3.58e-10***	4.02e-10***	3.76e-09***	5.79e-09***	-3.48e-10
INDGDP	-1.155	-10.715***	-10.159***	-6.03	-5.66	-4.059
SqINDGDP	0.12	0.226***	0.223***	0.165**	0.088	0.124
GDPPC	0.022	0.035***	-0.002	0.058**	0.081***	0.081***
SqGDPPC	-1.77e-06	-9.78e-07***	2.45e-08	-1.99e-06**	-3.06e-06***	-1.82e-06**

*, significant at 10%, **, significant at 5%, ***, significant at 1% level. Values in the table are coefficients.

Source: The authors used Stata 15 (for DKSE) and EViews 10 (for FMOLS)

to the dominant positive relationship between GDP/km^2 and ecosystem vitality observed in Table 4. INDGDP shows mixed relationships with ecosystem vitality components, which may lead to the insignificant relationship between INDGDP and ecosystem vitality in Table 4. The mixed relationships of GDPPC with ecosystem vitality components, especially with a larger share for climate change than for biodiversity and habitat, could lead to the negative and non-linear relationship between INDGDP and ecosystem vitality in Table 4.

For high-income countries, the scale effect has a dominant positive and non-linear relationship with ecosystem services, fisheries, climate change and pollution emissions, as shown in Table 7. This likely explains the positive and non-linear relationship between the scale effect and ecosystem vitality in Table 4. In contrast, the technique effect shows a predominantly negative and non-linear relationship with ecosystem services, climate change, pollution emissions and agriculture. In addition, INDGDP shows a U-shaped relationship with ecosystem services and fisheries.

Panel quantile results for the categories of EV

In transition economies, the scale effect shows a positive, non-linear relationship with ecosystem services, fisheries, and agriculture. Meanwhile, INDGDP mainly shows a positive, non-linear relationship with Biodiversity & Habitat and Agriculture, and an inverse relationship with Ecosystem Services. The relationship of the composition effect with pollutant emissions follows an almost inverted U-shape. The technique effect shows a non-linear and positive relationship with biodiversity & habitat, climate change, and pollution emissions, while its relationship with ecosystem services is non-linear and mostly negative. Uniquely, the technique effect consistently increases in relation to agriculture (as detailed in Table 8).

In low-income countries, the scale effect shows a non-linear, positive relationship only with ecosystem services. Similarly, INDGDP shows a non-linear, positive relationship with biodiversity and habitat, and a dominantly positive, non-linear relationship with ecosystem services. GDPPC shows a non-linear, positive relationship with biodiversity & habitat and climate change, but a dominantly negative, non-linear relationship with ecosystem services.

In lower-middle-income countries, GDP/km^2 is negatively and non-linearly associated with biodiversity and habitat, but positively associated with fisheries. INDGDP shows dominantly positive and non-linear relationships with biodiversity & habitat, ecosystem services, and agriculture, but inversely with fisheries and pollution emissions. The technique effect is mostly positively and non-linearly related to climate change and pollution emissions, but negatively related to ecosystem services and has an almost U-shaped relationship with biodiversity & habitat (see Table 8).

In upper-middle-income countries, the scale effect shows a non-linear, negative relationship with ecosystem services and agriculture, but a positive, non-linear relationship with fisheries. The composition effect is positively and non-linearly related to biodiversity and habitat and pollution emissions, while it has a U-shaped relationship with ecosystem services. GDPPC has a non-linear and predominantly positive relationship with biodiversity & habitat, but an inverted U-shape with fisheries.

For high-income countries, GDP/km^2 has a non-linear positive relationship only with fisheries. Conversely, INDGDP has a non-linear, predominantly positive relationship with biodiversity & habitat, climate change, pollutant emissions and agriculture, while the reverse is true for ecosystem services. GDPPC shows a non-linear and predominantly positive relationship with biodiversity & habitat, climate change and pollution emissions (as shown in Table 8).

Discussion

By comparing the results of the different techniques, the Driscoll and Kraay (1998) standard error, fully modified ordinary least squares, and panel quantile approaches provide insightful and diverse perspectives on the associations between environmental and economic factors. The scale effect consistently shows a predominantly positive influence on environmental health categories across all methods, regardless of income groupings. However, the technique effect, although mostly positive, shows more variability across economic classifications and techniques.

Examining the Driscoll and Kraay (1998) standard error and fully modified ordinary least squares results under the umbrella of ecosystem vitality categories, a positive and non-linear relationship with the scale effect is observed, particularly in total sampled countries. In low-income countries, this relationship is predominantly negative. Meanwhile, in lower-middle-income countries and upper-middle-income countries, the scale effect shows a more pronounced positive alignment with the ecosystem vitality, a pattern that also holds in high-income countries.

The panel quantile method provides a more refined set of results, highlighting the predominantly positive relationship between the scale effect and biodiversity and habitat, climate change, and pollution emissions across different income categories. GDP per capita and industrial GDP show varying associations with the ecosystem vitality categories, indicating the variable impact of different economic dimensions on environmental outcomes.

These findings are consistent with previous empirical research highlighting the complex relationship between economic growth and environmental sustainability and reinforce that these relationships are often non-linear and depend on a wide range of socio-economic contexts. This supports the argument that environmental impacts should not be considered in isolation but within their respective economic and social frameworks.

In contrast, certain findings diverge from previous studies, particularly regarding the relationships between some economic indicators and ecosystem vitality categories. This divergence may be due to different research methodologies, regional contexts, or temporal data variations. Such inconsistencies highlight the need for continued research to understand these differences further and contribute to a more holistic understanding of these complex relationships.

Our models reveal cointegration between decomposed growth and both environmental health and ecosystem vitality in the long run across all income groups, suggesting an integral relationship. Specifically, the panel mean results showed a predominantly positive and non-linear association between the scale effect and environmental health in total

Table 8 Panel quantile results

Variables /Categories	TSCs					
	Biodiversity & habitat	Ecosystem services	Fisheries	Climate change	Pollution emissions	Agriculture
GDP/km^2	-3.83e-07**	2.36e-07***	2.12e-07***	1.14e-07	1.13e-07	1.12e-07***
SqGDP/km^2	5.11e-16	-5.00e-16***	-2.41e-16***	-4.22e-16**	-3.65e-16**	-2.74e-16***
INDGDP	1.295***	-0.637***	-0.0437	0.237	0.963***	1.086***
SqINDGDP	-0.0215***	0.010***	0.001	-0.0036	-0.018***	-0.013***
GDPPC	0.0012***	-0.00023***	-3.69e-05	0.0008***	0.00153***	0.00015**
SqGDPPC	-1.10e-08***	2.78e-09***	-4.63e-10	-5.98e-09***	-1.33e-08***	2.89e-09***
			LICs			
GDP/km^2	-2.55e-05	5.02e-05**	-9.09e-07	-3.23e-05	-1.86e-05	2.53e-05
SqGDP/km^2	-3.77e-11	-9.42e-11*	-2.37e-11	1.70e-10	5.36e-11	-5.08e-11
INDGDP	0.739**	0.811**	-0.0211	-0.161	-1.149*	0.0062
SqINDGDP	-0.0104*	-0.016**	-0.0026	0.0064	0.0223*	-0.00059
GDPPC	0.0345***	-0.0418***	-0.002	-0.070***	-0.028*	0.015*
SqGDPPC	-1.46e-05***	2.29e-05***	1.43e-06	2.99e-05***	1.16e-05	-9.39e-06**
			LMICs			
GDP/km^2	-1.81e-05***	-1.61e-06	8.26e-06***	-1.83e-06	5.12e-07	-4.67e-06
SqGDP/km^2	1.92e-12***	6.77e-14	-1.06e-12***	2.88e-13	1.72e-13	7.96e-13**
INDGDP	2.65***	-0.62**	-0.77***	0.343	0.681**	0.932***
SqINDGDP	-0.035***	0.015***	0.0103**	-0.0054	-0.0198***	-0.0078***
GDPPC	-0.017***	-0.005**	-0.0014	0.014***	0.011*	-0.0042*
SqGDPPC	3.69e-06***	9.61e-07**	2.08e-08	-1.94e-06***	-1.88e-06*	4.16e-07
			UMICs			
GDP/km^2	5.82e-06	-9.31e-06***	8.04e-06***	-1.35e-06	-4.60e-07	-8.13e-06***
SqGDP/km^2	-1.97e-12	1.64e-12***	-1.21e-12***	1.08e-13	-2.71e-13	5.16e-13*
INDGDP	1.623***	-1.327***	0.152	0.0694	1.686***	0.646
SqINDGDP	-0.023***	0.0226***	-0.0022	-0.0007	-0.017*	-0.0039
GDPPC	0.0099***	-0.0027***	0.0007*	-0.00014	-0.00087	0.0006
SqGDPPC	-4.86e-07***	1.68e-07***	-6.22e-08***	4.94e-08	1.03e-07	7.68e-08
			HICs			
GDP/km^2	-2.35e-07*	9.69e-08	2.39e-07***	2.49e-08	2.04e-08	1.76e-08
SqGDP/km^2	1.55e-16	-2.56e-16	-2.77e-16***	-2.65e-16	-2.00e-16	-1.02e-16
INDGDP	0.663**	-1.003***	-0.175	0.823***	1.597***	2.525***
SqINDGDP	-0.011***	0.011***	0.0019	-0.015***	-0.029***	-0.037***
GDPPC	0.0011***	-0.0001	-0.0002***	0.0006***	0.0008***	0.00014
SqGDPPC	-1.01e-08***	-5.31e-11	9.38e-10	-3.83e-09**	-7.53e-09***	2.87e-09**

*, significant at 10%, **, significant at 5%, ***, significant at 1% level. Values in the table are coefficients. A bootstrap of 500 was used to acquire the results. The dependent variables are categories of EV.

Source: The authors used EViews 10

sampled countries and low-income countries. This positive association may suggest that an increase in the scale of economic activity can lead to improvements in environmental health indices, possibly due to increased investment in environmental protection. This finding aligns with (Beyene (2022) for total sampled and low-income countries.

However, the relationship between the scale effect and ecosystem vitality was found to be mostly positive and non-linear in lower-middle-income, upper-middle-income, and high-income countries (but reversed in low-income countries. This inconsistency may be due to differences in the level of environmental regulation, technological progress, and public awareness of environmental sustainability among these income groups. This result is in line with Beyenes (2022) for lower-middle-income countries and low-income countries. Nonetheless, by considering linear relationship between scale effect with environmental health and ecosystem vitality, our result is consistent with (Panayotou 1997; Antweiler et al. 2001; Tsurumi and Managi 2010; Ling et al. 2015; Mohapatra et al. 2016; Sadat and Alom 2016; Bakehe 2018; Jena 2018; Shahbaz et al. 2019; Nkengfack 2019; Ansari and Khan 2021).

The relationship between industrial share to GDP (INDGDP) and environmental health showed an inverted U-shape in lower-middle-income countries, suggesting the possibility of an EKC where environmental degradation increases in the early stages of economic development and decreases in later stages. However, this relationship became predominantly negative and nonlinear in low-income countries and high-income countries. This negative trend could indicate the increasing burden of industrial activities on environmental health in these regions. This result is in line with the findings of Beyene (2022) for low-income countries and high-income countries. However, regardless of the proxy variables and considering only linear relationships, our findings coincide with those (Panayotou 1997; Jena 2018; Bakehe 2018; Nkengfack 2019; Tenaw 2021).

In the case of GDP per capita (GDPPC), its association with environmental health was predominantly positive and non-linear across all income groups, except in low-income countries, where certain environmental health indicators showed negative effects. This suggests that while increases in GDPPC generally lead to improved environmental health, the benefits are not evenly distributed across all environmental health indicators, especially in low-income countries. Except for low-income countries, this result coincides with Beyene's (2022) and also supports Everett et al.'s (2010)[2] arguments when technologies improve energy efficiency). However, the reverse result between GDPPC and ecosystem vitality in lower-middle-income countries supports Everett et al.'s (2010) argument when technologies increase countries' energy uses. The positive impact of GDPPC on environmental health and ecosystem vitality in most sampled countries justified the similarity with (Panayotou 1997; Antweiler et al. 2001; Tsurumi and Managi 2010; Shahbaz et al. 2019; Tenaw 2021). However, the negative impact of GDPPC on environmental indicator/s in lower-middle-income countries and Upper-middle-income countries coincides with (Allard et al. 2018; Bakehe 2018; Tenaw 2021).

Our panel quantile results further complicate this narrative by revealing a dominantly positive and non-linear relationship between the scale effect and environmental health in low-income countries, upper-middle-income countries, and high-income countries, in contrast to a dominantly negative and non-linear trend for ecosystem vitality in lower-middle-income countries. These patterns highlight the mechanisms through which economic activities influence environmental health and ecosystem vitality and the need for targeted policy responses to manage these impacts. Considering ecosystem vitality and environmental health share 60% and 40% of the EPI, this result is in line with the findings of Beyene (2022), except for low-income countries.

[2] Technology advancement minimizes environmental degradation

In addition, the relationship between industrial GDP and both environmental health and ecosystem vitality showed mostly positive and non-linear associations in total sampled countries, lower-middle-income countries, and high-income countries, suggesting that industrial growth may contribute positively to both environmental health and environmental variables in these groups. This result is in line with the findings of Beyene (2022) in some quantiles.

These findings contribute to the broader academic literature by illustrating the non-linear and context-dependent relationships between economic growth and environmental outcomes. However, we must acknowledge the limitations of the study, including potential omissions due to the broad categorizations of income groups and the exclusion of certain societal, political, and cultural variables. Future research should aim to incorporate these nuances for a more holistic understanding of these complex interactions.

Conclusion

This study provides an in-depth exploration of the EKC hypothesis, moving beyond its traditional focus on limited sets of pollutants and extending its reach to the broader concept of environmental quality. By examining the impact of decomposed growth on environmental health and ecosystem vitality, this research brings a new perspective to study the relationship between economic growth and environmental sustainability.

Using panel mean and panel quantile estimation techniques for 121 countries from 2001 to 2019, the results reveal complex and income group-specific relationships. The study has the following main findings. First, for all sampled countries and low-income countries, where the relationship between scale effect and environmental health is dominantly positive and non-linear, it is crucial to adopt green and low-carbon technologies. This is particularly feasible for low-income countries as their infrastructure, manufacturing capacity and economies are still developing, providing opportunities to incorporate low-carbon and energy-efficient technologies from the outset. Second, the association between the composition effect and environmental health is inverted U-shaped in lower-middle-income countries, while it is mostly negative and non-linear in low-income and high-income countries. Third, for the ecosystem vitality, the composition effect shows a negative, non-linear relationship in all sampled countries, but a positive, non-linear relationship in higher-income countries. Forth, the relationship between the technology effect and environmental health is largely positive and non-linear in all sampled countries, lower-middle-income countries, upper-middle-income countries, and higher-income countries and the relationship is negative in lower-middle-income countries.

This study also offered the following policy recommendations: First, green practices are needed for lower-middle-income, upper-middle-income, and high-income countries, as economic growth in these countries correlates with improvements in ecosystem vitality. The development of environmentally friendly economic activities and technologies should be prioritized to protect biodiversity, mitigate climate change, reduce pollution emissions, and safeguard various ecosystem services. Second, stricter environmental regulations are needed. This will allow for sustainable industrial growth and employment of environmentally friendly practices. Comprehensive environmental regulations are required, such as introducing a levy or tax system, a cap-and-trade system, emission ceilings, and minimum waste reduction measures. At the same time, consumers must continue to pressure companies to be more environmentally responsible. Third, the technique effect, which shows a dominantly positive relationship with environmental health and a dominantly negative relationship with ecosystem vitality across most income groups, underscores the need to adopt green and low-carbon technologies. These technologies should specifically target sources of pollution within the environmental health and ecosystem vitality categories. Finally, it is necessary to increase awareness of the importance of environmentally-friendly practices from the supply and demand sides. This is key for shifting to a low-carbon economy and eco-friendly practices.

While this study has attempted to fill the gaps in the EKC literature, it acknowledges its limitations. The data, which ends in 2019, does not take into account recent global events such as the COVID-19 pandemic or geopolitical conflicts. Future studies could extend their analysis to account for these events and include additional control variables such as political stability, institutional performance, foreign direct investment, and countries' environmental policies. The use of updated statistical software would also be beneficial.

Finally, this study sheds light on the nuanced relationship between economic growth and environmental sustainability and provides insights into potential solutions to mitigate the negative effects of economic growth components. These findings are critical to informing sustainable development practices across income groups and promoting a more sustainable future for all.

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