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WORKING PAPER SERIES

231, 2024

Intelligence and its Effects on Environmental Decline: A Worldwide Analysis

Forthcoming: Journal of Environmental Management

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Abstract

The research investigates the relationship between intelligence quotient (IQ) and environmental degradation, aiming to understand how cognitive abilities influence environmental outcomes across different nations and time periods. The objective is to examine the impact of intelligence quotient (IQ) on environmental indicators such as carbon emissions, ecological demand, and the Environmental Kuznets Curve (EKC), seeking insights to inform environmental policy and stewardship. The study utilizes statistical techniques including Ordinary Least Squares (OLS), Two Stage Least Squares (2SLS), and Iteratively Weighted Least Squares (IWLS) to analyze data from 147 nations over the years 2000 to 2017. These methods are applied to explore the relationship between IQ and environmental metrics while considering other relevant variables. The findings reveal unexpected positive associations between human intelligence quotient and carbon emissions, as well as ecological demand, challenging conventional notions of "delay discounting." Additionally, variations in the Environmental Kuznets Curve (EKC) hypothesis are identified across different pollutants, highlighting the roles of governance and international commitments in mitigating emissions. The study concludes by advocating for the adoption of a "delay discounting culture" to address environmental challenges effectively. It underscores the complex interactions between intelligence, governance, and population dynamics in shaping environmental outcomes, emphasizing the need for targeted policies to achieve sustainability objectives.

Keywords: Human capital; intelligence quotient; population; output; carbon emission; EKC, World

*JEL Classification***:** C52; O38; O40; Q50; I20

1.0 Introduction

Humans and unexpected factors have substantially affected economic and environmental outcomes both historically and contemporarily (Esquivias et al., 2023; Amuda, 2023; Durmanov et al., 2023). The ongoing waves of environmental degradation witnessed globally, spanning hurricanes, earthquakes, droughts, floods, and other catastrophic natural events, are primarily attributed to unprecedented climate change. These occurrences incur substantial economic costs, amplifying the significance of addressing climate change and environmental sustainability within policy and academic discourse (Asongu, El Montasser, & Toumi, 2016; Asongu, Le Roux, & Biekpe, 2017). Despite concerted efforts outlined in international agreements, such as the 21st session of the Conference of Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCC) held in Paris in December 2015, the disparity between set targets and actual environmental outcomes persists. This disjuncture necessitates expanded empirical research to better understand and confront the global challenge of climate change-induced environmental degradation.

Several mechanisms have been proposed in the literature to deter activities contributing to environmental deterioration. These include market-based incentives, such as taxes and subsidies, along with consumer education and regulatory frameworks. Despite these proposed strategies, the menace of environmental degradation continues to loom large, highlighting the imperative for further global scrutiny and research into policy interventions (Asongu, El Montasser, & Toumi, 2016; Asongu, Le Roux, & Biekpe, 2017). Given the interconnectedness and global nature of environmental issues, collaborative efforts across nations are paramount to effectively addressing climate change and fostering environmental sustainability.

The pivotal role of human capital in influencing environmental and energy dynamics has garnered significant scholarly attention. This emphasis can be attributed in part to Gary Becker's seminal human capital model, which underscores the crucial significance of human capital across various socioeconomic realms. Scholars have underscored its relevance to diverse domains including economic development (Schultz, 1964; Romer, 1990; Lucas, 1993), crime (Becker, 1968), wage-earnings (Mincer, 1974), fertility (Becker, Murphy, and Tamura, 1990), health (Kenkel, 1991), poverty, and income distribution (Quang Dao, 2008; Winters and Chiodi, 2011).

However, despite acknowledging the importance of human capital, much of the research on the human capital-environment relationship has focused predominantly on conventional indicators. These metrics encompass aspects like average years of schooling, life expectancy, school enrollments at various levels, lifelong learning, and knowledge economy metrics frequently utilized in economic development analyses (Barro, 1991; Benhabib and Spiegel, 1994; Casell, Esquivel, and Lefort, 1996; Mankiw, Romer, and Weil, 1992; Sala-i-Martin, Doppelhofer, and Miller, 2004; Tchamyou, 2017, 2020).

Critiques of these studies highlight their limitations, including inconclusive findings and a narrow focus on quantitative measures. Moreover, they predominantly concentrate on human capital inputs rather than outputs, failing to capture the holistic nature of human capital development and its implications for the environment. Consequently, there is a pressing need for more comprehensive approaches to studying the interplay between human capital and environmental quality, incorporating qualitative dimensions and a broader array of environmental indicators to enhance understanding and inform more effective policy interventions.

In recent years, a burgeoning body of literature has emerged within the domain of the environment-human capital nexus, increasingly incorporating qualitative human capital factors such as The Program of International Student Assessment (PISA) and Trends in International Mathematics and Science Study (TIMSS) (Hanushek & Kimko, 2000; Hanushek & Woessmann, 2008, 2009). Notable contributions to this field include studies by Nilsson (2009), Sanders (2012), Zivin and Neidell (2013), Ball (2014), Lavy, Ebenstein, and Roth (2012), Stafford (2015), and Bharadwaj et al. (2017).

These studies collectively posit that environmental degradation exerts significant impacts on qualitative human capital indicators. These indicators encompass various aspects, including mathematics and language skills, long-term educational outcomes, school qualifications (A-level), standardized test scores, scholastic performance, and cognitive abilities, among others. This paradigm shifts towards considering qualitative dimensions of human capital represents a crucial advancement in comprehending the intricate interplay between environmental quality and human development (Nilsson, 2009; Sanders, 2012; Zivin & Neidell, 2013; Ball, 2014; Lavy, Ebenstein, & Roth, 2012; Stafford, 2015; Bharadwaj et al., 2017).

By expanding the scope to encompass a broader spectrum of human capital indicators, researchers can gain a more nuanced understanding of the multifaceted impacts of environmental degradation. This, in turn, enables the formulation of more comprehensive and effective policy interventions aimed at safeguarding human capital development amidst environmental challenges. Thus, the integration of qualitative human capital factors into the discourse not only enriches scholarly understanding but also holds profound implications for policy-making in the realm of environmental sustainability and human well-being. In specific terms, the paper is set out to investigate the impact of intelligence quotient on environment degradation.

This study diverges from previous research by specifically investigating the influence of human intelligence, a vital aspect of qualitative human capital, on environmental degradation from a global perspective. The choice to focus on intelligence quotient (IQ) stems from its conceptualization as a cognitive capacity encompassing reasoning, problem-solving, abstract thinking, and adaptability to one's environment. Numerous studies have explored the effects of IQ on various development outcomes, including financial development (Kodila-Tedika & Asongu, 2015), corruption (Potrafke, 2012), infant mortality (Lynn & Vanhanen, 2006; Kanazawa, 2006; Templer, 2008; Reeve, 2009), health (Lynn, 2010; McDaniel, 2006b), GDP (Lynn & Vanhanen, 2002; Weede & Kämpf, 2002; Ram, 2007; Meisenberg, 2012; Templer & Rushton, 2011), maternal mortality (Lynn & Vanhanen, 2006; Reeve, 2009), life expectancy (Lynn & Vanhanen, 2006; Lynn et al., 2007; Ram, 2007; Rushton & Templer, 2009), and HIV/AIDS (Templer, 2008; Rindermann, Sailer, & Thompson, 2009; Rushton & Templer, 2009; Reeve, 2009).

Given the significant impact of IQ on various developmental indicators, it is reasonable to hypothesize that intelligence levels could similarly affect the extent of environmental degradation. This study thus aims to explore this relationship and contribute to a more comprehensive understanding of the interplay between human intelligence and environmental outcomes.

In addition to theoretical underpinnings, investigations into the relationship between intelligence quotient (IQ[1]) and environmental dynamics have explored two primary perspectives. Firstly, scholars have proposed a positive correlation between IQ and income, implying that fluctuations in income levels may exert an impact on environmental[2]. outcomes. Secondly, IQ is believed to directly influence environmental behavior through a psychological concept known as "delay discounting." This phenomenon suggests that individuals with higher IQs are more likely to prioritize long-term benefits over short-term gains, particularly regarding environmental preservation (Obydenkova & Salahodjaev, 2016; Salahodjaev, 2016; Potrafke, 2012).

Salahodjaev (2015a) further suggests that societies with higher average IQs tend to allocate more resources to ecological conservation and adopt consumption patterns less detrimental to ecosystems. This inclination is attributed to the longer time horizons of intelligent individuals, which

[1]Varying correlation values have been documented with respect to this relationship (see, Lynn and Vanhanen (2012) for a summary of such correlations).
[2]The income-environment causal relationship has been established by Environmental Kuznets Curve by Grossman and Krueger (1991, 1995) and many others.

prompt them to consider the long-term benefits of environmental protection (Potrafke, 2012). Moreover, the Savanna-IQ Interaction Hypothesis posits that individuals with higher intelligence are more likely to prioritize values associated with environmentalism, reflecting a heightened awareness of environmental issues compared to their less intelligent counterparts.

Research has also demonstrated a direct association between the willingness to contribute to environmental quality and the level of human capital. For instance, surveys have indicated that college graduates exhibit a higher propensity for engaging in environmentally friendly behaviours such as recycling (Blomquist & Whitehead, 1998).

Despite the theoretical rationale, empirical investigations into the causal linkages between IQ and environmental outcomes remain limited. Among the few documented studies in this area are those conducted by Squalli (2014) and Obydenkova and Salahodjaev (2016). These studies represent notable attempts to unravel the intricate relationship between intelligence and environmental behavior.

In empirical studies, Squalli (2014) investigates the correlation between intelligence quotient (IQ) and emissions of CH4, CO2, and N2O using U.S. state-level data. Higher-IQ states are found to have higher N2O emissions, but no significant relationship is observed for CH4 and CO2 emissions. Obydenkova and Salahodjaev (2016) explore the determinants of nations' commitment to environmental protection across 152 countries. They measure national intelligence using nation-specific IQ scores and find that higher IQ levels significantly increase the likelihood of signing multilateral environmental agreements. Additionally, they reveal that countries with both high intelligence levels and democratic governance structures are more inclined to engage in international environmental cooperation. These studies shed light on the role of intelligence in shaping environmental behavior at both domestic and international levels, offering valuable insights into the interplay between human cognition and environmental sustainability (Squalli, 2014; Obydenkova & Salahodjaev, 2016). Salahodjaev (2016) also investigate the effect of intelligence on environmental sustainability using data from more than 150 nations over the period 2000–2014, while considering various control variables documented in related studies. The measure of intelligence used was national IQ scores. The results indicate that a 10-point increase in national IQ scores corresponds to a 12-point increase in sustainability, as measured by the Environmental Performance Index. Furthermore, the study documents that the relationship between intelligence and the environment varies with GDP per capita levels.

Obydenkova and Salahodjaev (2017) examine the interplay between cognitive abilities, democracy, and the Climate Laws, Institutions, and Measures Index (CLIMI) across 94 countries.

They find that a 1-point increase in the democracy index corresponds to nearly a 5-point increase in CLIMI adoption, while a 10-point rise in social cognitive capital is linked to almost a 16-point increase in CLIMI. While Squalli (2014) concludes that IQ might not mitigate greenhouse gas emissions, Obydenkova and Salahodjaev (2017) advocate for further empirical inquiries from diverse angles. Building on these insights, our study hypothesizes the significance of intelligence in influencing environmental degradation, aiming to contribute to the ongoing discussion on the intricate relationship between intelligence and environmental outcomes.

Our study contributes significantly to the existing literature from multiple perspectives. Firstly, it represents one of the limited empirical efforts linking human intelligence to environmental degradation. While numerous studies have explored the relationship between "environmental degradation" and "human capital," few have examined the reverse causation, as we have attempted, with the exception of Squalli (2014). Secondly, our research benefits from a broad sample encompassing 147 countries across different continents, aiming to ensure the relevance of policy implications on a global scale. By incorporating diverse geographical contexts, our findings seek to inform more globally harmonized policies, particularly concerning critical issues like global warming. Thirdly, in contrast to many studies grounded in psychology that rely on simple correlations and path analysis methodologies, we employ a range of estimators including OLS, Iterated Weight Least Squares (IWLS), and Two-Stage Least Squares (2SLS) for robustness purposes. Lastly, we evaluate the causal nexus between intelligence and the environment using five measures of environmental degradation, namely carbon emissions, methane, nitrous oxide, greenhouse gas emissions, and ecological footprints. This comprehensive approach enables policymakers to make more tailored and specific decisions rather than adopting generalized policy stances (Templer, 2008; Rindermann et al., 2009; Reeve, 2009; Squalli, 2014).

In synthesis, our study unveils several pivotal findings. Firstly, human intelligence quotient exhibits a consistent positive impact on carbon emissions and ecological demand, counteracting the assumed role of intelligence in "delay discounting" regarding the environment. Secondly, the Environmental Kuznets Curve (EKC) hypothesis holds for carbon and greenhouse gas emissions, while nitrous oxide emissions and ecological footprint follow an inverted EKC pattern with the 2SLS estimator. Thirdly, the mitigating effects of democracy and international environmental commitments persist for carbon and methane emissions. Fourthly, population serves as an amplifying factor for methane and nitrous oxide emissions but mitigates human ecological demand. Lastly, the impacts of other variables remain ambiguous across different environmental degradation measures (Templer, 2008; Rindermann et al., 2009; Reeve, 2009; Squalli, 2014). After the introduction, the empirical inquiry unfolds in the subsequent sections as follows: Section 2 outlines the data, empirical specifications, and methodology, all encompassed within the methods framework. Section 3 delves into the estimation findings, elucidating the empirical results. Finally, Section 4 draws conclusions and discusses policy implications stemming from the analysis.

1.1 Theoretical underpinning the relationship between Intelligence quotient and environment

This study's foundation is rooted on the principles of cognitive capitalism. The concept of cognitive capitalism, as explored by scholars like Yann Moulier Boutang, Franco Berardi, Maurizio Lazzarato, Antonio Negri, Michael Hardt, and Félix Guattari, emphasizes the critical role of knowledge and intellectual labor in modern economies. These thinkers highlight how cognitive work and information production drive economic value and societal transformation in an increasingly digital and knowledge-based era.

When considering the impact of intelligence quotient (IQ) on the environment within this framework, several key insights emerge. Firstly, individuals with higher IQs often lead innovations in technologies aimed at addressing environmental challenges, such as renewable energy and sustainable agriculture. These innovations are essential in mitigating ecological impacts associated with economic activities driven by cognitive capitalism.

Moreover, knowledge-intensive industries within cognitive capitalism heavily rely on skilled workers with high cognitive abilities. Sectors focused on clean technologies and environmental consulting leverage advanced cognitive skills to drive economic growth while addressing environmental concerns. Additionally, individuals with higher IQs exhibit more environmentally conscious behaviours, influencing consumer patterns towards eco-friendly products and lifestyles. This consumer behaviour shapes market demands and encourages businesses to adopt sustainable practices.

Furthermore, within the governance and policy realm, leaders with higher cognitive capacities are more inclined to prioritize environmental regulations and invest in green infrastructure based on scientific evidence. This proactive approach to policymaking contributes to sustainable resource management and environmental protection.

Education also plays a crucial role in this context. Higher IQ levels are associated with better educational attainment and environmental awareness. Therefore, investments in education within cognitive capitalism can promote environmental literacy and critical thinking, empowering individuals to make informed decisions and adopt sustainable behaviors.

In summary, understanding the impact of IQ on the environment within the framework of cognitive capitalism highlights the interconnectedness between cognitive abilities, economic activities, and environmental outcomes. By leveraging cognitive potential through education, innovation, and policy interventions, societies can address environmental challenges and promote sustainable development in the context of a knowledge-driven economy.

2. Methods

2.1 Data description

The study utilized a cross-sectional dataset encompassing 147 countries[3], with data averaged over the period 2000-2017. The selection of this dataset was primarily driven by data availability. Various sources were tapped into for this dataset, including the World Development Indicators (2018), Boden, Marland, and Andres (2017), Global Atlas, Polity IV Project (2018), and the United Nations Framework Convention on Climate Change (UNFCCC).

For intelligence data, the researchers leveraged contributions from psychologists and political scientists such as Richard Lynn and Tatu Vanhanen, who have played instrumental roles in gathering intelligence quotient (IQ) data from numerous countries. This dataset has been widely utilized across a considerable body of published works, as evidenced by its incorporation into studies by economists and non-economists alike. Notable references include works by Weede and Kämpf (2002), Jones and Schneider (2006), Ram (2007), Potrafke (2012), Kodila-Tedika and Kanyama-Kalonda (2012), Kodila-Tedika (2014), and Rindermann et al. (2015). Over time, the intelligence data provided by Lynn and Vanhanen has seen significant refinement and enhancement, with notable improvements highlighted in works by Rindermann (2007a,b) and Meisenberg and Lynn (2011). The latest iterations of this data, as presented by Meisenberg and Lynn (2011) and Lynn and Vanhanen (2012a,b), were recently employed in the study by Meisenberg and Lynn (2012).

2.2 Environmental Degradation Indices

Environmental degradation signifies the degree of decline in an environment due to a decrease in the quality of resources such as water, air, and land, and/or an increase in the damage to ecological systems, habitats, pollutants, and the extinction of flora and fauna. The study utilizes five measures of environmental degradation sourced from the World Bank Development Indicators (2018). These measures include carbon emissions (CO2), methane emissions (MEM), nitrous oxide emissions (NOE), greenhouse gases (GHG), and ecological footprint (EFC).

There is no universal criterion for environmental quality (Borghesi, 2006). Many studies use ecological footprint or greenhouse gas emissions as proxies for environmental sustainability. Despite using these indicators, there is often an assumption that they adequately represent the multifaceted nature of the environment. However, the environment encompasses multiple aspects of ecological change, including resource management, ecosystem protection, and

[3]The list of our 147 countries is presented in appendix.

environmental health. CO2 emissions constitute the majority of greenhouse gases released into the atmosphere, originating from human activities such as fossil fuel consumption, electricity production, transportation, and industrial practices. Measurement is typically in metric tons per capita. Methane emissions stem from various human activities including production processes, storage, and distribution of petroleum products, natural gas, coal, agricultural activities (farming and livestock), and municipal solid waste from organizations and individuals. Nitrous oxide emissions result from the use of nitrogen-based fertilizers, industrial chemical production, transportation, among others. Both methane and nitrous oxide emissions are measured in thousand metric tons of CO2 equivalent. These indicators are frequently employed because the necessary data is readily available.

Table 1 presents the descriptive statistics of the variables used. Mean values for CO2, methane, and nitrous emissions are 4.827, 15,227.3, and 1699.2 respectively. Variations among these variables appear significant, as indicated by their respective standard deviations and the wide range between maximum and minimum values. The study also considers greenhouse gases, representing the total atmospheric gases influencing global energy. However, the available sample data for this measure is relatively small (68 countries out of 147), compared to other indicators. Data for greenhouse gases is sourced from the World Bank (2018) database and is measured as net emissions/removal by Land Use, Land-Use Change, and Forestry (LUCF[4]) in million metric tons of CO2 equivalent.

Lastly, the study incorporates the ecological footprint, which quantifies the impact of human activities on the Earth's surface in terms of the biological resources needed to produce consumable products and process waste generated by humanity. The negative average value of greenhouse gas net emissions (-17.77) suggests an improvement in human approaches towards reducing emissions of carbon, methane, and nitrous oxide into the atmosphere. The ecological footprint has an average of 3.308 with a standard deviation of 2.529.

[4]It means Land-use Change and Forestry.

Table 1: Summary statistics

Variables	Measurements	Mean	Std Dev.	Max.	Min.	Obs.
co_2	CO_2 emissions (metric tons per capita) average 2000-2017	4.827	6.632	51.28	0.029	146
	Natural log of CO_2 emissions	0.655	1.611	3.937	-3.553	146
mem	Methane emissions in energy sector (thousand metric tons of CO_2 equivalent), average 2000-2017	15227.3	57505.4	540394	0	147
	Natural log of methane emissions	7.269	2.704	13.20	-2.943	143
noe	Nitrous oxide emissions in energy sector (thousand metric tons of CO_2 equivalent), average 2000-2017	1699.2	7297.2	74880.2	0	147
	Natural log of nitrous oxide	5.357	2.108	11.22	-2.205	143
ghg	GHG net emissions/removals by LUCF (Mt of CO_2 equivalent), average 2000-2017	-17.77	212.8	1329.1	-907.4	68
	Natural log of GHG net emissions	-1.148	2.827	7.192	-6.811	68
efc	Ecological footprint, average 2000-2017	3.308	2.529	14.72	0.687	137
	Natural log of ecological footprint	0.942	0.714	2.690	-0.375	137
iq	Intelligence quotient, average 2000-2012	85.04	10.94	106.9	61.2	147
	Natural log of intelligence quotient	4.435	0.132	4.672	4.114	147
gdppc	GDP per capita (constant 2010 US$), average 2000-2017	14863.4	22320.3	141200	229.5	146
	Natural log of GDP per capita	8.587	1.527	11.86	5.436	146
$gdppc^2$	Natural log of GDP per capita squared	76.06	26.44	140.6	29.55	146
hce	Households and NPISHs final consumption expenditure (% of GDP), average 2000-2017	63.82	15.49	97.15	17.39	140
manu	Manufacturing, value added (% of GDP), average 2000-2017	13.44	8.514	78.61	1.503	144
eupc	Energy use (kg of oil equivalent per capita), average 2000-2017	2309.7	2827.2	18136.8	12.40	129
	Natural log of energy use, average 2000-2017	7.160	1.153	9.806	2.518	129
ngr	Natural gas (% of GDP), average 2000-2017	0.360	0.906	6.386	0	145
ort	Oil (% of GDP), average 2000-2017	4.139	9.959	47.62	0	145
popt	Population, total ('000), average 2000-2017	42228.8	151141.3	1326576.1	35.63	147
	Natural log of population, total	15.91	1.883	21.01	10.48	147
pscr	Primary completion rate, total (% of relevant age group), average 2000-2017	87.19	18.21	114.4	31.82	138
dem	Democracy (Polity IV), average 2000-2017	4.193	5.942	10	-10	132
iec	International environmental commitment	0.959	0.199	1	0	147

Note: GDP is gross domestic product; GHG denotes greenhouse gas; std dev. Represents standard deviation; max. stands for maximum; min is minimum; and obs. represents observation.

2.3 Intelligence quotient (IQ)

According to Meisenberg and Lynn (2012) and Lynn and Vanhanen (2012a,b), the intelligence quotient (IQ) serves as a measure of human capital, reflecting the mental alertness and potential of a nation's populace to enhance living standards. Previous versions of the IQ data can be found in Lynn and Vanhanen's work from 2002 and 2006. IQ is computed using a compilation of national

IQ tests conducted throughout the 20th and 21st centuries (Lynn and Vanhanen, 2012a,b; Meisenberg and Lynn, 2012). The mean IQ value across nations is reported as 85.04, with a standard deviation of 10.94 (Meisenberg and Lynn, 2012). Notably, Singapore tops the list with the highest average IQ test score of 106.9, while Niger ranks lowest with a score of 61.2 (Meisenberg and Lynn, 2012).

2.4 Other environmental driving factors

The selection of confounding controls in environmental impact studies often draws upon existing literature for theoretical grounding and methodological guidance. In a study conducted by Squalli (2014), the inclusion of GDP per capita and its square value as confounding controls is justified by the Environmental Kuznets Curve (EKC) theory. The EKC posits an inverted U-shaped relationship between economic development and environmental degradation, suggesting that initially, as economies grow, environmental degradation worsens until reaching a certain income threshold, after which environmental quality begins to improve. By incorporating GDP per capita and its squared value into the analysis, researchers aim to account for the level of economic development within countries, thus controlling for its potential influence on environmental outcomes.

Additionally, population data is commonly presumed to have a direct positive relationship with environmental degradation, as higher population densities often lead to increased pollution levels (Squalli, 2014). Similarly, factors such as household consumption and expenses related to non-profit institutions serving households (NPISHs) are expected to exert pressure on the environment through increased energy consumption and waste generation. Moreover, manufacturing outputs are predicted to contribute to environmental degradation by intensifying energy usage and emissions associated with production processes.

The role of specific resource utilization in environmental degradation is also considered. For instance, natural gas and oil usage as a percentage of GDP are included as control variables due to their significant impact on energy consumption and emissions. Likewise, overall energy use is controlled for, given its direct association with environmental pollution. Furthermore, the study incorporates variables related to international environmental commitment and democratic governance. It is assumed that countries operating under democratic systems and demonstrating adherence to international agreements, such as the Doha agreement, are likely to exhibit lower levels of pollution emissions.

The analysis of correlations between variables provides insight into their interrelationships. For instance, the study finds weak positive correlations between intelligent quotient (IQ) and various measures of environmental degradation, including carbon emissions, methane emissions, nitrous emissions, and ecological footprint. However, a weak negative correlation is observed between IQ and greenhouse gas emissions. These findings suggest nuanced associations between cognitive ability and environmental outcomes, potentially indicating varying levels of environmental awareness or behavior among individuals with different levels of intelligence.

Moreover, the correlation coefficients between GDP per capita (and its square value) and environmental factors suggest a lack of support for the EKC hypothesis in this context. Positive correlations are observed between GDP per capita and measures such as carbon emissions, nitrous emissions, greenhouse gas emissions, and ecological footprint, while a negative correlation is found for methane emissions. This implies that, contrary to the EKC hypothesis, economic development does not necessarily lead to a reduction in environmental degradation in this study sample.

In summary, the incorporation of theoretical frameworks, such as the EKC theory, and the analysis of correlations provide valuable insights into the complex relationships between economic development, demographic factors, resource utilization, governance structures, and environmental outcomes. By controlling for these variables and examining their interplay, researchers can better understand the drivers of environmental degradation and inform policy interventions aimed at promoting sustainable development.

Table 2: Correlation matrix

	mem	*noe*	*ghg*	*efc*	*iq*	*gdppc*	*gdppc²*	*hce*	*manu*	*eupc*	*ngr*	*ort*	*popt*	*pscr*	*dem*	*iec*
co₂	0.157	0.195	-0.026	0.473	0.437	0.775	0.747	-0.631	0.271	0.724	0.300	0.215	-0.068	0.760	0.256	-0.093
mem	1	0.880	-0.240	-0.069	0.119	-0.016	-0.017	-0.190	0.142	0.260	0.361	0.308	0.726	-0.004	0.040	0.222
noe		1	-0.222	0.013	0.267	0.104	0.109	-0.171	0.122	0.302	0.102	0.044	0.784	0.060	0.118	0.174
ghg			1	0.026	-0.012	0.031	0.027	0.098	-0.101	-0.224	-0.160	-0.119	-0.227	0.239	0.143	-0.042
Efc				1	0.510	0.510	0.506	-0.212	0.034	0.432	-0.018	-0.176	-0.125	0.368	0.346	-0.060
Iq					1	0.774	0.759	-0.480	0.220	0.709	0.066	-0.074	0.018	0.705	0.237	-0.137
gdppc						1	0.796	-0.668	0.196	0.749	0.140	0.116	-0.188	0.678	0.311	-0.163
gdppc²							1	-0.666	0.178	0.748	0.139	0.106	-0.191	0.639	0.311	-0.176
hce								1	-0.201	-0.677	-0.378	-0.490	-0.004	-0.341	-0.045	0.075
manu									1	0.175	0.183	0.010	0.195	0.184	-0.160	0.112
eupc										1	0.321	0.202	0.027	0.529	0.285	-0.048
ngr											1	0.385	0.086	0.082	-0.026	0.083
Ort												1	0.046	-0.023	-0.138	0.087
popt													1	-0.126	-0.111	0.201
pscr														1	0.213	-0.021
dem															1	-0.094

Note: $C0_2$ - CO_2 emissions (metric tons per capita); mem - Methane emissions in energy sector (thousand metric tons of CO2 equivalent); noe - Nitrous oxide emissions in energy sector (thousand metric tons of CO2 equivalent); ghg - GHG net emissions/removals by LUCF (Mt of CO2 equivalent); efc - Ecological footprint consumption per capita; iq - Intelligence quotient; gdppc - GDP per capita (constant 2010 US$); $gdppc^2$ - Natural log of GDP per capital squared; hce - Households and NPISHs final consumption expenditure (% of GDP); manu - Manufacturing, value added (% of GDP); eupc - Energy use (kg of oil equivalent per capita); ngr - Natural gas (% of GDP); ort - Oil (% of GDP); popt - Population, total ('000); pscr - Primary completion rate, total (% of relevant age group); dem - Democracy (polity IV); and iec - International environmental commitment.

The scatter plots displayed in Figures 1(a-d) visually depict the relationships between human intelligence and environmental degradation indicators, aligning with the findings from the correlation matrix table (Table 2). These scatter diagrams offer a clear representation of the associations between intelligence quotient (IQ) and various measures of environmental degradation, providing insight into both the strength and direction of these relationships.

Through simple linear regression analyses of environmental degradation indicators regressed on IQ, parameter estimates are derived. Specifically, parameter estimates of 0.156, 1.641, 1.211, -0.255, and 0.215 are obtained for CO_2 emissions per capita, methane emissions, nitrous oxide emissions, greenhouse gas (GHG) emissions, and ecological footprint respectively. These estimates indicate the expected change in each environmental degradation indicator corresponding to a one-unit increase in IQ.

Moreover, the coefficient of determination (R-squared) values resulting from these regressions elucidate the proportion of variance in each environmental degradation indicator that can be explained by IQ. The R-squared values reveal that IQ accounts for approximately 15.2%, 87.4%, 86.4%, 12.9%, and 64.4% of the variations in CO_2 emissions, methane emissions, nitrous oxide emissions, GHG emissions, and ecological footprint respectively.

It is crucial to recognize that these findings serve as preliminary analyses and necessitate further validation in subsequent sections of the study. Future iterations of the analysis will incorporate additional factors influencing environmental degradation to offer a more comprehensive understanding of the relationships between human intelligence and environmental outcomes. By integrating these supplementary factors, researchers can refine their interpretations and ascertain the relative significance of IQ in explaining variations in environmental degradation indicators.

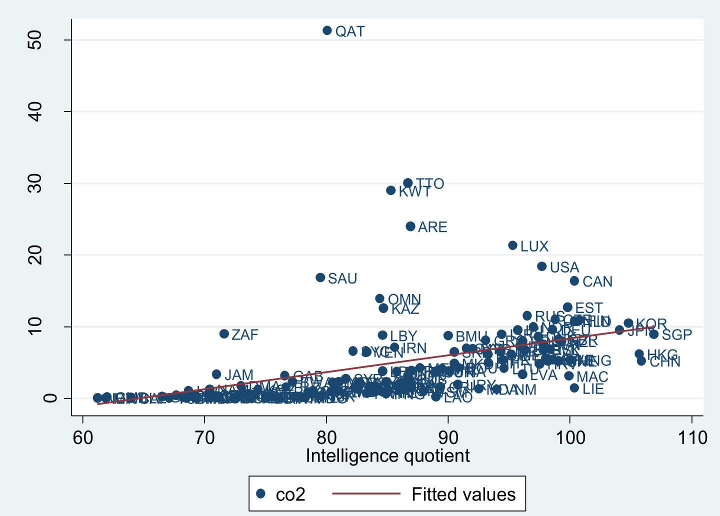

Figure 1a: Carbon emission and intelligence quotient

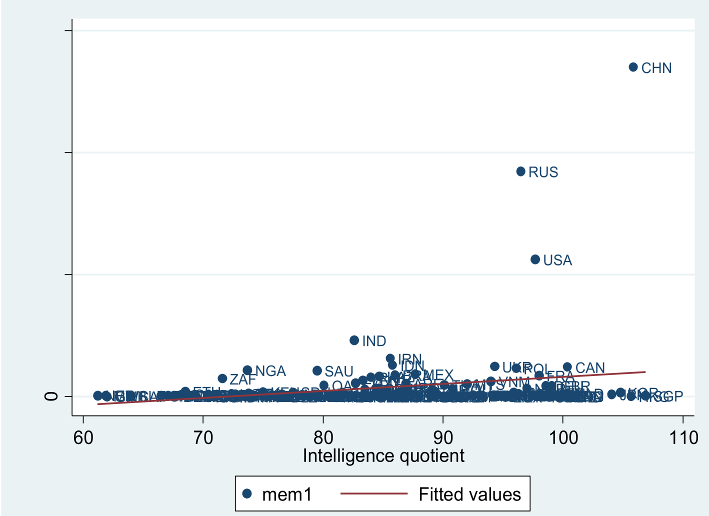

Figure 1b: Methane emission and intelligence quotient

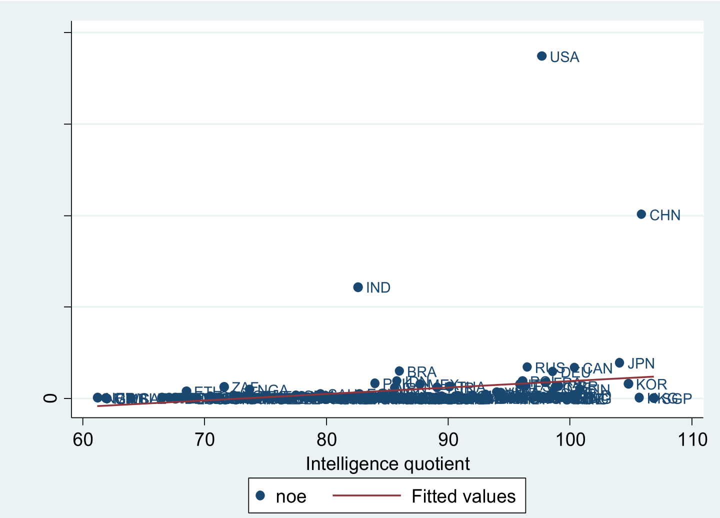

Figure 1c: Nitrous oxide emission and intelligence quotient

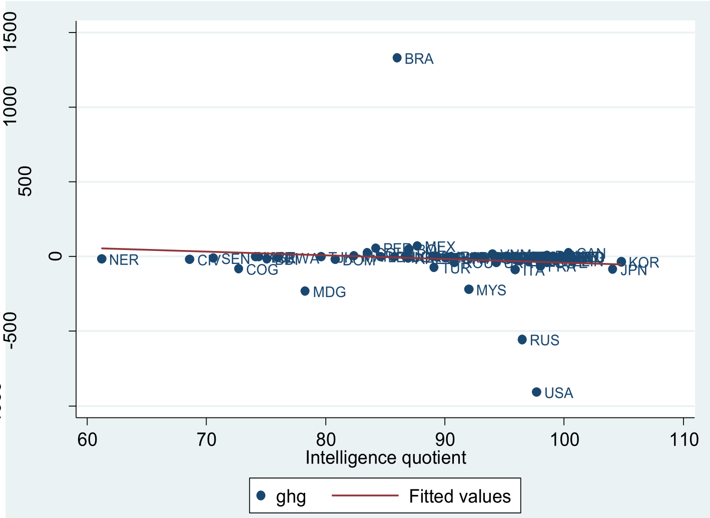

Figure 1d: Greenhouse gas emission and intelligence quotient

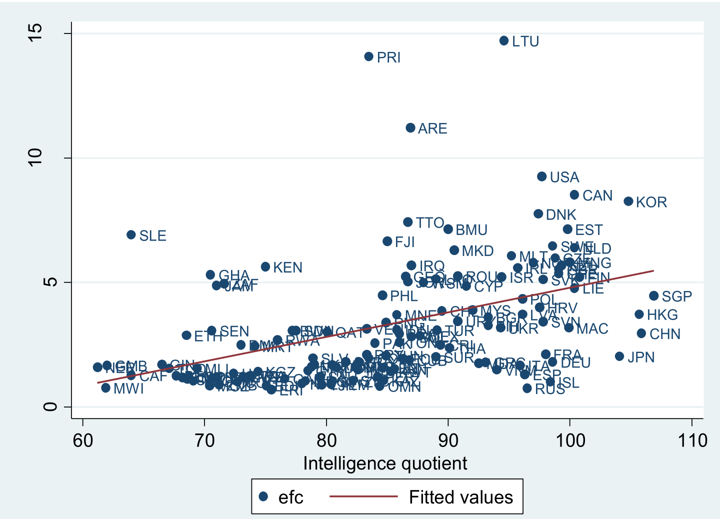

Figure 1e: Ecological footprint and intelligence quotient

Figure 1(a-e): Environmental degradation indices and intelligence quotient

2.5 Empirical model specification

The specification of the empirical model used to analyze the impact of human intelligence on environmental degradation follows the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) method developed by Dietz and Rosa (1994). Several studies, including those by Squalli (2014), Noorpoor and Kudahi (2015), Ji and Chen (2017), Shuai et al. (2018), Wang et al. (2017), and Yeh and Liao (2017), have employed the STIRPAT framework to model the determinants of environmental impact. The STIRPAT model serves as a popular mathematical representation of motivating factors used to assess the impact of human activity on the environment within the ecological sciences field. The structure of the STIRPAT model is expressed as:

$$ENV_i = \phi P_i^{\alpha} A_i^{\beta} T_i^{\varphi} \mu_i \quad (1)$$

The equation provided specifies the current environmental condition in country *i* as a function of population (*P*), affluence (*A*), and technology (*T*). We expand upon the STIRPAT modeling framework by incorporating intelligence quotient, income per capita and its squared value, alongside other control variables. Additionally, we apply log-linearization to the equation, resulting in the model outlined in Equation (2).

$$\ln ENV_i = \phi_0 + \theta_1 \ln GDPPC_i + \theta_2 \ln GDPPC_i^2 + \theta_3 \ln POPT_i + \theta_4 \ln IQ_i + \sigma' CV_i + \mu_i \quad (2)$$

Where *ENV* represents a vector of environmental degradation indices which include carbon emission per capita (CO_2), methane emissions (*MEM*), nitrous oxide emission (*NOE*), greenhouse gas (*GHG*), and ecological footprint (*EFC*); *POPT* denotes total population; *GDPPC* is real income (measured by gross domestic per capita); $GDPPC^2$ signifies the square of GDP per capita; *IQ* stands for intelligence quotient; and *CV* is other controlling variables. The variables used to control for environmental degradation are manufacturing outputs (MANU), households' consumption expenditure as a ratio country GDP (HCE), oil as a ratio of country GDP (ORT), natural gas as a ratio of country GDP (NGR), energy use per capita (EUPC), democracy (DEM), and international environment commitment (IEC). The parameters are represented by $\phi_0, \theta_{1-4}, \sigma'$, whereas μ symbolizes disturbance term and *i* stands for individual country. For the Environmental Kuznets Curve (EKC) to occur i.e. the inverted U-shaped between GDP per capita and environmental pollution, it is presumed that $\theta_1 > 0$ and $\theta_2 < 0$, and both must be significant at the conventional level (Lee, Chiu and Sun, 2010; Sulemana, James and Rikoon, 2017). Taking the first derivative of environmental degradation with respect to income and equating it to zero, the turning point income after solving for GDP per capita is obtained at:

$$GDPPC^* = \exp\left(-\frac{\theta_1}{2\theta_2}\right) \tag{3}$$

2.6 Estimation approaches

This study employs both the ordinary least square (OLS) and two-stage least square (2SLS) methods to estimate the parameters of the variables in equation (2). For a multiple linear regression model, the above equation (2) is re-written in a simple as:

$$y_i = x_i\beta + \varepsilon_i \qquad \text{where } \ i = 1,..., I \tag{4}$$

The dependent variable denoted by *y* is specified with respect to the $1\times M$ vector of regressor x_i which include the constant and error term ε. The $M\times 1$ coefficient of our variables of interest is represented by β. It is important to note that the most important assumption designed for the OLS estimation approach is that the regressors x_i are not correlated with the stochastic term ε, $\mathrm{E}(x_i'\varepsilon_i) = 0$. Rewriting the I observation in equation (4) in a matrix form becomes:

$$Y = X\beta + \varepsilon \tag{5}$$

In the equation (5), the vector of the endogenous variable is denoted by Y, while the $1\times M$ matrix of the explanatory variables is represented by X. For the matrix notation, the least square estimator of β is specified as:

$$\hat{\beta}_{OLS} = (X'X)^{-1} X'Y \tag{6}$$

However, when a regressor like intelligence becomes endogenous due to correlation with the error term, OLS estimation is biased. Instrumental Variable (IV) methods, specifically Two-Stage Least Squares (2SLS), resolve this issue. First, regress the endogenous variable on instruments (variables correlated with it but not the error). Next, use predicted values from this regression in the main model. 2SLS provides consistent and efficient estimates by isolating exogenous variation. Careful instrument selection is crucial for valid results, ensuring instruments affect the endogenous regressor but not the error term.

An instrument is considered as a good tool if it has a high correlation value with the endogenous regressor but uncorrelated with the stochastic term in the structural model (Chen and Lee, 2010).

Thus, the solution of the instrumental variable estimator for β can be stated in the following moment form:

$$E[h_i'\varepsilon_i] = E[h_i'(y_i - x_i'\beta)] \tag{7}$$

The $1\times N$ vector of the instrumental variables is denoted by h_i which is presumed to be correlated with x_i and uncorrelated with ε_i. The moment condition of the sample is stated as:

$$\frac{1}{I}\sum_{i=1}^{I} h_i'(y_i - x_i'\beta) = 0 \tag{8}$$

For instance, the H represents a $I\times N$ instruments matrix, if the number of instrument is the same as the number of regressors $(N = M)$ and is invertible, a unique solution is obtainable for the system of sample moment condition in equation (6). The IV estimator of $\hat{\beta}_{IV}$ is stated as:

$$\hat{\beta}_{IV} = (H'X)^{-1} H'Y \tag{9}$$

Meanwhile, the system of equation in equation (6) is over-identified if the number of explanatory indices is higher than the number of instruments $(M < N)$. Chen and Lee (2010) note that an important question arises in regard to the selection or combination of more than required moment conditions to derive M equations. They further revealed that the 2SLS approach which is explicitly the most efficient instrumental variable estimator from all the potential linear arrangements of the suitable instruments under homoskedasticity is used in this state. The expression of the first stage of 2SLS method in following matrix form $\left[\hat{X} = H(H'H)^{-1} H'X\right]$ shows the regression of each endogenous regressor on all instrumental variables to derive the ordinary least square prediction. For the second stage process, the dependent variable is regressed on $\hat{X}$ to drive the 2SLS estimates of β, i.e. $\hat{\beta}_{2SLS} = (X'X)^{-1} X'Y$. After substituting $H(H'H)^{-1} H'X$ in place of $\hat{X}$, the parameter estimator of $\hat{\beta}_{2SLS}$ therefore becomes:

$$\hat{\beta}_{2SLS} = \left[(X'H)(H'H)^{-1} H'X\right]^{-1} (X'H)(H'H)^{-1} H'Y \tag{10}$$

In this study, the instrumental variables used in the Two Stage Least Squares (2SLS) estimator include basic education level, measured by primary education completion rate, income per capita growth, and household consumption expenditure. The choice of the 2SLS estimator is motivated by its ability to address simultaneity and endogeneity issues effectively.

The first stage of the 2SLS estimator involves regressing intelligence quotient on the instrumental variables, with the coefficients being statistically significant at the 5% level. The fitted values from this stage are then saved for subsequent analysis. In the second stage, these fitted values are added as regressors into the main model to further refine the estimation process.

As mentioned earlier, corrections for heteroskedasticity are applied to both the Ordinary Least Squares (OLS) and 2SLS estimators to ensure the reliability of parameter estimates. To enhance the robustness of the parameter coefficients, the Iteratively Weighted Least Squares (IWLS) approach is employed. IWLS offers the advantage of controlling for outliers in the dataset and correcting for heteroskedasticity issues.

In the IWLS estimation process, both intelligence quotient and income per capita are considered as weighting factors. Additionally, the option of using the absolute value of residuals is explored to further refine the estimation process. This approach helps to ensure that the resulting coefficient estimates are robust and reliable, thereby enhancing the validity of the study's findings.

Overall, the combination of 2SLS and IWLS estimators provides a robust framework for analyzing the relationship between intelligence quotient, socioeconomic factors, and environmental degradation, while addressing potential methodological challenges such as endogeneity, heteroskedasticity, and outliers in the dataset.

3.0 Results and Discussion

The study explores the relationship between intelligence quotients (IQ) and environmental quality across 147 countries, employing both Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) methods for empirical analysis, with a preference for the latter due to inherent limitations of OLS, particularly regarding endogeneity issues (see preceding section). Post-estimation tests of overidentifying restrictions validate the instruments' credibility, with non-rejection of null hypotheses at a 5% significance level, albeit some rejections at 10%. Similarly, null hypotheses on the exogeneity of variables are rejected at conventional levels, affirming the treatment of IQ as an endogenous regressor. Post-estimation statistics are computed using Woodridge's (1995) test scores, assuming robust and heteroskedasticity-adjusted standard errors.

Empirical estimations in Table 3, using carbon emissions per capita as the regressand to gauge environmental degradation levels, yield several noteworthy findings: Intelligence exhibits a significant positive impact on environmental degradation across model specifications, implying an amplifying effect on total carbon emissions into the atmosphere (see Table 3). Notably, coefficients are significant at notable levels, indicating a deviation from the delay discounting principle's application to carbon emissions. Both income and its squared value show statistical significance at the 5% level, suggesting substantial impacts on carbon emissions (see Table 3). Consistently negative and positive coefficients support the Environmental Kuznets Curve hypothesis for carbon pollutants. The estimated turning points of income for the Environmental Kuznets Curve range between US$42,038.2 and US$127,627.7 using 2SLS, and between US$35,785.1 and US$118,071.6 using OLS (see Table 3). This implies a potential reduction in carbon emissions at income thresholds ranging from US$42,038.2 to US$127,627.7.

Controlling for democracy and international environmental commitment reveals their statistically significant mitigating impacts on carbon emissions, with democracy showing a more pronounced effect (see Table 3). This underscores democracy's role in reducing the increasing effect of carbon emissions, consolidating prior evidence of its mitigating impact on environmental pollution. Population does not emerge as a significant driver of high carbon dioxide emissions, with the majority of parameter estimates lacking statistical significance (see Table 3). However, other controlling regressors such as natural gas, oil, and energy consumption exhibit expected signs and statistical significance at the 5% level.

In summary, the findings underscore the significant positive association between IQ and environmental degradation, alongside the substantial impacts of income and its squared value on carbon emissions. The Environmental Kuznets Curve hypothesis is supported, suggesting potential income thresholds for reducing carbon emissions. Moreover, the mitigating effects of democracy and international environmental commitment on carbon emissions are highlighted, underscoring their roles in environmental policy. These results contribute to understanding the complex interplay between socio-economic factors and environmental degradation, informing policy interventions aimed at mitigating environmental impact.

Table 3: OLS and 2SLS estimates of the relationship intelligence quotient (IQ) and carbon dioxide emissions

Variables	**Dependent variables:** Carbon dioxide emissions per capita (logCO_2)											
	Ordinary least square approach						**Two-stage least square method**					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intelligence quotient(log)	**1.213*** **	**1.511*** **	**1.421*** **	**1.606*** **	**1.205*** **	**1.416*** **	**4.155** **	**6.608*** **	**5.189*** **	**7.222*** **	**2.976** **	**4.372* **
	(0.458)	**(0.453)**	**(0.449)**	**(0.441)**	**(0.436)**	**(0.461)**	**(1.710)**	**(2.396)**	**(1.775)**	**(2.695)**	**(1.487)**	**(2.349)**
GDP per capita (log)	**3.457*** **	**3.562*** **	**3.590*** **	**3.465*** **	**2.852*** **	**2.927*** **	**2.972*** **	**2.563*** **	**3.012*** **	**2.424*** **	**2.619*** **	**2.425*** **
	(0.394)	**(0.377)**	**(0.315)**	**(0.360)**	**(0.402)**	**(0.372)**	**(0.545)**	**(0.745)**	**(0.584)**	**(0.805)**	**(0.483)**	**(0.631)**
GDP per capita^2(log)	**-0.148*** **	**-0.156*** **	**-0.157*** **	**-0.149*** **	**-0.136*** **	**-0.135*** **	**-0.123*** **	**-0.109*** **	**-0.129*** **	**-0.097** **	**-0.123*** **	**-0.110*** **
	(0.023)	**(0.022)**	**(0.019)**	**(0.021)**	**(0.023)**	**(0.022)**	**(0.031)**	**(0.041)**	**(0.033)**	**(0.044)**	**(0.028)**	**(0.035)**
Log of population	0.027	0.029	0.028	0.034	-0.005	-0.015	-0.016	-0.047	-0.042	-0.047	-0.035	-0.053
	(0.035)	(0.034)	(0.030)	(0.033)	(0.028)	(0.033)	(0.049)	(0.068)	(0.053)	(0.075)	(0.041)	(0.054)
Democracy	-0.011	**-0.018* **	-0.013	-0.013	**-0.019** **	**-0.018* **	**-0.035** **	**-0.046*** **	**-0.037** **	**-0.048** **	**-0.033** **	**-0.035** **
	(0.010)	**(0.011)**	(0.010)	(0.010)	**(0.009)**	**(0.010)**	**(0.015)**	**(0.017)**	**(0.014)**	**(0.019)**	**(0.014)**	**(0.017)**
International environment commt.	0.361	0.406	0.294	0.358	0.031	0.133	**-0.267** **	**-0.431*** **	**-0.330*** **	**-0.289** **	0.028	0.128
	(0.494)	(0.626)	(0.497)	(0.517)	(0.119)	(0.146)	**(0.117)**	**(0.154)**	**(0.112)**	**(0.114)**	(0.118)	(0.148)
Manufacturing output	**0.010** **					0.004	**0.010* **					0.002
	(0.005)					(0.006)	**(0.005)**					(0.007)
Household consumption expenses		-0.006				**0.010* **		**-0.016* **				0.007
		(0.006)				**(0.005)**		**(0.009)**				(0.006)
Natural gas (% of GDP)			**0.301*** **			**0.168*** **			**0.324*** **			**0.151** **
			(0.029)			**(0.060)**			**(0.051)**			**(0.061)**
Oil (% of GDP)				**0.017** **		0.011				**0.029** **		**0.017* **
				(0.008)		(0.007)				**(0.012)**		**(0.009)**
Energy use (log)					**0.548*** **	**0.450* **					**0.505*** **	**0.435** **
					(0.205)	**(0.236)**					**(0.193)**	**(0.197)**
Constant	**-23.9*** **	**-25.1*** **	**-25.3*** **	**-25.8*** **	**-22.50*** **	**-24.2*** **	**-34.2*** **	**-41.2*** **	**-38.3*** **	**-44.6*** **	**-28.6*** **	**-34.1*** **
	(2.345)	**(2.542)**	**(2.271)**	**(2.293)**	**(2.029)**	**(2.407)**	**(6.449)**	**(7.937)**	**(6.336)**	**(9.281)**	**(5.780)**	**(8.558)**
Turning point (US$)	118071.6	90822.2	92329.0	112140.6	35785.1	51058.8	176538.2	127627.7	117525.5	266955.4	42038.2	61250.0
Adj. R-squared	0.858	0.869	0.889	0.867	0.873	0.883	0.822	0.739	0.818	0.721	0.854	0.823
Fisher statistics/ Wald chi^2 test	**168.9*** **	**165.3*** **	**187.1*** **	**165.1*** **	**164.6*** **	**175.5*** **	**600.6*** **	**364.3*** **	**535.6*** **	**320.3*** **	**801.8*** **	**786.1*** **
Endogeneity chi^2 stat (prob.)	-	-	-	-	-	-	(0.056)	(0.013)	(0.024)	(0.007)	(0.051)	(0.047)
Over-identification restrict. (prob.)	-	-	-	-	-	-	(0.088)	(0.158)	(0.341)	(0.528)	(0.563)	(0.238)
Observations	127	125	129	129	115	110	108	105	109	109	109	104

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; and commt. denotes commitment. The values in bold forms show that the estimated parameters, F-test and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*. n.a. denotes not applicable due to insignificant of parameters.

Table 4: OLS and 2SLS estimates of the relationship between intelligence quotient (IQ) and methane emissions

Variables	**Dependent variables:** Methane emissions (log, mem)											
	Ordinary least square approach						**Two-stage least square method**					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intelligence quotient (log)	-0.003	0.746	0.235	**1.242***	-0.200	1.106	-2.084	5.473	0.864	7.741	**-7.472****	0.829
	(0.900)	(0.735)	(0.841)	**(0.743)**	(0.941)	(0.709)	(3.344)	(5.293)	(3.582)	(5.479)	**(3.622)**	(0.701)
GDP per capita (log)	0.497	-0.100	0.306	-0.358	0.079	-0.050	1.004	-0.920	0.523	-1.445	1.431	-0.502
	(1.033)	(0.868)	(0.668)	(0.736)	(0.948)	(0.664)	(1.023)	(1.427)	(0.892)	(1.416)	(1.188)	(1.212)
GDP per capita^2(log)	-0.017	-0.003	-0.013	0.025	-0.016	0.002	-0.043	0.037	-0.027	0.077	-0.077	0.031
	(0.062)	(0.052)	(0.040)	(0.045)	(0.055)	(0.039)	(0.061)	(0.072)	(0.047)	(0.074)	(0.069)	(0.068)
Log of population	**1.177*****	**1.151*****	**1.144*****	**1.153*****	**1.080*****	**1.067*****	**1.216*****	**1.092*****	**1.107*****	**1.080*****	**1.201*****	**1.084*****
	(0.091)	**(0.087)**	**(0.065)**	**(0.069)**	**(0.085)**	**(0.066)**	**(0.086)**	**(0.092)**	**(0.064)**	**(0.094)**	**(0.137)**	**(0.061)**
Democracy	**-0.073*****	**-0.053*****	**-0.051*****	0.045	-0.012	0.008	**-0.066*****	**-0.052*****	**-0.047*****	-0.009	**-0.053*****	0.004
	(0.018)	**(0.017)**	**(0.014)**	(0.041)	(0.023)	(0.018)	**(0.018)**	**(0.017)**	**(0.014)**	(0.019)	**(0.018)**	(0.015)
International environment commt.	**-1.277****	**-1.568*****	**-1.251*****	1.053	**-0.983*****	**-1.42*****	**-1.525*****	**-2.213*****	**-1.632*****	**-1.518*****	**-1.06*****	**-1.385*****
	(0.493)	**(0.544)**	**(0.434)**	(1.674)	**(0.279)**	**(0.285)**	**(0.228)**	**(0.249)**	**(0.183)**	**(0.203)**	**(0.275)**	**(0.272)**
Manufacturing output	-0.010					0.004	**0.026***					0.005
	(0.042)					(0.008)	**(0.015)**					(0.007)
Household consumption expenses		**-0.043*****				-0.007		**-0.046*****				-0.001
		(0.014)				(0.009)		**(0.009)**				(0.008)
Natural gas (% of GDP)			**0.817*****			**0.544*****			**0.731*****			**0.519*****
			(0.117)			**(0.098)**			**(0.077)**			**(0.099)**
Oil (% of GDP)				**0.079*****		**0.047*****				**0.068*****		**0.049*****
				(0.017)		**(0.011)**				**(0.013)**		**(0.010)**
Energy use (log)					**0.753****	0.193					**0.778****	**0.367****
					(0.315)	(0.222)					**(0.310)**	**(0.151)**
Constant	**-15.7*****	**-12.08****	**-15.1*****	**-16.9*****	**-12.69****	**-14.3*****	-9.247	**-28.12***	-18.19	**-39.5****	12.36	**-12.1****
	(5.425)	**(5.223)**	**(4.258)**	**(4.316)**	**(4.842)**	**(4.122)**	(14.41)	**(16.99)**	(12.90)	**(18.6)**	(13.43)	**(5.124)**
Turning points	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Adj. R-squared	0.612	0.649	0.720	0.710	0.740	0.843	0.601	0.585	0.709	0.610	0.598	0.860
Fisher statistics/ Wald chi^2 test	**43.87*****	**41.59*****	**78.64*****	**59.80*****	**68.40*****	**71.03*****	**288.3*****	**244.0*****	**570.6*****	**551.3*****	**263.6*****	**188.3*****
Endogeneity chi^2 stat (prob.)	-	-	-	-	-	-	(0.032)	(0.042)	(0.058)	(0.043)	(0.018)	(0.017)
Over-identification restrict. (prob.)	-	-	-	-	-	-	(0.457)	(0.294)	(0.149)	(0.178)	(0.378)	(0.070)
Observations	127	125	129	129	114	109	107	104	108	108	108	103

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; and commt. denotes commitment. The values in bold forms show that the estimated parameters, F-test and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*. n.a. denotes not applicable due to insignificant of parameters.

Table 5: OLS and 2SLS estimates of the relationship between intelligence quotient and nitrous oxide emissions

Variables	**Dependent variables:** Nitrous oxide emission (log, noe)											
	Ordinary least square approach						**Two-stage least square method**					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intelligence quotient (log)	0.120	0.310	0.172	0.162	0.032	-0.140	0.648	2.774	1.120	1.905	-1.764	-3.302
	(0.402)	(0.402)	(0.405)	(0.411)	(0.398)	(0.375)	(2.366)	(3.775)	(2.597)	(3.845)	(1.908)	(2.488)
GDP per capita (log)	-0.305	**-0.636***	-0.543	-0.537	-0.401	-0.368	-1.261	-1.305	-1.083	-1.482	-1.501	**-1.751****
	(0.469)	**(0.377)**	(0.367)	(0.365)	(0.452)	(0.455)	(1.024)	(0.870)	(0.974)	(0.923)	(0.955)	**(0.876)**
GDP per capita²(log)	0.037	**0.051****	**0.049****	**0.049****	0.040	0.033	0.096	**0.096***	0.087	**0.110****	**0.102***	**0.111****
	(0.028)	**(0.022)**	**(0.022)**	**(0.022)**	(0.025)	(0.026)	(0.059)	**(0.050)**	(0.057)	**(0.054)**	**(0.055)**	**(0.049)**
Log of population	**1.078*****	**1.073*****	**1.077*****	**1.077*****	**1.043*****	**1.030*****	**1.072*****	**1.040*****	**1.064*****	**1.056*****	**1.065*****	**1.076*****
	(0.044)	**(0.043)**	**(0.038)**	**(0.038)**	**(0.029)**	**(0.030)**	**(0.046)**	**(0.059)**	**(0.046)**	**(0.054)**	**(0.046)**	**(0.053)**
Democracy	**0.036***	0.048	0.041	0.041	0.013	**0.017***	**0.038***	**0.036***	**0.041***	**0.037***	0.029	**0.036***
	(0.021)	(0.033)	(0.030)	(0.030)	(0.008)	**(0.010)**	**(0.020)**	**(0.021)**	**(0.024)**	**(0.021)**	(0.018)	**(0.020)**
International environment commt.	**1.250***	1.182	**1.137***	**1.135***	**0.244****	0.147	**1.308***	**1.378***	**1.215****	**1.271****	0.116	-0.109
	(0.687)	(0.718)	**(0.607)**	**(0.606)**	**(0.115)**	(0.185)	**(0.685)**	**(0.775)**	**(0.588)**	**(0.599)**	(0.236)	(0.292)
Manufacturing output	-0.019					0.001	0.004					0.005
	(0.022)					(0.004)	(0.008)					(0.006)
Household consumption expenses		-0.009				-0.011		**-0.009****				**-0.012****
		(0.008)				(0.007)		**(0.005)**				**(0.006)**
Natural gas (% of GDP)			-0.009			-0.079			-0.054			-0.117
			(0.061)			(0.069)			(0.038)			(0.087)
Oil (% of GDP)				-0.001		**-0.016*****				-0.006		**-0.014*****
				(0.008)		**(0.005)**				(0.004)		**(0.005)**
Energy use (log)					**0.238***	0.290					**0.205***	**0.240****
					(0.126)	(0.186)					**(0.117)**	**(0.096)**
Constant	**-13.7*****	**-12.4*****	**-12.99*****	**-12.98*****	**-12.57*****	**-10.8*****	**-8.59****	**-8.68*****	**-9.77*****	**-7.97****	**-8.951****	**-6.227***
	(2.553)	**(2.067)**	**(1.973)**	**(1.991)**	**(1.949)**	**(1.741)**	**(3.768)**	**(3.349)**	**(3.538)**	**(3.338)**	**(3.503)**	**(3.702)**
Turning points	n.a.	510.4	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	2663.5
Adj. R-squared	0.827	0.817	0.826	0.826	0.920	0.914	0.811	0.792	0.808	0.801	0.900	0.871
Fisher statistics/ Wald chi² test	**164.8*****	**157.2*****	**174.5*****	**172.4*****	**173.3*****	**183.9*****	**731.4*****	**570.2*****	**751.5*****	**664.7*****	**982.2*****	**963.7*****
Endogeneity chi² stat (prob.)	-	-	-	-	-	-	(0.036)	(0.098)	(0.032)	(0.051)	(0.025)	(0.083)
Over-identification restrict. (prob.)	-	-	-	-	-	-	(0.332)	(0.310)	(0.239)	(0.121)	(0.521)	(0.328)
Observations	127	125	129	129	114	109	107	104	108	108	108	103

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; and commt. denotes commitment. The values in bold forms show that the estimated parameters, F-test and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*. n.a. denotes not applicable due to insignificant of parameters.

Table 6: OLS and 2SLS estimates of the relationship between intelligence quotient and greenhouse gas emissions

Variables	**Dependent variables:** Greenhouse gas emission (log, ghg)											
	Ordinary least square approach						**Two-stage least square method**					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intelligence quotient (log)	-1.668	-2.443	-1.942	-5.174	8.386	6.066	-8.127	-10.484	-11.613	**-16.633****	-7.106	-11.715
	(6.053)	(6.203)	(5.942)	(6.554)	(6.206)	(6.523)	(7.049)	(6.805)	(7.485)	**(7.941)**	(11.535)	(12.396)
GDP per capita (log)	3.748	3.527	3.191	4.312	1.093	5.057	**17.61*****	**15.342*****	**17.043*****	**18.244*****	**24.507****	**33.15****
	(3.050)	(2.637)	(2.689)	(2.623)	(3.946)	(4.352)	**(5.879)**	**(5.177)**	**(5.865)**	**(6.081)**	**(11.261)**	**(13.045)**
GDP per capita²(log)	-0.210	-0.182	-0.178	-0.225	-0.011	-0.217	**-0.972*****	**-0.809*****	**-0.934*****	**-0.975*****	**-1.244****	**-1.697****
	(0.165)	(0.144)	(0.145)	(0.140)	(0.201)	(0.229)	**(0.325)**	**(0.280)**	**(0.323)**	**(0.330)**	**(0.597)**	**(0.689)**
Log of population	-0.074	-0.169	-0.070	-0.156	-0.133	-0.055	0.183	-0.097	0.042	-0.116	-0.081	0.131
	(0.359)	(0.335)	(0.342)	(0.324)	(0.321)	(0.389)	(0.333)	(0.307)	(0.332)	(0.321)	(0.363)	(0.408)
Democracy	-0.023	-0.050	-0.039	-0.115	-0.043	**-0.194****	-0.035	-0.095	-0.068	-0.208	-0.124	**-0.487****
	(0.093)	(0.089)	(0.090)	(0.089)	(0.081)	**(0.090)**	(0.105)	(0.105)	(0.108)	(0.128)	(0.132)	**(0.211)**
International environment commt.	-0.240	0.131	-0.380	-0.674	-0.343	-0.632	0.240	0.823	-0.417	-0.863	-1.787	-2.316
	(0.815)	(0.836)	(0.754)	(0.915)	(0.705)	(1.205)	(2.509)	(2.492)	(2.511)	(2.476)	(2.841)	(3.154)
Manufacturing output	-0.073					-0.107	**-0.212***					**-0.259****
	(0.078)					(0.090)	**(0.109)**					**(0.104)**
Household consumption expenses		0.034				-0.007		**0.060***				-0.010
		(0.033)				(0.045)		**(0.036)**				(0.052)
Natural gas (% of GDP)			-0.506			-0.108			-0.716			-0.139
			(0.735)			(0.739)			(0.842)			(0.833)
Oil (% of GDP)				**-0.111*****		**-0.176****				**-0.199****		**-0.445****
				(0.041)		**(0.085)**				**(0.086)**		**(0.183)**
Energy use (log)					**-1.693***	**-1.737***					**-2.958****	**-2.577****
					(0.888)	**(0.958)**					**(1.339)**	**(1.225)**
Constant	-23.13	-21.72	-18.94	-15.67	-13.75	-22.10	**-67.76***	**-56.94***	**-56.45***	-43.04	**-97.24***	**-93.37****
	(19.18)	(16.07)	(15.90)	(16.39)	(20.51)	(24.97)	**(39.38)**	**(31.38)**	**(32.39)**	(28.44)	**(59.02)**	**(39.60)**
Turning points	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	8592.4	13122.3	9169.7	11566.8	18959.8	17452.4
Adj. R-squared	0.043	0.050	0.052	0.076	0.126	0.202	0.232	0.235	0.193	0.286	0.204	0.575
Fisher statistics/ Wald chi² test	1.64	1.91	1.62	4.17	3.23	**9.65****	**18.56*****	**19.22*****	**24.47*****	**26.08*****	**19.87*****	**28.27*****
Endogeneity chi² stat (prob.)	-	-	-	-	-	-	(0.010)	(0.019)	(0.008)	(0.019)	(0.007)	(0.008)
Over-identification restrict. (prob.)	-	-	-	-	-	-	(0.575)	(0.553)	(0.710)	(0.661)	(0.798)	(0.694)
Observations	62	62	62	62	59	59	54	54	54	54	54	54

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; and commt. denotes commitment. The values in bold forms show that the estimated parameters, F-test and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*. n.a. denotes not applicable due to insignificant of parameters.

Table 7: OLS and 2SLS estimates of the relationship between intelligence quotient and ecological footprint

Variables	**Dependent variables:** ecological footprint (log, efc)											
	Ordinary least square approach						**Two-stage least square method**					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intelligence quotient (log)	**3.596*** **	**3.474*** **	**3.560*** **	**3.449*** **	**3.599*** **	**3.466*** **	**3.859*** **	**3.826*** **	**3.841*** **	**3.811*** **	**3.876*** **	**3.824*** **
	(0.293)	**(0.280)**	**(0.280)**	**(0.303)**	**(0.316)**	**(0.332)**	**(0.323)**	**(0.349)**	**(0.317)**	**(0.344)**	**(0.317)**	**(0.355)**
GDP per capita (log)	-0.104	-0.218	-0.166	-0.094	-0.129	-0.157	**-1.324***	**-2.040*** **	**-1.362***	**-1.571** **	**-1.510***	**-2.231*** **
	(0.319)	(0.293)	(0.294)	(0.301)	(0.411)	(0.400)	**(0.765)**	**(0.724)**	**(0.708)**	**(0.691)**	**(0.788)**	**(0.785)**
GDP per capita²(log)	0.013	0.021	0.016	0.013	0.012	0.013	**0.082***	**0.123*** **	**0.084** **	**0.097** **	**0.090** **	**0.129*** **
	(0.018)	(0.017)	(0.017)	(0.017)	(0.023)	(0.022)	**(0.044)**	**(0.041)**	**(0.041)**	**(0.040)**	**(0.044)**	**(0.044)**
Log of population	**-0.055*** **	**-0.045** **	**-0.054*** **	**-0.047** **	**-0.060*** **	**-0.060*** **	**-0.059*** **	**-0.052*** **	**-0.059*** **	**-0.054*** **	**-0.065*** **	**-0.067*** **
	(0.019)	**(0.020)**	**(0.018)**	**(0.019)**	**(0.016)**	**(0.019)**	**(0.019)**	**(0.019)**	**(0.017)**	**(0.019)**	**(0.017)**	**(0.018)**
Democracy	0.003	0.002	0.006	-0.003	0.008	0.000	0.000	0.002	0.003	-0.000	0.004	0.003
	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.006)
International environment commt.	-0.037	-0.054	-0.036	-0.062	0.057	0.009	-0.049	-0.103	-0.048	-0.047	0.060	0.014
	(0.142)	(0.141)	(0.140)	(0.137)	(0.140)	(0.142)	(0.209)	(0.208)	(0.198)	(0.210)	(0.191)	(0.192)
Manufacturing output	-0.004					-0.007	-0.004					0.000
	(0.011)					(0.006)	(0.009)					(0.009)
Household consumption expenses		0.004				0.001		0.001				-0.001
		(0.004)				(0.005)		(0.005)				(0.006)
Natural gas (% of GDP)			**0.097*** **			**0.103*** **			**0.100*** **			**0.091*** **
			(0.019)			**(0.034)**			**(0.026)**			**(0.035)**
Oil (% of GDP)				-0.005		**-0.008***				0.000		-0.004
				(0.005)		**(0.005)**				(0.003)		(0.004)
Energy use (log)					**0.197** **	**0.163***					**0.196*** **	**0.145*** **
					(0.078)	**(0.095)**					**(0.043)**	**(0.050)**
Constant	**-14.9*** **	**-14.5*** **	**-14.5*** **	**-14.3*** **	**-15.3*** **	**-15.4*** **	**-11.1*** **	**-8.417** **	**-10.9*** **	**-9.85*** **	**-10.61*** **	**-8.088** **
	(1.988)	**(1.845)**	**(1.785)**	**(1.809)**	**(2.396)**	**(2.568)**	**(3.438)**	**(3.327)**	**(3.094)**	**(3.011)**	**(3.355)**	**(3.361)**
Turning points	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	3207.2	3994.5	3318.1	3287.7	4397.9	5694.6
Adj. R-squared	0.597	0.609	0.602	0.609	0.623	0.650	0.317	0.294	0.379	0.256	0.430	0.523
Fisher statistics/ Wald chi² test	**42.09*** **	**45.01*** **	**45.94*** **	**45.64*** **	**42.03*** **	**49.20*** **	**58.35*** **	**42.27*** **	**58.42*** **	**39.96*** **	**127.2*** **	**72.95*** **
Endogeneity chi² stat (prob.)	-	-	-	-	-	-	(0.003)	(0.004)	(0.001)	(0.000)	(0.011)	(0.001)
Over-identification restrict. (prob.)	-	-	-	-	-	-	(0.060)	(0.102)	(0.173)	(0.475)	(0.063)	(0.168)
Observations	127	125	129	129	114	109	108	105	109	109	109	104

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; and commt. denotes commitment. The values in bold forms show that the estimated parameters, F-test and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*.n.a. denotes not applicable due to insignificant of parameters.

Table 4 sheds light on the potential impact of intelligence on methane emissions. The findings from the table are as follows:

Firstly, intelligence does not emerge as a significant factor influencing methane emissions, unlike carbon emissions in Table 3. This is evident from the mixed signs of parameter estimates, along with mostly insignificant coefficients, except in column 11. Secondly, the non-linearity results of income growth do not significantly affect methane pollution, suggesting that an Environmental Kuznets Curve (EKC) does not hold for methane pollutants due to coefficients mostly appearing in the opposite direction. This finding aligns with Squalli (2014). Thirdly, the establishment of threshold income points for methane emission is not achieved since the parameters of income and its squared value are not jointly significant. Fourthly, the joint control of both democracy and international environmental commitment negatively affects methane emissions and is statistically significant. The significance is more pronounced for international environmental commitments than for democracy. This suggests that international environmental commitment and democracy have depleting effects on total methane pollutants emitted into the atmosphere. Fifthly, the findings support the economic intuition that population is positively related to methane emissions. Lastly, similar to carbon emissions in Table 3, it is noteworthy that natural gas amplifies methane production, along with energy use and oil, while household consumption expenses exert a mitigating impact.

The empirical results regarding the correlation between intelligence and nitrous emissions, as detailed in Table 5, can be summarized as follows: (i) Similar to the findings for methane emissions in Table 4, the influence of intelligence on nitrous pollution is not statistically significant across the models. This suggests that IQ does not play a significant role in determining the total volume of nitrous oxide emissions released into the environment. (ii) The coefficients on income per capita do not conform to theoretical expectations across the specifications, except for significant estimates in columns 2 and 12. Additionally, the signs on income and its square values appear in a random manner, contradicting the Environmental Kuznets Curve hypothesis for nitrous oxide emissions. (iii) Only two coefficients of income and its squared values are statistically significant at the 5% level, but they are in opposite directions. This implies an inverted Environmental Kuznets Curve for nitrous oxide pollutants, with turning points of income per capita at US$510.4 and US$2,663.5 for OLS and 2SLS estimators, respectively. (iv) Neither democracy nor international environment commitment exhibit a tendency to significantly reduce nitrous gas emissions. However, the statistical significance level of the parameter estimates for democracy is higher than that for international environment commitment. Lastly, Population has a positive influence on nitrous gas emissions, akin to its impact on methane emissions. Energy consumption also amplifies methane emissions, while household expenses on consumption and oil have neutralizing effects. In summary, these empirical findings suggest that intelligence, income, democracy, and international environment commitment do not significantly affect nitrous oxide emissions, while population and energy consumption play significant roles. Additionally, the relationship between income and nitrous emissions follows an inverted Environmental Kuznets Curve pattern.

Table 8: IWLS estimates of the relationship between intelligence quotient and environmental degradation indicators

Variables	**Dependent Variable:** Environmental Degradation Indices (log)				
	Carbon Emission	Methane Emission	Nitrous Emission	Greenhouse Gas Emission	Ecological Footprint
Intelligence quotient (log)	**1.547*** **	1.073	-0.133	**10.077***	**3.209*** **
	(0.431)	(0.675)	(0.435)	**(6.025)**	**(0.342)**
GDP per capita (log)	**2.853*** **	-0.188	-0.493	5.315	**-2.226*** **
	(0.426)	(0.671)	(0.432)	(3.583)	**(0.837)**
GDP per capita^2(log)	**-0.127*** **	0.012	**0.043***	-0.228	**0.116*** **
	(0.025)	(0.039)	**(0.025)**	(0.195)	**(0.040)**
Log of population	-0.025	**1.033*** **	**1.022*** **	-0.029	-0.001
	(0.033)	**(0.052)**	**(0.034)**	(0.278)	(0.026)
Democracy	**-0.020** **	0.007	**0.018***	**-0.181***	**0.021*** **
	(0.010)	(0.015)	**(0.010)**	**(0.109)**	**(0.008)**
International environment commitment	0.117	**-1.428***	0.036	-0.285	**0.661***
	(0.482)	**(0.757)**	(0.488)	(1.974)	**(0.378)**
Manufacturing output	0.007	0.004	-0.001	-0.128	-0.006
	(0.007)	(0.011)	(0.007)	(0.092)	(0.006)
Household consumption expenses	**0.011***	-0.008	**-0.015** **	-0.007	-0.001
	(0.006)	(0.009)	**(0.006)**	(0.047)	(0.004)
Natural gas (% of GDP)	**0.179** **	**0.525*** **	-0.055	0.216	**0.106***
	(0.074)	**(0.116)**	(0.074)	(0.515)	**(0.058)**
Oil (% of GDP)	0.009	**0.046*** **	**-0.017** **	**-0.153***	-0.003
	(0.007)	**(0.011)**	**(0.007)**	**(0.089)**	(0.005)
Energy use (log)	**0.365*** **	0.133	0.130	**-2.926*** **	0.088
	(0.087)	(0.137)	(0.088)	**(1.057)**	(0.068)
Constant	**-23.99*** **	**-12.64*** **	**-9.306*** **	**-49.208** **	**-13.80*** **
	(2.480)	**(3.901)**	**(2.514)**	**(22.760)**	**(1.949)**
Turning points	75529.3	n.a.	n.a.	n.a.	14688.5
Adj. R-squared	0.883	0.850	0.915	0.214	0.656
Fisher statistics	**75.99*** **	**56.53*** **	**106.2*** **	**13.52*** **	**19.71*** **
Observations	110	109	109	59	109

Note: standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10. The values in bold forms show that the estimated parameters and F-statistics are statistically significant at the critical values identified above. n.a. denotes not applicable due to insignificant of parameters. The residual plots presented in Figures 2(a-e) are good as they are at random space around the horizontal axis. It therefore shows an improvement in regards to heteroskedasticity.

The findings from Table 6 on the causal links between intelligence quotient (IQ) and greenhouse gas emissions, along with other variables, suggest several noteworthy points:

Intelligence tends to have negative coefficients, indicating a potential for reducing greenhouse gas emissions. However, these coefficients are mostly not statistically significant, except for one instance. This suggests that while intelligence may theoretically influence emissions, its effect is not robustly supported by the data.

The non-linear specification of income supports the Environmental Kuznets Curve hypothesis for greenhouse gas emissions. This suggests that as income increases, emissions initially rise but then begin to decline after reaching a certain threshold. The statistically significant coefficients point to specific income levels where this turning point occurs.

Variables such as democracy and international environmental commitment show potential for reducing greenhouse gas emissions. However, only a few estimates are statistically significant at conventional levels when controlling for other variables. Population has a negative influence on greenhouse gas emissions but lacks statistical significance. Manufacturing outputs, energy use, and oil consumption are shown to mitigate emissions, suggesting that improvements in these areas could help reduce environmental impact. Household consumption spending shows an increasing impact on greenhouse gas emissions, albeit at a lower significance level. This suggests that consumer behavior and spending patterns contribute to emissions growth.

Overall, the findings highlight the complex interplay of various factors in influencing greenhouse gas emissions, with intelligence, income, political systems, economic activities, and consumption behaviors all playing significant roles.

Table 7 presents empirical findings on the relationship between intelligence and ecological footprint, revealing several key results:

Intelligence shows a consistently positive influence on ecological footprint across different model specifications. This indicates that human intelligence significantly affects the overall demand of human activities on the Earth's surface. Income has a negative effect on the ecological system, particularly evident in the 2SLS estimator in models 7 through 12. However, the signs of income squared unexpectedly move in the opposite direction from the expected Environmental Kuznets Curve (EKC) hypothesis, yet they are statistically significant. This suggests an inverted EKC hypothesis for ecological footprint. The income threshold points for human ecosystem fall between US$3,207.2 and US$5,694.6. It's noteworthy that these income threshold points are lower than those reported for other environmental pollutants' turning points, such as carbon emissions. While most coefficients on variables related to international environmental commitment enter negatively, they do not show a statistically significant relationship with human ecological environments. Similarly, democracy has an insignificant impact, but it seemingly exhibits a positive link with ecological footprint.

Unlike methane and nitrous oxide emissions, population has a statistically significant mitigating effect on both human ecological flora and fauna across various specifications. In conclusion, the roles of natural gas and energy use in driving human ecological demands are notably escalating, evident in statistically significant ways.

Discussion of the main findings

Human intelligence consistently shows a positive and significant impact on carbon emissions across various specifications. While this may seem counter-intuitive, it aligns with current trends in environmental degradation. There are several channels by which this finding may be plausible. First, higher IQ individuals might be more likely to be engaged in certain professions or industries that contribute to environmental degradation, such as technology, manufacturing, or finance. These industries often have significant ecological footprints due to resource consumption and waste generation. Second, Individuals with higher IQs might be more influential in policy-making or corporate decisions. If these decision-makers prioritize economic growth over environmental sustainability, it can lead to policies and practices that contribute to environmental degradation. Last but not least, Intelligence often correlates with innovation and technological advancement. While these advancements can lead to more efficient resource use, they can also result in new technologies that unintentionally harm the environment (e.g., certain manufacturing processes, energy production methods).

Many high-IQ societies exhibit a tendency towards delay discounting, where immediate benefits take precedence over long-term consequences. Examples from countries like China, the USA, Russia, and Japan illustrate this phenomenon. Despite their participation in agreements like the Kyoto Protocol, their carbon emissions continue to rise. China, as the most populous country with a significant export market, has seen its industrial growth pose a serious threat to the planet, contributing approximately 30% of global carbon emissions. Similarly, the USA, despite leading initiatives to combat climate change, has been criticized for insufficient efforts, particularly under certain administrations like that of Trump, which rolled back environmental policies. In the same

vein, Russia relies heavily on products such as oil, coal, gas, and fossil fuels, experiencing environmental emergencies and high levels of deforestation and animal hunting. Japan, known for its high level of urban development, is labelled as one of the biggest consumers of fossil fuels and a significant emitter of greenhouse gases.
These countries prioritize short-term benefits over long-term gains, contradicting the delay discounting principle. However, our finding contradicts the studies conducted by Salahodjaev (2016; 2018), which demonstrated a positive and significant impact of intelligence on environmental sustainability. In Salahodjaev's earlier study, a 10-point increase in national IQ scores was associated with a 12-point increase in sustainability, as measured by the Environmental Performance Index. Furthermore, his later study indicated that a one-standard-deviation increase in cognitive abilities led to a 19% increase in climate change awareness. Similarly, Obydenkovaa and Salahodjaev (2017) also found that a 10 points increase in social cognitive capital is associated with a nearly 16 points increase in Climate Laws, Institutions and Measures Index (CLIMI).

Regarding ecological footprints, data from the 2018 edition of the National Footprint Accounts show a consistent increase in human ecological demand on nature since 1961, averaging 2.1% growth per year. This demand rose from 7.0 billion gha in 1961 to 20.6 billion gha in 2014, with the world-average ecological footprint in 2014 being 2.8 global hectares per person.

Most high-IQ nations operate in deficits in biocapacity, further indicating their contribution to environmental degradation. These cases collectively suggest a positive correlation between intelligence and environmental degradation.

Apart from the main variable of interest, GDP per capita enters the equation with a positive coefficient but becomes negative when squared. This result is consistent with Stern's argument (2004, p. 1419), which suggests that during the initial stages of economic growth, degradation and pollution tend to increase. However, once a certain level of income per capita is achieved (this threshold varies depending on the specific environmental indicator), the trend reverses. At higher income levels, economic growth leads to environmental improvement. This finding is consistent with Salahodjaev (2016, 2018), Obydenkovaa and Salahodjaev (2017) among others

Robustness Checks

The passage describes a series of robustness checks conducted on empirical findings regarding the relationship between intelligence and environmental degradation indices. These checks involve employing different statistical methods and varying sample restrictions to test the consistency of the results.

IWLS Estimator: The text mentions the use of the Iteratively Weighted Least Squares (IWLS) estimator to address issues such as heteroskedasticity and outliers in the data. Results from these robustness checks are reported in Table 8, showing consistency with earlier findings.

Additional Robustness Tests: Three additional sets of robustness tests are conducted by restricting samples based on countries' intelligence quotients (IQs). Countries with IQs equal to or above 105[5], 100[6] and 90[7] are considered separately. The results, presented in Table 9, indicate:

Similarity in results for countries with IQs above 105 and 100 compared to earlier findings, except for the insignificance of human intelligence variable in countries with IQs above 100. Countries with IQs above 105 significantly contribute to global carbon dioxide emissions and human ecological demand, with higher magnitude compared to those with IQs above 100 and 90. Excluding countries with higher IQs (105 and above) reduces statistical significance from 1% to 5%, reinforcing the importance of IQ in the intelligence-environment literature. The Environmental Kuznets Curve (EKC) hypothesis fails to hold for CO2 and greenhouse gas (GHG) models in countries with IQs above 90, suggesting the use of environmentally unfriendly technologies to boost national output. The significance of democracy varies across different emission models and sample restrictions, while the coefficient of international environment commitment lacks empirical support in certain cases. Population coefficients remain robust across methane and nitrous emission models.

Overall, these robustness tests provide insights into the relationship between intelligence and environmental degradation, highlighting the importance of IQ levels and other factors in understanding environmental impact at the national level.

[5]The list of countries with an average IQ above 105 includes China, Hong Kong SAR, China, and Singapore.

[6]Countries with an average IQ above 100 are: China, Hong Kong SAR, China, Singapore, Canada, Finland, Japan, Korea Republic, Liechtenstein, Mongolia, and Netherlands.

[7]The fifty-five countries with an average IQ above 90 are :Bermuda, Bosnia and Herzegovina, Bulgaria, Canada, Chile, China, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR China, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea Rep., Latvia, Liechtenstein, Lithuania, Luxembourg, Macao SAR China, Macedonia, Malaysia, Malta, Moldova, Mongolia, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Serbia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay and Vietnam.

Table 9: Robustness check results of countries with IQ below 105, 100 and 90 quotients using 2SLS method

Variables	Below 105					Below 100					Below 90				
	Dependent Variable: Environmental Degradation Indices (log)														
	Carbon Emission	Methane Emission	Nitrous Emission	GHG Emission	Ecological Footprint	Carbon Emission	Methane Emission	Nitrous Emission	GHG Emission	Ecological Footprint	Carbon Emission	Methane Emission	Nitrous Emission	GHG Emission	Ecological Footprint
Intelligence quotient (log)	1.751**	-0.472	0.457	-11.715	0.671*	1.333	-0.215	0.212	-2.828	0.244	0.703	-4.384***	-3.456***	34.71***	-0.477
	(0.784)	(1.181)	(0.755)	(12.396)	(0.401)	(0.830)	(1.254)	(0.756)	(9.521)	(0.405)	(1.183)	(1.537)	(1.080)	(4.826)	(0.564)
GDP per capita (log)	2.297***	0.372	-1.046	33.150**	-0.206	2.291***	0.162	-0.867	19.90**	-0.095	2.506**	2.032	2.121**	-5.520*	-0.021
	(0.725)	(1.081)	(0.691)	(13.045)	(0.371)	(0.731)	(1.090)	(0.658)	(7.881)	(0.357)	(1.132)	(1.466)	(1.031)	(3.322)	(0.540)
GDP per capita^2(log)	-0.101**	-0.021	0.070*	-1.697**	0.028	-0.098**	-0.011	0.060*	-0.989**	0.025	-0.093	-0.099	-0.110*	0.138	0.030
	(0.040)	(0.060)	(0.038)	(0.689)	(0.020)	(0.040)	(0.060)	(0.036)	(0.411)	(0.020)	(0.069)	(0.090)	(0.063)	(0.189)	(0.033)
Log of population	-0.040	0.981***	0.999***	0.131	-0.075***	-0.025	0.975***	1.003***	0.047	-0.062***	0.007	1.045***	1.056***	1.469***	-0.034
	(0.035)	(0.055)	(0.035)	(0.408)	(0.018)	(0.037)	(0.058)	(0.035)	(0.324)	(0.018)	(0.047)	(0.065)	(0.045)	(0.192)	(0.022)
Manufacturing output	0.003	-0.002	0.001	-0.409**	-0.000	0.004	-0.000	0.001	-0.257**	0.000	-0.000	-0.007	-0.004	-0.212***	-0.002
	(0.006)	(0.009)	(0.006)	(0.171)	(0.003)	(0.006)	(0.009)	(0.005)	(0.130)	(0.003)	(0.006)	(0.008)	(0.006)	(0.079)	(0.003)
Household conspt. expenses	0.011**	0.002	-0.012**	-0.077	0.000	0.013**	0.001	-0.013**	-0.049	0.001	0.018**	0.009	-0.005	-0.115***	0.004
	(0.006)	(0.009)	(0.006)	(0.078)	(0.003)	(0.006)	(0.009)	(0.006)	(0.059)	(0.003)	(0.007)	(0.009)	(0.006)	(0.028)	(0.003)
Natural gas (% o GDP)	0.184***	0.547***	-0.080	0.439	0.100***	0.187***	0.517***	-0.071	0.207	0.104***	0.246**	0.633***	0.105	-0.751*	0.140***
	(0.068)	(0.103)	(0.066)	(0.768)	(0.035)	(0.069)	(0.105)	(0.063)	(0.622)	(0.034)	(0.106)	(0.138)	(0.097)	(0.394)	(0.051)
Oil (% o GDP)	0.011	0.042***	-0.011	-0.445**	-0.003	0.010	0.043***	-0.011	-0.306**	-0.004	0.009	0.043***	-0.007	-0.069	-0.005
	(0.008)	(0.012)	(0.008)	(0.183)	(0.004)	(0.008)	(0.012)	(0.007)	(0.127)	(0.004)	(0.008)	(0.011)	(0.007)	(0.046)	(0.004)
Energy use (log)	0.407***	0.389**	0.239**	-2.888*	0.152***	0.398***	0.390**	0.206**	-3.183**	0.143***	0.216*	0.198	0.167	2.066**	0.037
	(0.097)	(0.151)	(0.097)	(1.560)	(0.050)	(0.098)	(0.153)	(0.092)	(1.255)	(0.048)	(0.122)	(0.162)	(0.114)	(0.998)	(0.058)
Democracy	-0.008	0.003	0.014	-0.487**	0.006	-0.010	0.004	0.012	-0.354**	0.003	-0.008	-0.018	-0.013	0.225***	0.001
	(0.012)	(0.018)	(0.012)	(0.211)	(0.006)	(0.012)	(0.019)	(0.011)	(0.151)	(0.006)	(0.014)	(0.019)	(0.013)	(0.061)	(0.007)
Int. env. commitment	-0.126	-0.718	0.120	-2.316	0.037	-0.218	-0.705	0.046	-1.752	-0.045	-0.253	-0.647	0.032	-1.102	-0.053
	(0.373)	(0.573)	(0.366)	(3.154)	(0.191)	(0.376)	(0.581)	(0.350)	(2.494)	(0.183)	(0.403)	(0.594)	(0.175)	(2.018)	(0.174)
Constant	-21.96***	-10.178**	-9.864***	-69.66*	-2.352	-20.48***	-10.13**	-9.336***	-51.42	-1.265	-19.57***	-2.203	-7.144*	-143.4***	0.995
	(3.177)	(4.846)	(3.096)	(40.096)	(1.625)	(3.212)	(4.932)	(2.974)	(31.746)	(1.568)	(4.009)	(5.256)	(3.694)	(15.653)	(1.911)
Turning point	86792.8	n.a.	n.a.	17452.4	n.a.	119225.0	n.a.	n.a.	23404.0	n.a.	n.a.	n.a.	15381.2	n.a.	n.a.
Adj. R-squared	0.876	0.835	0.906	0.452	0.865	0.874	0.833	0.912	0.538	0.873	0.864	0.857	0.901	0.804	0.827
Wald chi^2 test	785.8***	576.9***	884.5***	27.69**	743.9***	785.8***	576.9***	884.5***	24.69**	743.9***	483.4***	461.7***	689.9***	213.5***	366.2***
Endogeneity chi^2 stat (prob)	(0.038)	(0.019)	(0.073)	(0.010)	(0.004)	(0.048)	(0.039)	(0.027)	(0.052)	(0.015)	(0.058)	(0.042)	(0.043)	(0.014)	(0.043)

Over-idn. restriction (prob)	(0.253)	(0.083)	(0.301)	(0.581)	(0.182)	(0.102)	(0.089)	(0.102)	(0.103)	(0.201)	(0.094)	(0.145)	(0.294)	(0.236)	(0.075)
Observations	101	99	99	53	101	97	95	95	49	97	62	61	61	27	62

Note: Heteroskedasticity adjusted robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10; int. env. denotes international environment; over-idn. is over-identification; prob - probability. The values in bold forms show that the estimated parameters and Wald tests are statistically significant at the identified critical levels. Instruments: *pscr*, *gdppcg*, *hce*.n.a. denotes not applicable due to insignificant of parameters.

4.0 Conclusion and policy implications

The concern regarding climate change and environmental sustainability persists as it entails significant socioeconomic and political costs. Efforts to address this issue have spurred renewed research interest, seeking to uncover proximate causes and solutions. This study explores the relationship between intelligence and environmental degradation using various measures such as carbon emissions, methane, nitrous oxide, greenhouse gas emissions, and ecological footprints. It employs several estimators including Ordinary Least Squares (OLS), Two Stage Least Squares (2SLS), and Iteratively Weight Least Squares (IWLS) on data from 147 cross-sectional countries over the period of 2000-2017.

The empirical findings reveal several key insights. Firstly, contrary to expectations, human intelligence quotient exhibits a significant positive effect on carbon emissions and ecological demand, challenging the assumption that higher intelligence would mitigate environmental degradation. Secondly, the Environmental Kuznets Curve (EKC) hypothesis is supported for carbon emissions and greenhouse gas emissions, indicating an initial rise in environmental degradation with economic development followed by a decline beyond a certain income level. However, for nitrous emission and ecological footprint, an inverted EKC condition is observed under certain estimation methods.

Additionally, the study highlights the mitigating impacts of democracy and international environmental commitments on carbon and methane emissions. It also finds that population dynamics play a complex role, acting as a magnifying factor for methane and nitrous oxide emissions but as a mitigating factor for human ecological demand. However, the impacts of other confounding variables remain ambiguous across different measures of environmental degradation.

Practical Applicability of the findings

The practical applicability of the conclusion from your study on the relationship between intelligence and environmental degradation, along with associated findings, can have several implications and applications:

(i) **Policy Development and Implementation**: The findings suggesting that higher human intelligence quotient (IQ) is associated with increased carbon emissions and ecological demand challenge conventional assumptions. Policymakers can use this insight to develop more nuanced environmental policies that consider factors beyond intelligence in addressing environmental degradation.

(ii) **Environmental Planning and Management**: Understanding the Environmental Kuznets Curve (EKC) dynamics for different environmental indicators (e.g., carbon emissions, greenhouse gases) can inform sustainable development strategies. Policymakers and planners can aim to achieve economic growth while minimizing environmental impact by targeting specific income thresholds.

(iii) **Democracy and International Cooperation**: The study highlights the role of democracy and international environmental commitments in mitigating carbon and methane emissions. This underscores the importance of fostering democratic governance and strengthening international agreements to address global environmental challenges effectively.

(iv) **Population Dynamics Considerations**: Recognizing the complex role of population dynamics (e.g., population growth) in environmental degradation can guide population policies that balance economic development with environmental sustainability.

(v) **Estimation Methods and Further Research**: The use of various estimation methods (OLS, 2SLS, IWLS) highlights the importance of robust statistical analysis in environmental research. Future studies can build upon these methods to deepen understanding and refine policy recommendations.

(vi) **Public Awareness and Education**: Communicating these findings to the public can raise awareness about the complexities of environmental degradation and the need for multifaceted approaches in addressing environmental challenges.

Limitations of the study

While the conclusion of your study provides valuable insights, it's important to acknowledge potential limitations that can impact the interpretation and generalizability of the findings. Here are some limitations to consider: first, the study relies on data from cross-sectional countries over a specific period (2000-2017). The quality and availability of data for intelligence quotient (IQ), environmental indicators, and other variables may vary across countries and time periods, potentially affecting the robustness of the results. Second, the use of proxies like national IQ scores and ecological footprint to measure complex constructs like intelligence and environmental degradation may introduce measurement biases and limitations. Alternative measures or additional data sources could provide different perspectives. Third, the study identifies associations between intelligence and environmental degradation but may not establish causal relationships. Other unobserved factors or reverse causation could influence the observed relationships. Fourth, the choice of estimation methods (OLS, 2SLS, IWLS) is crucial but may have inherent limitations or assumptions. Sensitivity analyses or alternative modeling approaches could provide additional insights. Fifth, environmental degradation is multifaceted and influenced by diverse factors beyond intelligence and economic indicators. The study's focus on specific aspects of environmental degradation may overlook broader environmental complexities. Lastly, while the study identifies patterns and relationships, translating these findings into actionable policies requires consideration of broader societal, economic, and political contexts, as well as stakeholder perspectives.

Addressing these limitations can enhance the robustness and relevance of the study's conclusions. Transparently discussing these limitations in the research report is essential for providing a balanced interpretation of the findings and guiding future research directions.

Suggestions for further studies

Based on the conclusion of this study, the followings are several suggestions for further research that could build upon or complement our findings: (i) Conduct longitudinal studies to explore how the relationship between intelligence and environmental degradation evolves over time. Examining trends and changes in environmental outcomes relative to intelligence levels could provide deeper insights into causality and dynamics. (ii) Explore the impact of intelligence at different levels (individual, community, national) on environmental outcomes. Understanding how intelligence operates at various scales could elucidate nuanced relationships and potential interventions. (iii) Complement quantitative analyses with qualitative research methods to understand the underlying mechanisms and contextual factors influencing the observed relationships. In-depth interviews or case studies could provide rich insights into the complex interplay between intelligence and environmental behaviour. (iv) Extend the analysis to include a broader range of countries and cultures to assess the generalizability of findings across diverse socio-cultural contexts. Comparing intelligence-environment relationships across different regions could reveal context-specific dynamics. (v) Design experimental or intervention studies to test the effectiveness of intelligence-related interventions (e.g., education programs, cognitive training) in promoting environmentally sustainable behaviours or policies. (vi) Investigate potential mediating and moderating factors that influence the relationship between intelligence and environmental outcomes. For example, exploring the role of psychological traits, social norms, or institutional factors could provide a more comprehensive understanding. (vii) Conduct policy analyses to evaluate the implications of intelligence-environment relationships for policy design and implementation. Assessing how intelligence considerations could inform environmental governance and decision-making could guide evidence-based policy interventions. (viii) Develop integrated models that incorporate multiple dimensions of environmental sustainability beyond carbon emissions and ecological footprints. Considering broader indicators of environmental health, biodiversity, and ecosystem resilience could offer a holistic perspective. (xi) Explore advanced statistical techniques (e.g., machine learning, spatial analysis) to uncover complex patterns and interactions within large-scale datasets. Leveraging innovative methodologies could enhance the precision and reliability of findings. (x) Foster collaborations between environmental scientists, psychologists, economists, and policymakers to tackle the multidimensional nature of intelligence-environment relationships. Integrating diverse perspectives and expertise could lead to innovative research frameworks and policy solutions.

By pursuing these avenues for further study, researchers can deepen understanding of the relationship between intelligence and environmental degradation, contribute to interdisciplinary knowledge, and inform evidence-based interventions for sustainability.

References

Amuda, Y. J. (2023). Impact of COVID-19 on Oil and Gas Sector in Nigeria: A Condition for Diversification of Economic Resources. Emerging Science Journal, 7, 264-280.

Asongu, S. A., El Montasser, G., & Toumi, H. (2016). Testing the relationships between energy consumption, CO_2 emissions, and economic growth in 24 African countries: A panel ARDL approach. *Environmental Science and Pollution Research*, 23(7), 6563-6573.

Asongu, S. A., Le Roux, S., & Biekpe, N. (2017). Environmental degradation, ICT and inclusive development in Sub-Saharan Africa. *Energy Policy*, 111(December), 353-361.

Ball, A. (2014). Air pollution, foetal mortality, and long-term health: Evidence from the Great London Smog. MPRA paper 63229. Available at https://mpra.ub.uni-muenchen.de/id/eprint/63229

Barro, R. J. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, 106(2), 407-443.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2) (Mar-Apr., 1968): 169-217.

Becker, G. S., Murphy, K. M., & Tamura, R. (1990). Human capital, fertility, and economic growth. *Journal of Political Economy*, 98(5, Part 2), S12-S37.

Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary economics*, 34(2), 143-173.

Bharadwaj, P., Gibson, M., Zivin, J. G., & Neilson, C. (2017). Gray matters: fetal pollution exposure and human capital formation. *Journal of the Association of Environmental and Resource Economists*, 4(2), 505-542.

Blomquist, G. C., & Whitehead, J. C. (1998). Resource quality information and validity of willingness to pay in contingent valuation. *Resource and Energy Economics*, 20(2), 179-196.

Boden, T. A, Marland, G. & Andres, R. J. (2017). *Global, Regional, and National Fossil-Fuel CO_2 Emissions*. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., USA. DOI: 10.3334/CDIAC/00001_V2017.

Caselli, F., Esquivel, G., & Lefort, F. (1996). Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics. *Journal of Economic Growth*, 1(3), 363–389.

Chen, C. R., & Lee, C. F. (2010). Application of simultaneous equation in finance research. In *Handbook of Quantitative Finance and Risk Management* (pp. 1301-1306). Springer, Boston, MA.

Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human Ecology Review*, 1(2), 277-300.

Durmanov, A., Saidaxmedova, N., Mamatkulov, M., Rakhimova, K., Askarov, N., Khamrayeva, S., ... & Kurbanova, K. (2023). Sustainable growth of greenhouses: investigating key enablers and impacts. Emerging Science Journal, 7(5), 1674-1690.

Esquivias, M. A., Jayadi, A., Shafiai, S., Abd Rashid, I. M., Borhanordin, A. H., Agusti, K. S., & Yahwidya, L. (2023). The Nexus between Food Security and Investment, Exports, Infrastructure, and Human Capital Development. Journal of Human, Earth, and Future, 4(2), 221-240.

Greshko, Michael, (2017). A running list of how trump is changing the environment. Available online at http://news.nationalgeographic.com/2017/03/how-trump-ischanging-science-environment/

Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American Free Trade Agreement*. National Bureau of Economic Research Working Paper 3914.NBER, Cambridge MA.

Grossman, G., & Krueger, A. (1995). Economic growth and the environment. *Quarterly Journal of Economics*, 110,353–377.

Hanushek, E. A., & Kimko, D. D. (2000). Schooling, labor-force quality, and the growth of nations. *American Economic Review*, 90, 1184-1208.

Hanushek, E.A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3), 607–668.

Hanushek, E. A. & Woessmann, L. (2009). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. IZA discussion paper no. 4575.

Ji, X., & Chen, B. (2017). Assessing the energy-saving effect of urbanization in China based on stochastic impacts by regression on population, affluence and technology (STIRPAT) model. *Journal of Cleaner Production*, 163, S306-S314.

Jones, G., & Schneider, W. J. (2006). Intelligence, human capital, and economic growth: A Bayesian averaging of classical estimates (BACE) approach. *Journal of Economic Growth*, 11(1), 71-93.

Kanazawa, S. (2006). IQ and the wealth of states. *Intelligence*, 34, 593-600.

Kenkel, D. S. (1991). Health behavior, health knowledge, and schooling. *Journal of Political Economy*, 99(2), 287-305.

Kodila-Tedika, O & Kalonda-Kanyama, I. (2012). *Quality of institutions: Does intelligence matter?* Working Papers 308, Economic Research Southern Africa.

Kodila-Tedika, O. & Asongu, S. A. (2015a). Intelligence, human capital and HIV/AIDS: Fresh exploration. *Intelligence*, 53, 154-159.

Kodila-Tedika, O. & Asongu, S. A. (2015b). The effect of intelligence on financial development: A cross-country comparison. *Intelligence*, 51, 1-9.

Kodila-Tedika, O. (2014). Governance and intelligence: Empirical analysis from African data. *Journal of African Development*, 16(1), 83–97.

Lavy, V., Ebenstein, A. & Roth, S. (2012). The impact of air pollution on cognitive performance and human capital formation. Unpublished. Available at http://www2.warwick.ac.uk/fac/soc/economics/staff/academic/lavy/text_and_tables_air_pollution_draft_20_09_12.pdf

Lee, C. C., Chiu, Y. B. & Sun, C. H. (2010). The Environmental Kuznets Curve hypothesis for water pollution: Do regions matter? *Energy Policy*, 38(1), 12-23.

Lin, D; Hanscom, L; Murthy, A; Galli, A; Evans, M; Neill, E; Mancini, MS; Martindill, J; Medouar, F-Z; Huang, S; & Wackernagel, M. (2018). Ecological footprint accounting for countries: Updates and results of the National Footprint Accounts, 2012-2018. *Resources* 7(3), 58. Available at https://www.doi.org/10.3390/resources7030058

Lucas Jr, R. E. (1993). Making a miracle. *Econometrica: Journal of the Econometric Society*, 251-272.

Lynn, R. & Vanhanen, T. (2012a). *Intelligence: A unifying construct for the social science*. London: Ulster Institute.

Lynn, R. (2010). In Italy, north–south differences in IQ predict differences in income, education, infant mortality, stature, and literacy. Intelligence, 38, 93–100.

Lynn, R., & Meisenberg, G. (2010). The average IQ of sub-Saharan Africans: Comments on Wicherts, Dolan, and van der Maas. *Intelligence*, 38, 21–29.

Lynn, R., & Vanhanen, T. (2001). National IQ and economic development: A study of eighty-one nations. *Mankind Quarterly*, 41, 415-435.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality*. Augusta GA: Washington Summit.

Lynn, R., & Vanhanen, T. (2012a). *Intelligence: A unifying construct for the social sciences*. London: Ulster Institute.

Lynn, R., & Vanhanen, T. (2012b). National IQs: A review of their educational, cognitive, economic, political, demographic, sociological, epidemiological, geographic and climatic correlates. *Intelligence*, 40, 226-234.

Lynn, R., Meisenberg, G., Mikk, J., & Williams, A. (2007). National differences in intelligence and educational attainment. *Journal of Biosocial Science*, 39, 861–874.

Lynn, R., & Vanhanen, T. (2006). *IQ and global inequality*. Washington Summit Publishers, Augusta, GA.

Lynn, R., & Vanhanen, T. (2002). *IQ and the wealth of nations*. Praeger: Westport CT.

McDaniel, M. A. (2006). Estimating state IQ: Measurement challenges and preliminary correlates. *Intelligence*, 34, 607-619.

Meisenberg, G., & Lynn, R. (2011). Intelligence: A measure of human capital in nations. *Journal of Social, Political and Economic Studies*, 36(4), 421-454.

Meisenberg, G., & Lynn, R. (2012). Cognitive human capital and economic growth: Defining the causal paths. *Journal of Social, Political and Economic Studies*, 37(4), 141-179.

Meisenberg, G. (2012). National IQ and economic outcomes. *Personality and Individual Difference*, 53 (2), 103–107.

Mincer, J. (1974). *Schooling, Experience, and Earnings*. New York: National Bureau of Economic Recsearch.

Nilsson, J. P. (2009). The long-term effects of early childhood lead exposure: Evidence from the phase-out of leaded gasoline. Chapter included in doctoral thesis, Department of Economics, Uppsala University, December 2009.

Noorpoor, A. R., & Kudahi, S. N. (2015). CO_2 emissions from Iran's power sector and analysis of the influencing factors using the stochastic impacts by regression on population, affluence and technology (STIRPAT) model. *Carbon Management*, 6(3-4), 101-116.

Obydenkova, A. V., & Salahodjaev, R. (2017). Climate change policies: The role of democracy and social cognitive capital. *Environmental Research*, 157, 182-189.

Obydenkova, A., & Salahodjaev, R. (2016). Intelligence, democracy, and international environmental commitment. *Environmental Research*, 147, 82-88.

Potrafke, N. (2012). Intelligence and corruption. *Economics Letters*, 114(1), 109-112.

Quang Dao, M. (2008). Human capital, poverty, and income distribution in developing countries. *Journal of Economic Studies*, *35*(4), 294-303.

Ram, R. (2007). IQ and economic growth: Further augmentation of Mankiw–Romer–Weil model. *Economics Letters*, 94, 7-11.

Reeve, C. I. (2009). Expanding the g-nexus: Further evidence regarding the relations among IQ, religiosity, and national health outcomes. *Intelligence*, 37, 495-505.

Rindermann, H. (2007a). Author's response. The big g-factor of national cognitive ability. *European Journal of Personality*, 21, 767-787.

Rindermann, H. (2007b). The g-factor of international cognitive ability comparisons: The homogeneity of results in PISA, TIMSS, PIRLS, and IQ-tests across nations. *European Journal of Personality*, 21, 667-706.

Rindermann, H., Kodila-Tedika, O., & Christainsen, G. (2015). Cognitive capital, good governance, and the wealth of nations. *Intelligence*, 51, 98-108.

Rindermann, H., Sailer, S., & Thompson, J. (2009). The impact of smart fractions, cognitive ability of politicians and average competence of peoples on social development. *Talent Development and Excellence*, 1, 3-25.

Romer, P. M. (1990). Human capital and growth: Theory and evidence. *Carnegie-Rochester Conference Series on Public Policy*, 32, 251-286.

Rushton, J. P., & Templer, D. I. (2009). National differences in intelligence, crime, income and skin color. *Intelligence*, 37, 341-346.

Salahodjaev, R. (2016). Intelligence and deforestation: international data. *Forest Policy and Economics*, 63, 20-27.

Salahodjaev, R. (2015a). Intelligence and shadow economy: A cross-country empirical assessment. *Intelligence*, 49, 129-133.

Sala-i-Martin, X., Doppelhofer, G, & Miller, R. (2004). Determinants of long-run growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review*, 94, 813-35.

Sanders, N. J. (2012). What doesn't kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *Journal of Human Resources*, 47(3), 826-850.

Schultz, T. W. (1964). *Transforming traditional agriculture*. New Haven: Yale University Press

Shuai, C., Chen, X., Wu, Y., Tan, Y., Zhang, Y., & Shen, L. (2018). Identifying the key impact factors of carbon emission in China: Results from a largely expanded pool of potential impact factors. *Journal of Cleaner Production*, 175, 612-623.

Squalli, J. (2014). Intelligence and environmental emissions. *Intelligence*, 44, 33-39.

Stafford, T. M. (2015). Indoor air quality and academic performance. *Journal of Environmental Economics and Management*, 70, 34-50.

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World development*, *32*(8), 1419-1439.

Tchamyou, V. S., (2017). The role of knowledge economy in African business. *Journal of Knowledge*, 8(4), 1189-1228.

Tchamyou, V. S. (2020). Education, lifelong learning, inequality and financial access: Evidence from African countries. *Contemporary Social Science*, 15(1), 7-25.

Templer, D. I. (2008). Correlational and factor analytic support for Rushton's differential K life history theory. *Personality and Individual Differences*, 45, 440-444.

Templer, D. I., & Rushton, J. P. (2011). IQ, skin color, crime, HIV/AIDS, and income in 50 U.S. states. *Intelligence*, 39, 437–442.

Wang, S., Zhao, T., Zheng, H. & Hu, J. (2017). The STIRPAT analysis on carbon emission in Chinese cities: An asymmetric Laplace distribution mixture model. *Sustainability*, 9, 1-23.

Weede, E., & Kämpf, S. (2002). The impact of intelligence and institutional improvements on economic growth. *Kyklos*, 55, 361-380.

Winters, P. C., & Chiodi, V. (2011). Human capital investment and long-term poverty reduction in rural Mexico. *Journal of international development*, *23*(4), 515-538.

Yeh, J. C., & Liao, C. H. (2017). Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT. *Sustainable Environment Research*, *27*(1), 41-48.

York, R. (2007). Demographic trends and energy consumption in European Union Nations, 1960-2025. *Social Science Research* 36(3), 855-872.

Zivin, J. G., & Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3), 689-730.

Appendix

List of countries

Belize	Denmark	India	Madagascar	Papua New Guinea	Sweden
Benin	Dominica	Indonesia	Malawi	Paraguay	Switzerland
Bermuda	Dominican Republic	Iran, Islamic Rep.	Malaysia	Peru	Syrian Arab Republic
Bolivia	Ecuador	Iraq	Maldives	Philippines	Tajikistan
Bosnia and Herzegovina	Egypt, Arab Rep.	Ireland	Mali	Poland	Tanzania
Botswana	El Salvador	Israel	Malta	Portugal	Thailand
Brazil	Eritrea	Italy	Marshall Islands	Puerto Rico	Togo
Bulgaria	Estonia	Jamaica	Mauritania	Qatar	Tonga
Burkina Faso	Eswatini (Swaziland)	Japan	Mexico	Romania	Trinidad and Tobago
Burundi	Ethiopia	Jordan	Moldova	Russian Federation	Tunisia
Cameroon	Fiji	Kazakhstan	Mongolia	Rwanda	Turkey
Canada	Finland	Kenya	Montenegro	Samoa	Uganda
Central African Republic	France	Korea, Rep.	Morocco	Saudi Arabia	Ukraine
Chad	Gabon	Kuwait	Mozambique	Senegal	United Arab Emirates
Chile	Gambia, The	Kyrgyz Republic	Namibia	Serbia	United Kingdom
China	Georgia	Lao PDR	Nepal	Seychelles	United States
Colombia	Germany	Latvia	Netherlands	Sierra Leone	Uruguay
Comoros	Ghana	Lebanon	New Zealand	Singapore	Venezuela, RB
Congo, Rep.	Greece	Lesotho	Nicaragua	Slovak Republic	Vietnam
Costa Rica	Guatemala	Libya	Niger	Slovenia	Yemen, Rep.
Cote d'Ivoire	Guinea	Liechtenstein	Nigeria	South Africa	Zambia
Croatia	Honduras	Lithuania	Norway	Spain	Zimbabwe
Cuba	Hong Kong SAR, China	Luxembourg	Oman	Sri Lanka	
Cyprus	Hungary	Macao SAR, China	Pakistan	Sudan	
Czech Republic	Iceland	Macedonia, FYR Now North Macedonia	Panama	Suriname	

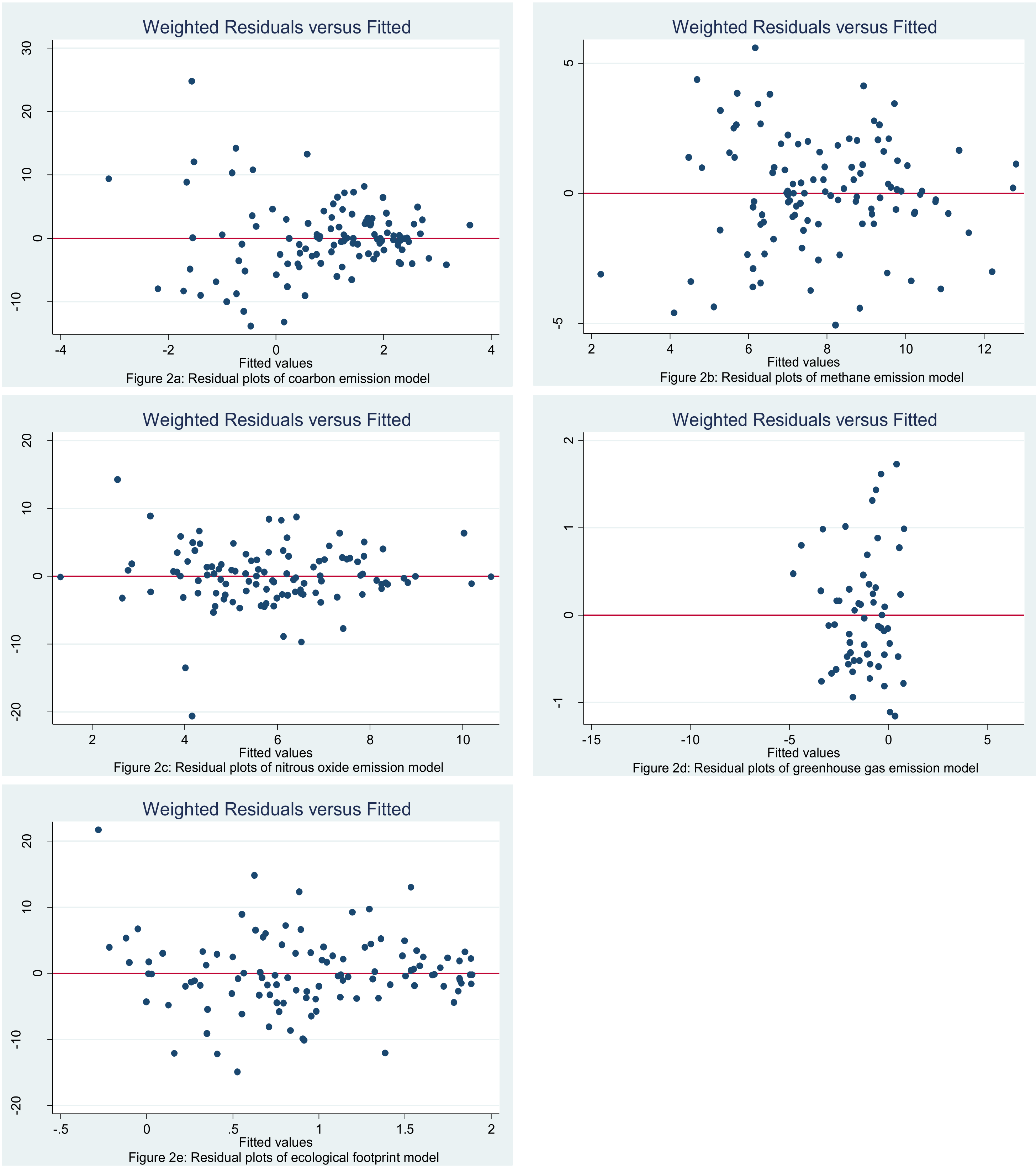

Figure 2a: Residual plots of coarbon emission model

Figure 2b: Residual plots of methane emission model

Figure 2c: Residual plots of nitrous oxide emission model

Figure 2d: Residual plots of greenhouse gas emission model

Figure 2e: Residual plots of ecological footprint model

Figure 2(a-e): Residual plots of environmental degradation models using IWLS estimator