ABSTRACT

1. Introduction:

Recent global warming and climate change concerns have highlighted the adverse effects of industrialization on the environment. Industrialization is inevitable for achieving economic growth. At the same time, it has been marked as one of the most influential factors that lead to environmental pollution (Aslam et al., 2021; Mahmood et al., 2020). Reliance on fossil fuel energy, chemical processing, waste disposal, deforestation, etc. are the industrial activities leading to significant environmental damages. Thus, industrial growth is being achieved at the cost of environmental deterioration. Emphasis should be placed on adopting sustainable means of industrialization to overcome the ecological challenges posed by rapid industrialization, especially in developing countries. The need of the hour is to balance economic growth and ecological health to achieve sustainable development. The environmental Kuznets curve (EKC) hypothesis is a commonly used assessment method for a country's sustainable development (Itoo and Ali, 2023; Pata, 2018). Applying this hypothesis to assess sustainable industrial development can determine if a country's industrial growth causes environmental destruction over time. Accordingly, industries can resort to proper measures aimed at greener industrial development.

Carbon dioxide (CO_2) emission has been recognized as the primary cause of increasing global warming and climate change issues. Previous studies have shown how industrialization has significantly added to the CO_2 emission levels in countries (Aslam et al., 2021; Pata, 2018). The existing literature recognizes similar alarming threats posed by the Indian industries (Rai and Rawat, 2022; Sarangi et al., 2019). The country's industrialization in the last few decades has undoubtedly contributed to its rapid economic progress but at the grave expense of environmental degradation. India is in a difficult spot of being the third-highest carbon-emitting country in the world. Due to its industries' massive reliance on fossil fuel energies, the nation accounted for 7% of the total global fossil CO_2 emissions in 2021 (Global Carbon Project, 2022). The magnitude of climate-change effects is expected to be more serious for India because majority of its population is dependent on climate-sensitive livelihoods such as agriculture, fisheries, forestry and other allied services (Mehta et al., 2022).

Considering India's and its industries' environmental position, it has become essential to estimate the industries' future ecological destruction levels so that precautionary steps can be taken to mitigate such circumstances. In this regard, the EKC hypothesis can be beneficial in determining the long-term possible environmental effects of the industries. Even though few studies have investigated the industry-specific EKC (IEKC) hypothesis to estimate industries' sustainable growth dimensions (Du et al., 2020; Lv et al., 2021), its exploration is minimal in the established literature and negligible in the case of Indian core industries. Therefore, the present study investigates, as its primary motivation, the applicability of the IEKC hypothesis in the Indian core industries due to these industries' high significance in India's economic development and their worsening environmental profiles. Further, the study aims to identify the driving factors of the core industries' emission levels and explores the role of environmental policy stringency and industrial structure in limiting these industries' pollution levels in India.

2. Review of Literature:

2.1. Environmental Kuznets Curve (EKC) hypothesis:

Simon Kuznets initially suggested the Kuznets curve (1955), depicting an inverted U-shaped relationship between economic growth and income inequality. Subsequently, Grossman and Krueger (1991) added the environmental aspect, arguing that the inverted U-shaped curve also applies to economic growth and environmental deterioration. It posits that economic growth initially contributes to a country's environmental degradation. Later, only after crossing its threshold point, economic growth helps improve the environmental conditions. In a nutshell, the inverted U-shaped EKC asserts that the ecological benefits from economic growth are expected to gradually reflect only in the long run.

The prior studies have empirically investigated the validity of the EKC hypothesis in different geographical locations with different statistical approaches. While some researchers have confirmed the hypothesis (Aslam et al., 2021; Rana and Sharma, 2019), some have denied its validity (Alola and Donve, 2021; Hasanov et al., 2019). The substance of the EKC hypothesis is examined in the case of various developing countries by studies like Pata (2018) in Turkey, Nazir *et al.* (2018) in Pakistan and Aslam *et al.* (2021) in China. In India, mixed findings are found as Sinha and Shahbaz (2018), Rana and Sharma (2019) established the validity of the EKC hypothesis, whereas Villanthenkodath *et al.* (2021), Itoo and Ali (2023) denied its existence in the country.

In the existing literature, very few studies have attempted to test the IEKC hypothesis to identify the long-run environmental consequences of industries. Zhao et al. (2019) tested the IEKC hypothesis in China's textile industry by considering the disaggregated water footprint of the industry to measure its environmental degradation level. The regression analysis showed mixed findings, suggesting that the blue water, original grey water and residual grey water models depict inverted U-shaped, inverted N-shaped and N-shaped curves in the textile industry, respectively. Likewise, Du et al. (2020) investigated the IEKC in China's construction industry, resulting in mixed findings of the hypothesis. Overall, the study reported inverted N-shaped, inverted U-shaped and U-shaped relationships in the construction industry separately operating in five different provinces. Lv *et al.* (2021) validated the IEKC hypothesis in China's manufacturing industries. Considering China's primary, secondary and tertiary sectors, Wu *et al.* (2022) found evidence for the IEKC hypothesis only in the tertiary sector through the panel-corrected standard error method results.

2.2. Environmental degrading effects of industries:

In all countries, industrial activities have been adding to severe environmental damage. Isaksson (2016) and Zeb et al. (2019) have identified the environmentally threatening traits of cement and construction industries. Chen et al. (2017) estimated that carbon emissions from the construction industry witnessed an increase of approximately 400 percent between 1995 and 2011 in China. Likewise, notable environmental deteriorating effects from the steel industry are also recognized by Gao et al. (2015). Among all, electricity consumption and coal usage are found to emit heavy carbon elements into the atmosphere from China's manufacturing industries (Yan and Fang, 2015). Coal consumption has become a notable reason for the highly-pollutive nature of the Chinese iron and steel industry (Xu et al., 2016). Likewise, the utilization of chemically processed synthetic fertilizers in modern agricultural practices has become a common custom, which often harms the surface of the soil and results in several other negative environmental impacts (Gatsios et al., 2021). Nevertheless, the scope of reducing carbon emissions depends on a nation's technologies and policies in practice. It has always been acknowledged that controlling the environmental degradation effects of any industry is challenging in the practical world because industries in developing countries like India often depend primarily on energy generated from fossil fuel sources.

3. Research gap:

After reviewing the prior literature, the following research gaps are identified:

- Although studies have focused on the EKC hypothesis for different geographical locations, only limited studies have addressed the applicability of the IEKC in examining industrial sustainability. Besides, no such studies have been found in the Indian context.
- Focus on the environmental impact of the Indian core industries is utterly negligible in the prior literature.
- Studies were found using the decoupling approach to analyze an economy's environmental efficiency. Very few studies have adopted it to assess the environmental efficiency of industries.
- Studies have mostly considered economic determinants of industries' environmental degradation. However, studies addressing the role of factors such as industrial design, certified emission reductions (CERs), education, poverty, etc. have not been found, particularly in the Indian context.
- Studies have not explored the moderating roles of environmental policy stringency and industrial structure improvement in the relationship between industrial growth and environmental degradation.
- Modern literature has explored the existence of an N-shaped EKC in countries. Limited studies have looked into the N-shaped IEKC for industries, and no such studies have been conducted in the Indian context.

4. **Research objectives:** The present research work aims to fulfil the following objectives:
   - To compare the levels of carbon emissions across the core industries.
   - To identify the driving forces of carbon emissions in the core industries.
   - To analyze the relationship between industrial growth and environmental degradation in the core industries.
5. **Hypotheses:** The present research work considers the following hypotheses:

For Objective 2:

$H_{2.1}$: There exists a significant positive relationship between economic growth and core industries' carbon emission levels in India.

***H**$_{2.2}$*: There exists a significant positive relationship between FDI and core industries' carbon emission levels in India.

***H**$_{2.3}$*: There exists a significant positive relationship between agricultural production and core industries' carbon emission levels in India.

***H**$_{2.4}$*: There exists a significant negative relationship between R&D and core industries' carbon emission levels in India.

***H**$_{2.5}$*: There exists a significant positive relationship between industrialization and core industries' carbon emission levels in India.

***H**$_{2.6}$*: There exists a significant positive relationship between energy consumption and core industries' carbon emission levels in India.

***H**$_{2.7}$*: There exists a significant negative relationship between financial support and core industries' carbon emission levels in India.

***H**$_{2.8}$*: There exists a significant negative relationship between industrial design and the core industries' carbon emission levels in India.

***H**$_{2.9}$*: There exists a significant positive relationship between population density and the core industries' carbon emission levels in India.

***H**$_{2.10}$*: There exists a significant positive relationship between urbanization and the core industries' carbon emission levels in India.

***H**$_{2.11}$*: There exists a significant positive relationship between poverty and the core industries' carbon emission levels in India.

***H**$_{2.12}$*: There exists a significant negative relationship between education and the core industries' carbon emission levels in India.

***H**$_{2.13}$*: There exists a significant positive relationship between tree cover loss and the core industries' carbon emission levels in India.

***H**$_{2.14}$*: There exists a significant positive relationship between water stress and the core industries' carbon emission levels in India.

***H**$_{2.15}$*: There exists a significant negative relationship between environmental technology and the core industries' carbon emission levels in India.

***H*$_{2.16}$**: There exists a significant negative relationship between CER and the core industries' carbon emission levels in India.

For Objective 3:

***H*$_{3.1}$**: There exists a significant inverted U-shaped relationship between the core industries' growth and their emission levels.

***H*$_{3.2}$**: There exists a significant negative moderating role of environmental policy stringency in the relationship between the core industries' growth and their emission levels.

***H*$_{3.3}$**: There exists a significant negative moderating role of industrial structural improvement in the relationship between the core industries' growth and their emission levels.

***H*$_{3.4}$**: There exists a significant N-shaped relationship between the core industries' growth and their emission levels.

6. Methodology/approach(es) applied:

6.1. Study sample:

The study is carried out with a sample of the eight core industries in India, namely coal, crude oil, cement, natural gas, refinery products, fertilizers, steel, and electricity. The Government of India recognizes these eight industries as the *'core industries'* of the country due to their economic significance in the Indian industrial sector. In 2021, they contributed 40.27 per cent of the overall industrial growth in India (Office of Economic Adviser, 2022). The study considers an unbalanced panel data from 2005 to 2021 as the fertilizers and natural gas industries came to be recognized as the country's core industries since 2005.

6.2. Variable description and methodology:

6.2.1. Objective 1: To measure the environmental degradation levels of the core industries, CO_2 emissions of the respective industries have been considered, as CO_2 is the most dominant component of all greenhouse gases (GHGs). The Index of Eight Core Industries (*ICI*) is applied to represent the growth levels of the core industries. The index is published by the Government of India to reflect these industries' production and growth levels (Office of Economic Adviser, 2022).

Methodology: To compare the levels of carbon emissions across industries, the study gives a graphical representation of the industries' carbon profile. Further, the study considers Tapio's (2005) decoupling method for assessing the environmental efficiency levels of the core industries using Model 1.

$$DI = \frac{\frac{CO_{2t} - CO_{2t-1}}{CO_{2t-1}}}{\frac{ICI_t - ICI_{t-1}}{ICI_{t-1}}} = \frac{\Delta CO_2\%}{\Delta \text{ICI}\%} \quad \text{--- (1)}$$

In Model 1, DI stands for decoupling index. Here, *t* and *t-1* refer to the current and preceding years, respectively. Based on the value of *DI*, each industry's decoupling state would be determined, and the decoupling state would indicate the industry's environmental efficiency level. Table 1 lists the ranges of Tapio's eight decoupling elasticity degrees. It provides the scores assigned to each of these elasticity degrees, ranging from 1 (least pollutive state) to 8 (most pollutive state), depending on the environmental efficiency level reflected by the decoupling elasticity states of the industries in each year. An average score will be given to the industries to indicate their overall pollution level, as demonstrated in Table 2.

Table 1: Decoupling elasticities and scores

DE	Abbreviation	$\Delta CO_2\%$	ΔICI%	Elasticity degree	DS
Strong decoupling	SD	< 0	> 0	$[0, -\infty)$	1
Weak decoupling	WD	> 0	> 0	[0,0.8)	2
Weak negative decoupling	WND	< 0	< 0	[0,0.8)	3
Expansive coupling	EC	> 0	> 0	[0.8,1.2)	4
Recessive coupling	RC	< 0	< 0	[0.8,1.2)	5
Expansive negative decoupling	END	> 0	> 0	$[1.2, +\infty)$	6
Recessive decoupling	RD	< 0	< 0	$[1.2, +\infty)$	7
Strong negative decoupling	SND	> 0	< 0	$[0, -\infty)$	8

(Author's compilation)

Table 2: Average decoupling score ranges

Average score range	Remarks
1-3.5	Low-polluting/clean industry
3.5-5.5	Moderate-polluting industry
5.5-8	High-polluting/dirty industry

(Author's compilation)

6.2.2. Objective 2: This objective deals with identifying the potential determinants of carbon emission in the core industries. For its fulfilment, the following regression model is considered.

$$lnCO_2 = \alpha + \beta_1 GDP_{it} + \beta_2 R\&D_{it} + \beta_3 EC_{it} + \beta_4 POV_{it} + \beta_5 EDU_{it} + \beta_6 lnTCL_{it} + \beta_7 WS_{it} + \beta_8 lnCER_{it} + \varepsilon_{it} \quad \text{--- (2)}$$

In addition, the study classifies the potential driving factors of carbon emissions into four categories: economic, industrial, demographic and environmental, as shown in Table 3. It is to conduct an in-depth analysis of the drivers of industrial emissions, which is believed to offer more insights for policy formulation.

Methodology: The following regression models are considered.

$$lnCO_2 = \alpha + \beta_1 GDP_{it} + \beta_2 lnFDI_{it} + \beta_3 lnAGR_{it} + \beta_4 R\&D_{it} + \varepsilon_{it} \quad \text{--- (3)}$$

$$lnCO_2 = \alpha + \beta_1 IVA_{it} + \beta_2 EC_{it} + \beta_3 BANK_{it} + \beta_4 INDES_{it} + \varepsilon_{it} \quad \text{--- (4)}$$

$$lnCO_2 = \alpha + \beta_1 POP_{it} + \beta_2 lnURB_{it} + \beta_3 POV_{it} + \beta_4 EDU_{it} + \varepsilon_{it} \quad \text{--- (5)}$$

$$lnCO_2 = \alpha + \beta_1 lnTCL_{it} + \beta_2 WS_{it} + \beta_3 ENVTECH_{it} + \beta_4 lnCER_{it} + \varepsilon_{it} \quad \text{--- (6)}$$

Table 3: List of variables (Objective 2)

Variables	Indicators, *Abbreviations*	References
Dependent variable:		
Environmental degradation	Natural log of carbon dioxide emission levels (tonnes), ***lnCO₂***	(Afriyie et al., 2023; Sreenu, 2022)
Explanatory variables:		
<u>*Economic factors*</u>:		
Economic growth	Gross domestic product per capita, Constant LCU (annual percentage growth), ***GDP***	(Aslam et al., 2021; Awan and Azam, 2021)
Foreign investments	Natural log of FDI inwards financial flows, ***lnFDI***	(Nazir et al., 2018; Sreenu, 2022)
Agricultural activities	Natural log of agricultural production, gross value (2014-2016 US$ constant value), **ln*AGR***	(Anwar et al., 2019; Phiri et al., 2021)
Research and development	Patent application by residents (annual percentage growth), ***R&D***	(Awan and Azam, 2021; Lee et al., 2015)
<u>*Industrial factors*</u>:		
Industrialization	Industry (including construction) value added (percentage of GDP), ***IVA***	(Aslam et al., 2021; Mahmood et al., 2020)
Energy consumption	Industry electricity energy consumption in Giga Watt Hour (annual percentage growth), ***EC***	(Awan and Azam, 2021; Phiri et al., 2021)
Financial credits	Industry Deployment of Gross Bank Credit in India, outstanding amount (annual percentage growth), ***BANK***	-
Industrial innovation	Industrial design applications by residents (annual percentage growth), ***INDDEG***	-
<u>*Demographic factors*</u>:		
Population	Natural log of population density (people per sq. km of land area), ***lnPOP***	(Aslam et al., 2021; Itoo and Ali, 2023)
Urbanization	Population in urban agglomerations of more than 1 million (annual percentage growth), ***URB***	(Afriyie et al., 2023; Mahmood et al., 2020)
Poverty	People with no access to safely managed sanitation services (percentage of total population), ***POV***	-
Education	Number of pupils in secondary education (annual percentage growth), ***EDU***	(Xin et al., 2023)
<u>*Environmental factors*</u>:		
Tree cover loss	Natural log of tree cover loss (hectare), ***lnTCL***	(Minlah et al., 2021)
Water stress	Water withdrawal, percentage of total water, ***WS***	(Driscoll et al., 2024)
Ecological innovation	Environment-related technologies, Number of patents, ***ENVTECH***	-
Environmental credits	Natural log of number of CERs issued projects in India, ***lnCER***	-

(Author's compilation)

In Models 2-6, α refers to the intercept, β_n captures the coefficient values of the explanatory variables and ε is the error term; i and t represent the cross-section item and time period, respectively. To estimate the driving factors of industrial emissions, the study proceeds with the Pooled ordinary Least Squares (POLS), Fixed Effect Model (FEM) or Random Effect Model (REM), depending on the statistical suitability of the dataset from the Breusch-Pegan test and Hausman test. Also, to resolve the possible issues of heteroscedasticity, robust standard errors are applied for the panel regression models to attain reliable and consistent results (White, 1980). In order to conduct a robustness test for the reported results, the Dynamic Ordinary Least Squares (DOLS) approach is adopted.

6.2.3. Objective 3: The list of variables considered for Objective 3 is provided in Table 4.

Table 4: List of variables (Objective 3)

Variables	Indicators	References
Dependent variable:		
Environmental degradation	Natural log of carbon dioxide emission levels (tonnes) ***lnCO₂***	(Afriyie et al., 2023; Sreenu, 2022)
Explanatory variables:		
Industrial growth	Index of Eight Core Industries, ***ICI***	-
Economic growth	Gross domestic products, Constant LCU (annual percentage growth), ***GDP***	(Aslam et al., 2021; Awan and Azam, 2021)
Energy consumption	Industry electricity energy consumption, Giga-Watt Hour (annual percentage growth), ***EC***	(Awan and Azam, 2021; Phiri et al., 2021)
Water stress	Water withdrawal by industries (percentage of total water), ***WS***	(Driscoll et al., 2024)
Moderating variables:		
Environmental policy	Sectoral Environmental Policy Stringency Index, ***SECP***	(Çetinkaya et al., 2024)
Industrial structure	Ratio of value added of the tertiary sector to that of the secondary sector, ***INDSTR***	(J. Zhao et al., 2022)

(Author's compilation)

Methodology: To investigate the relationship between the core industries' growth and carbon emission levels, Model 7 is formulated. Then, Models 8 and 9 test the moderating roles of *SECP* and *INDSTR* in the relationship between industrial growth and carbon emissions, with the inclusion of the interaction terms *SECP_ICI* and *INDSTR_ICI*, respectively. The models will confirm the IEKC hypothesis in the industries if $\beta_1 > 0, \beta_2 < 0$, and reject otherwise. To test the N-shaped IEKC, Model 10 is formulated by introducing the cubic term of *ICI*. The N-shaped IEKC hypothesis is confirmed if $\beta_1 > 0, \beta_2 < 0, \beta_3 > 0$. Any variation in the β-values will lead to rejecting the N-shaped IEKC hypothesis.

$$lnCO_2 = \alpha + \beta_1 ICI_{it} + \beta_2 ICI_{it}^2 + \beta_3 GDP_{it} + \beta_4 EC_{it} + \beta_5 WS_{it} + \beta_6 SECP_{it} + \beta_7 INDSTR_{it} + \varepsilon_{it} \quad \text{---(7)}$$

$$lnCO_2 = \alpha + \beta_1 ICI_{it} + \beta_2 ICI_{it}^2 + \beta_3 SECP\_ICI_{it} + \beta_4 GDP_{it} + \beta_5 EC_{it} + \beta_6 WS_{it} + \beta_7 INDSTR_{it} + \varepsilon_{it} \quad \text{---(8)}$$

$$lnCO_2 = \alpha + \beta_1 ICI_{it} + \beta_2 ICI_{it}^2 + \beta_3 INDSTR\_ICI_{it} + \beta_4 GDP_{it} + \beta_5 EC_{it} + \beta_6 WS_{it} + \beta_7 SECP_{it} + \varepsilon_{it} \quad \text{---(9)}$$

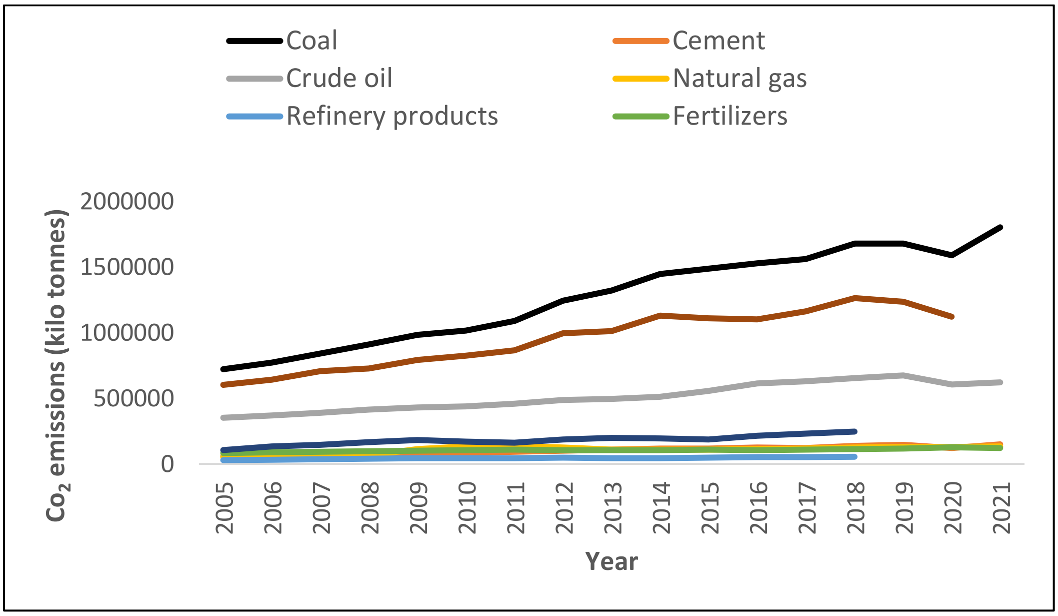
$$lnCO_2 = \alpha + \beta_1 ICI_{it} + \beta_2 ICI_{it}^2 + \beta_3 ICI_{it}^3 + \beta_4 GDP_{it} + \beta_5 EC_{it} + \beta_6 WS_{it} + \beta_7 SECP_{it} + \beta_8 INDSTR_{it} + \varepsilon_{it} \quad \text{---(10)}$$

Here, α are the constants and ε are the error terms of the regression models, while *i* and *t* represent the cross-section item and time period, respectively. β_n is the estimated coefficient value that indicates the explanatory variables' degree of impact on the dependent variable. The Fully-Modified Ordinary Least Squares (FMOLS) approach is employed to test the IEKC hypothesis as it is capable of providing robust estimations while overcoming the possible issues of serial correlation and endogeneity in the empirical models (Chowdhury et al., 2022), even when a small sample size is considered (Kao and Chiang, 2001; Pedroni, 2000). The DOLS approach is employed for the robustness check of the results from Objective 3.

7. Results and discussion:

Objective 1: Figure 1 presents a graphical outlook on the absolute emission levels of the core industries.

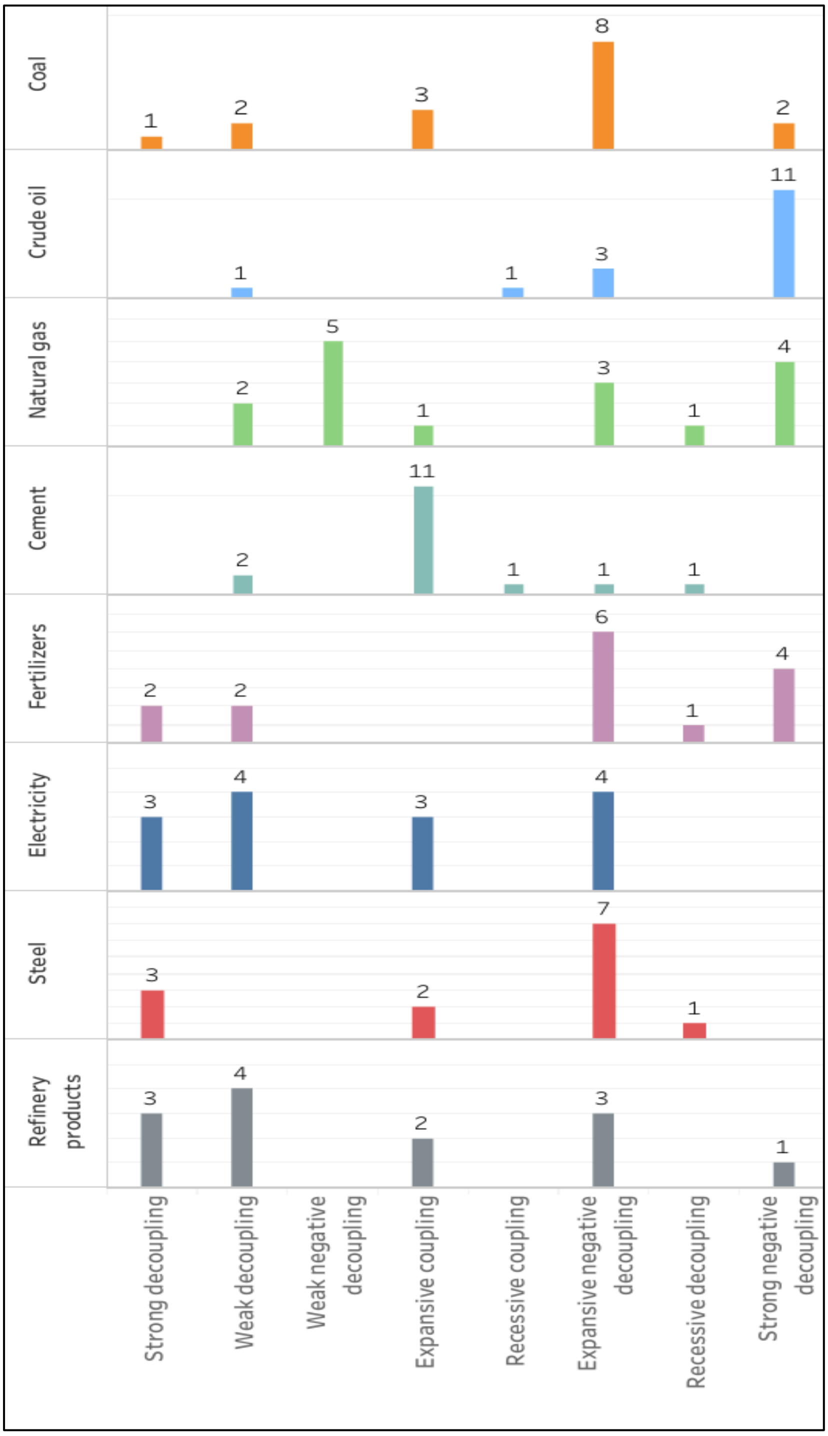
Figure 1: Industrial emissions



(Author's compilation)

Table 5 shows the core industries' decoupling elasticity degrees and the decoupling scores obtained by each industry. India's electricity industry is the only low-polluting industry, whereas fertilizers and crude oil are the two highly-polluting industries. The remaining five industries are moderately polluting. Figure 2 shows a comparative picture of the various elasticity degree frequencies depicted by each core industry. The crude oil industry possesses the highest frequency of strong negative decoupling elasticity and therefore, it is the most harmful. The coal, fertilizers, and steel industries have shown high frequencies of expansive negative decoupling states, meaning that the rate of carbon emission increase is higher than the rate of industrial growth in these cases.

Figure 2: Frequencies of the decoupling elasticity degrees



(Author's compilation)

Table 5: Decoupling elasticity degrees of the Indian core industries

Year	Coal		Crude oil		Natural gas		Cement		Fertilizers		Electricity		Steel		Refinery products	
	DE	**DS**	**DE**	**DS**	**DE**	**DS**	**DE**	**DS**	**DE**	**DS**	**DE**	**DS**	**DE**	**DS**	**DE**	**DS**
2006	END	6	END	6	RD	7	WD	2	END	6	EC	4	END	6	WD	2
2007	END	6	END	6	END	6	WD	2	SND	8	END	6	EC	4	EC	4
2008	EC	4	SND	8	END	6	EC	4	SND	8	WD	2	END	6	END	6
2009	EC	4	SND	8	END	6	EC	4	WD	2	END	6	END	6	SND	8
2010	END	6	WD	2	WD	2	EC	4	END	6	WD	2	SD	1	SD	1
2011	SND	8	EC	4	SND	8	EC	4	END	6	WD	2	SD	1	WD	4
2012	END	6	SND	8	WND	3	EC	4	RD	7	END	6	END	6	WD	4
2013	END	6	SND	8	WND	3	END	6	SD	1	WD	2	END	6	SD	1
2014	END	6	SND	8	WND	3	EC	4	END	6	EC	4	SD	1	SD	1
2015	WD	2	SND	8	WND	3	EC	4	EC	4	SD	1	RD	7	END	6
2016	EC	4	SND	8	SND	8	EC	4	SD	1	SD	1	END	6	EC	4
2017	WD	2	SND	8	EC	4	RD	7	SND	8	EC	4	EC	4	END	6
2018	EC	4	SND	8	SND	8	EC	4	SND	8	END	6	END	6	WD	2
2019	SND	8	SND	8	SND	8	EC	4	END	6	SD	1				
2020	SD	1	RD	7	WND	6	RC	5	END	6	SD	1				
2021	END	6	SND	8	WD	2	EC	4	RD	7						
Average DS		4.94		7.06		5.19		4.13		5.63		3.20		4.62		3.77

(Author's calculations)

***Note**: DE stands for decoupling elasticity and DS stands for decupling score.*

Objective 2: Table 6 reports the results of Model 2. Here, GDP, EC, lnTCL and WS show a positive impact on the core industries' carbon emission levels, indicating that they lead to greater emissions. In contrast, R&D and lnCER are found to have favourable effects, signifying that they help mitigate the emissions from the core industries. Lastly, POV and EDU show non-significant influence. The Adjusted R^2 value implies that the model explains 99.8% variations in the dependent variable. Further, the non-significant test statistics of the Breusch-Pagan test and the Breusch-Godfrey LM test confirm that the model does not suffer from heteroscedasticity and autocorrelation.

Table 6: DOLS results

Variable	**Coefficient**	**Std. error**	**t-statistics**
GDP	0.018*	0.001	-6.469
R&D	-0.001*	0.000	-2.846
EC	0.001*	0.001	2.971
POV	0.134	0.013	1.313
EDU	-0.002	0.001	0.150
lnTCL	0.027*	0.004	6.003
WS	0.098*	0.007	14.122
lnCER	-0.002	0.001	-2.846
Adjusted R^2		0.998	
Breusch-Pagan test		0.26 (0.613)	
Breusch-Godfrey LM Test		1.500 (0.0919)	

(Author's calculations)

***Note**: *, ** and *** represent significance levels at 1%, 5% and 10%, respectively.*

Table 7 shows the empirical results for the different categories of driving factors. Among the economic factors, *GDP*, *lnFDI*, and *lnAGR* have significantly and positively impacted CO_2, implying an increase in carbon emissions, while the negative coefficient of *R&D* indicates a reduction in industrial emission levels with a rise in *R&D* activities. Hence, the results support $\boldsymbol{H_{2.1}}$, $\boldsymbol{H_{2.2}}$, $\boldsymbol{H_{2.3}}$ and $\boldsymbol{H_{2.4}}$. Next, among the industrial factors, it is observed that *EC* and *INDDES* both have significant positive coefficient values, confirming their role in raising industrial emissions. In contrast, the negative coefficients of *IVA* and *BANK* indicate their contribution towards reducing emission levels. The results support $\boldsymbol{H_{2.6}}$ and $\boldsymbol{H_{2.7}}$ but reject $\boldsymbol{H_{2.5}}$ and $\boldsymbol{H_{2.8}}$. Regarding the demographic factors, only *POP* and *URB* have demonstrated significant and positive coefficients, reflecting their escalating impact on the core industries' emission levels. However, the effects of *POV* and *EDU* are not found to be non-significant. Therefore, $\boldsymbol{H_9}$ and $\boldsymbol{H_{10}}$ are supported by the empirical results and $\boldsymbol{H_{11}}$ and $\boldsymbol{H_{12}}$ are rejected. Lastly, with respect to the environmental factors, *lnTCL* and *WS* have shown significant and positive coefficient values, indicating their increasing influence on the emission levels. Contrastingly, the negative and significant coefficient of *ENVTECH* and *lnCER* assert their favourable roles in curbing the industries' emissions. Here, the results approve $\boldsymbol{H_{2.13}}$, $\boldsymbol{H_{2.14}}$, $\boldsymbol{H_{2.15}}$ and $\boldsymbol{H_{2.16}}$.

Table 8 reports the results of the DOLS approach and confirms the robustness of the results obtained, proving their consistency and reliability.

Table 7: Results for the driving factors of industrial emissions

Economic factors			Industrial factors		
Variable	**Coefficient**	**z-statistic**	**Variable**	**Coefficient**	**z-statistic**
GDP	0.011*	4.91	IVA	-0.067*	-3.55
lnFDI	0.062*	2.88	EC	0.004*	4.06
lnAGR	0.982*	3.62	BANK	-0.004*	-7.93
R&D	-0.001**	-1.97	INDDES	0.001*	2.64
Constant	-3.350	-0.99	Constant	18.423*	7.06
R^2	0.641		R^2	0.597	
Wald chi^2 statistic (p-value)	182.92* (0.000)		Wald chi^2 statistic (p-value)	222.66* (0.000)	
Hausman test (p-value)	1.183 (0.757)		Hausman test (p-value)	1.185 (0.756)	
Breusch-Pagan test (p-value)	1035.50* (0.000)		Breusch-Pagan test (p-value)	1038.46* (0.000)	
Breusch-Godfrey LM Test (p-value)	1.405 (0.122)		Breusch-Godfrey LM Test (p-value)	1.418 (0.119)	
Demographic factors			**Environmental factors**		
Variable	**Coefficient**	**z-statistic**	**Variable**	**Coefficient**	**z-statistic**
lnPOPD	2.714*	3.17	lnTCL	0.146***	1.66
URB	0.540**	2.35	WS	0.224*	12.33
POV	0.001	1.54	ENVTECH	-0.001***	-1.89
EDU	0.001	0.63	lnCER	-0.014**	-2.03
Contant	-1.411	-0.45	Contant	0.308	0.22
R^2	0.661		R^2	0.676	
Wald chi^2 statistic (p-value)	75.98* (0.000)		Wald chi^2 statistic (p-value)	236.93* (0.000)	
Hausman test (p-value)	1.189 (0.753)		Hausman test (p-value)	0.231 (0.630)	
Breusch-Pagan test (p-value)	1035.29* (0.000)		Breusch-Pagan test (p-value)	835.72* (0.000)	
Breusch-Godfrey LM Test (p-value)	1.262 (0.253)		Breusch-Godfrey LM Test (p-value)	1.332 (0.197)	

(Author's calculations)

***Note**: *, ** and *** represent significance levels at 1%, 5% and 10%, respectively.*

Table 8: Robustness test results for the driving factors of industrial emissions

Economic factors			Industrial factors		
Variable	**Coefficient**	**t-statistic**	**Variable**	**Coefficient**	**z-statistic**
GDP	0.007**	2.578	IVA	-0.069*	-28.013
lnFDI	0.084*	6.963	EC	0.004*	5.056
lnAGR	0.003*	19.819	BANK	-0.001*	-18.206
R&D	-0.001**	-2.283	INDDES	0.008***	1.890
R^2	0.979		R^2	0.947	
Adjusted R^2	0.977		Adjusted R^2	0.942	
Demographic factors			**Environmental factors**		
Variable	**Coefficient**	**z-statistic**	**Variable**	**Coefficient**	**z-statistic**
lnPOPD	3.0985*	17.558	lnTCL	0.145*	11.113
URB	0.325**	2.074	WS	0.223*	20.733
POV	-0.000	-0.021	ENVTECH	-0.014*	-3.756
EDU	-0.002	-0.650	lnCER	-0.001**	-2.231
R^2	0.978		R^2	0.440	
Adjusted R^2	0.969		Adjusted R^2	0.382	

(Author's calculations)

***Note**: *, ** and *** represent significance levels at 1%, 5% and 10%, respectively.*

Objective 3: Table 9 provides the FMOLS results for Models 7-9 that explore the relationship between industrial growth and emission levels. The results from Model 7 validate an inverted U-shaped IEKC for the Indian core industries. This implies that even though the growth of the core industries causes ecological damage initially, it is expected to reduce its harmful environmental impact in the long run. The validity of the inverted U-shaped IEKC is also confirmed by Models 8 and 9, thereby supporting $\boldsymbol{H_{3.1}}$.

Next, the study finds significant and negative effects of both the moderating variables *SECP_ICI* and *INDSTR_ICI* in the relationship between industrial growth and carbon emissions. This implies that stringent environmental policies and improving the country's industrial structure help trim down the scale of carbon emissions. In terms of environmental policy stringency, the government can regulate industries to emit CO_2 within a prescribed limit, failing to which leads to legal charges and penalties by sectors. Such measures will help control the industries' environmental destruction. On the other hand, industrial structure improvement (higher growth of the tertiary sector in relation to the secondary sector's growth) will lead to lesser energy consumption and aid the required investments and funds to industries for eco-friendly projects. The sector can also offer the education and training necessary for the industries' sustainable growth. Thus, the results support $\boldsymbol{H_{3.2}}$ and $\boldsymbol{H_{3.3}}$.

Table 10 provides estimates of the turning points in the IEKC are provided, with and without the moderating roles of *SECP* and *INDSTR*. As per reports, the average *ICI* value of the eight core industries is 125.75 in 2021 (Office of Economic Adviser, 2022), which is lower than all the estimated turning points in Table 10. It infers that the Indian core industries have not yet reached the threshold growth point of the IEKC.

Table 11 highlights the validity of the N-shaped IEKC in the Indian core industries using Model 10. It indicates the possibility that the core industries might further lead to environmental degrading effects, even after achieving the inverted U-shaped IEKC. The government and policymakers should take it as a warning sign, signifying that industries should continuously reassess innovation and research and development activities. Thus, the results support $\boldsymbol{H_{3.4}}$.

The DOLS results from Tables 9 and 11 prove the robustness of the reported results in Objective 3.

Table 9: Results for the IEKC hypothesis (Objective 3)

Variable	Model 7				Model 8				Model 9			
	FMOLS		DOLS		FMOLS		DOLS		FMOLS		DOLS	
	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
ICI	0.037*	7.639	0.020*	5.549	0.036*	7.233	0.024*	7.440	0.040*	8.037	0.0413*	13.662
ICI^2	-0.000*	-6.318	-0.000*	-3.598	-0.000*	-5.784	-0.000*	-1.811	-0.000*	-6.543	-0.000*	-11.382
SECP_ICI	-	-	-	-	-0.009*	-4.843	-0.003***	-1.766	-	-	-	-
INDSTR_ICI	-	-	-	-	-	-	-	-	-0.001**	-2.623	-0.001*	-9.111
GDP	0.003**	2.544	0.008*	5.517	0.002***	1.771	0.006*	4.858	0.003*	2.597	0.001***	1.714
EC	0.001*	3.612	0.001***	1.930	0.001**	3.372	0.001**	2.139	0.001*	3.671	0.001*	5.570
WS	0.053*	4.658	0.045**	2.190	0.056*	4.759	0.043**	2.303	0.051*	4.537	0.067*	8.942
SECP	-0.100*	-5.844	-0.047*	-2.153	-	-	-	-	-0.100*	-5.783	0.067*	8.942
INDSTR	-0.037	-1.087	0.027	-1.021	-0.046	-1.269	-0.013	-0.524	-	-	-	-
Adjusted R^2	0.972		0.998		0.977		0.999		0.967		0.847	
White's heteroscedasticity	1.11 (0.292)				0.87 (0.351)				1.13 (0.287)			
Breusch–Godfrey LM test	122.812 (0.061)				122.728 (0.061)				122.918 (0.060)			
Pesaran CD cross-sectional	1.223 (0.221)				1.276 (0.202)				1.345 (0.178)			

(Author's calculations)

Note: **, ** and *** represent significance levels at 1%, 5% and 10%, respectively.*

Table 10: Estimates of the IEKC turning points

Particulars	Model 7		Model 8 (Stringent environmental policy)			Model 9 (Industrial structure improvement)		
	Y*	Y**	Y*	Y**	Difference	Y*	Y**	Difference
FMOLS	184.80	-	178.92	172.94	5.98	202.40	189.87	12.53
DOLS	179.06	-	181.84	178.30	3.55	206.57	187.80	18.77

(Author's calculations)

Note: Y indicates turning point without moderating effects, Y** indicates turning point with moderating effect.*

. **Table 11: Results for the N-shaped IEKC hypothesis (Model 10)**

Variable	**FMOLS**		**DOLS**	
	Coefficient	**t-Statistics**	**Coefficient**	**t-Statistics**
ICI	0.031*	6.637	0.232***	1.705
ICI2	-0.003*	-6.066	-0.002***	-1.965
ICI3	0.000*	5.662	0.000**	2.310
GDP	0.001**	2.079	0.038***	1.689
EC	0.0004***	1.944	0.032*	3.466
WS	0.032*	3.614	0.152***	1.938
SECP	-0.069*	-5.262	-0.294***	-1.705
INDSTR	-0.029	-1.594	0.628	1.454
Adjusted R^2	0.510		0.597	

(Author's calculations)

***Note**: *, ** and *** represent significance levels at 1%, 5% and 10%, respectively.*

8. **Conclusion**:

The study highlights the environmental degrading effects of the Indian core industries. The core industries should not merely anchor on achieving growth to contribute towards India's economic development. The country's ecological health should also be given equal attention to secure a better and healthier future for the coming generations. As highlighted by the results, innovation, quality improvement, policy stringency and industrial structure are significant to achieve a reduction in carbon emission levels of the core industries. The sole efforts of the government or policymakers cannot achieve industrial sustainability. Industrialists, investors, financial institutions, the general public, etc. must come forward together to promote healthier industrial practices in the country.

Bibliography:

Afriyie, D., Wang, Z., Hu, S., Ampofo, G. K. M., and Asante, D. A. (2023). Exploring the dynamic nexus between urbanization and industrialization with carbon emissions in sub-Saharan Africa: evidence from panel PMG-ARDL estimation. *Environmental Science and Pollution Research*, 30:6373–6389.

Alola, A. A., and Donve, U. T. (2021). Environmental implication of coal and oil energy utilization in Turkey: is the EKC hypothesis related to energy? *Management of Environmental Quality: An International Journal*, 32(3):543–559.

Anwar, A., Sarwar, S., Amin, W., and Arshed, N. (2019). Agricultural practices and quality of environment: evidence for global perspective. *Environmental Science and Pollution Research*, 26:15617–15630.

Aslam, B., Hu, J., Shahab, S., Ahmad, A., Saleem, M., Shah, S. S. A., Javed, M. S., Aslam, M. K., Hussain, S., and Hassan, M. (2021). The nexus of industrialization, GDP per capita and CO_2 emission in China. *Environmental Technology and Innovation,* 23:101674.

Awan, A. M., and Azam, M. (2021). Evaluating the impact of GDP per capita on environmental degradation for G-20 economies: Does N-shaped environmental Kuznets curve exist? *Environment, Development and Sustainability*, 24(9):11103–11126.

Çetinkaya, O. A., Çatik, A. N., Balli, E., Manga, M., and Destek, M. A. (2024). Assessing the influence of green innovation and environmental policy stringency on CO_2 emissions in BRICS. *Environment, Development and Sustainability*.

Chen, J., Shen, L., Song, X., Shi, Q., and Li, S. (2017). An empirical study on the CO_2 emissions in the Chinese construction industry. *Journal of Cleaner Production*, 168:645–654.

Chowdhury, S., Khan, S., Sarker, M. F. H., Islam, M. K., Tamal, M. A., and Khan, N. A. (2022). Does agricultural ecology cause environmental degradation? Empirical evidence from Bangladesh. *Heliyon*, 8(6).

Driscoll, A. W., Conant, R. T., Marston, L. T., Choi, E., and Mueller, N. D. (2024). Greenhouse gas emissions from US irrigation pumping and implications for climate-smart irrigation policy. *Nature Communications*, 15.

Du, Q., Lu, X., Yu, M., Yan, Y., and Wu, M. (2020). Low-carbon development of the construction industry in china's pilot provinces. *Polish Journal of Environmental Studies*, 29(4):2617–2629.

Gao, C., Wang, D., Zhao, B., Chen, S., and Qin, W. (2015). Analyzing and forecasting CO_2 emission reduction in China's steel industry. *Frontiers of Earth Science,* 9(1):105–113.

Gatsios, A., Ntatsi, G., Celi, L., Said-Pullicino, D., Tampakaki, A., and Savvas, D. (2021).

Impact of legumes as a pre-crop on nitrogen nutrition and yield in organic greenhouse tomato. *Plants*, 10(3):468.

Global Carbon Project. (2022). *Global Carbon Budget 2022*. https://www.globalcarbonproject.org/carbonbudget/

Grossman, G. M., and Krueger, A. B. (1991). Environmental Impacts of a North American Free Trade Agreement. *NBER Working Papers 3914*.

Hasanov, F. J., Mikayilov, J. I., Mukhtarov, S., and Suleymanov, E. (2019). Does CO2 emissions–economic growth relationship reveal EKC in developing countries? Evidence from Kazakhstan. *Environmental Science and Pollution Research*, 26(29):30229–30241.

Isaksson, R. (2016). Process based system models for detecting opportunities and threats – the case of World Cement Production. *International Journal of Quality and Service Sciences*, 8(3):246–262.

Itoo, H. H., and Ali, N. (2023). Analyzing the causal nexus between CO_2 emissions and its determinants in India: evidences from ARDL and EKC approach. *Management of Environmental Quality: An International Journal*, 34(1):192–213.

Kao, C., and Chiang, M. H. (2001). On the estimation and inference of a cointegrated regression in panel data. In *Advances in Econometrics* (Vol. 15, pp. 179–222).

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, 45(1):1–28.

Lee, K. H., Min, B., and Yook, K. H. (2015). The impacts of carbon (CO_2) emissions and environmental research and development (R&D) investment on firm performance. *International Journal of Production Economics*, 167:1–11.

Lv, D., Wang, R., and Zhang, Y. (2021). Sustainability Assessment Based on Integrating EKC with Decoupling: Empirical Evidence from China. *Sustainability*, 13(2):1–22.

Mahmood, H., Alkhateeb, T. T. Y., and Furqan, M. (2020). Industrialization, urbanization and CO_2 emissions in Saudi Arabia: Asymmetry analysis. *Energy Reports*, 6:1553–1560.

Mehta, L., Adam, H. N., and Srivastava, S. (2022). *The Politics of Climate Change and Uncertainty in India*. Routledge.

Minlah, M. K., Zhang, X., Ganyoh, P. N., and Bibi, A. (2021). Does the environmental Kuznets curve for deforestation exist for Ghana? Evidence from the bootstrap rolling window Granger causality test approach. *Forestry Economics Review*, 3(1):38–52.

Nazir, M. I., Nazir, M. R., Hashmi, S. H., and Ali, Z. (2018). Environmental Kuznets Curve hypothesis for Pakistan: Empirical evidence form ARDL bound testing and causality approach. *International Journal of Green Energy*, 15(14–15):947–957.

Office of Economic Adviser. (2022). *Index of Eight Core Industries (Base: 2011-12=100)* *for June, 2022*.

Pata, U. K. (2018). The effect of urbanization and industrialization on carbon emissions in Turkey: evidence from ARDL bounds testing procedure. *Environmental Science and Pollution Research*, 25(8):7740–7747.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. In *Advances in Econometrics* (Vol. 15, pp. 93–130).

Phiri, J., Malec, K., Kapuka, A., Maitah, M., Appiah-Kubi, S. N. K., Gebeltová, Z., Bowa, M., and Maitah, K. (2021). Impact of agriculture and energy on CO_2 emissions in zambia. *Energies*, 14(24):8339.

Rai, S. K., and Rawat, A. (2022). Exploring the nexus between environment quality, economic development and industrialization in BRICS nations: the role of technological innovation and income inequality. *Environmental Science and Pollution Research*, 29(25):37842–37853.

Rana, R., and Sharma, M. (2019). Dynamic causality testing for EKC hypothesis, pollution haven hypothesis and international trade in India. *Journal of International Trade and Economic Development*, 28(3):348–364.

Sarangi, G. K., Mishra, A., Chang, Y., and Taghizadeh-Hesary, F. (2019). Indian electricity sector, energy security and sustainability: An empirical assessment. *Energy Policy*, 135.

Sinha, A., and Shahbaz, M. (2018). Estimation of Environmental Kuznets Curve for CO_2 emission: Role of renewable energy generation in India. *Renewable Energy*, 119:703–711.

Sreenu, N. (2022). Impact of FDI, crude oil price and economic growth on CO2 emission in India: - symmetric and asymmetric analysis through ARDL and non-linear ARDL approach. *Environmental Science and Pollution Research*, 29(28):42452–42465.

Tapio, P. (2005). Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transport Policy*, 12(2):137–151.

Villanthenkodath, M. A., Gupta, M., Saini, S., and Sahoo, M. (2021). Impact of Economic Structure on the Environmental Kuznets Curve (EKC) hypothesis in India. *Journal of Economic Structures*, 10.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, 48(4):817–838.

Wu, L. kang, Feng, T. tian, Luo, H., Gong, X. lei, and Ge, J. ping. (2022). Testing environmental Kuznets curve hypothesis: considering the impact of Sino-US trade on three main industries in China. *Environmental Science and Pollution Research*, 29:54796–54812.

Xin, Y., Yang, S., and Rasheed, M. F. (2023). Exploring the impacts of education and unemployment on CO2 emissions. *Economic Research-Ekonomska Istrazivanja*, 36(2):2110139.

Xu, W., Wan, B., Zhu, T., and Shao, M. (2016). CO2 emissions from China's iron and steel industry. *Journal of Cleaner Production*, 139:1504–1511.

Yan, X., and Fang, Y. P. (2015). CO2 emissions and mitigation potential of the Chinese manufacturing industry. *Journal of Cleaner Production*, 103:759–773.

Zeb, K., Ali, Y., and Khan, M. W. (2019). Factors influencing environment and human health by cement industry: Pakistan a case in point. *Management of Environmental Quality: An International Journal*, 30(4):751–767.

Zhao, H., Lu, X., and Shao, Z. (2019). Empirical analysis on Relationship between Water Footprint of China's Textile Industry and Eco-environment. *Ekoloji*, 28(107):1067–1076.

Zhao, J., Jiang, Q., Dong, X., Dong, K., and Jiang, H. (2022). How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China. *Energy Economics*, 105:105704.