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The Impacts of Human Capital and Corruption on Environmental Pollution: Evidence from ARDL and NARDL Models

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Abstract

This study has investigated that how corruption and human capital can affect environmental pollution in Bangladesh in terms of CO2 emission and PM2.5 as environmental indicators. The Auto Regressive Distributed Lag (ARDL) and Nonlinear ARDL (NARDL) are used to analyze annual data from 2001-2023 in order to test symmetric and asymmetric effects. The results reveal that there is a long-run Cointegration relationship between corruption, human capital, economic growth, energy consumption, and environmental pollution. The presence of corruption heavily leads to the environment pollution and human capital decreases the amount of CO2 emission both in short- and long-run. With asymmetric analysis results reveal that the positive shocks to corruption are stronger in their effects of increasing environmental pollution than the negative ones decrease environmental pollution, and the results validate the hypothesis of Environmental Kuznets Curve (EKC) in Bangladesh. Policy implications suggestion includes institutional empowering, anti-corruption implementation, and investment in education as a way of enhancing the environment sustainability.

Keywords: Environmental pollution, human capital, corruption, ARDL & NARDL models, Bangladesh

1. Introduction

Corruption has several impacts on environmental changes, exacerbating environmental pollution and hindering efforts to address environmental challenges. Corrupt practices in carbon credit renewable energy projects lead to fraud and mismanagement, reducing the effectiveness of initiatives in reducing greenhouse gas emissions. Economic growth is hindered by corruption because it distorts economic activity and discourages investment, resulting in inefficiency and slower development and directly affecting environmental damage [1]. Additionally, corruption impacts the human capital index by weakening healthcare and education systems, leading to lower-quality services and less growth of human capital and directly disrupting environmental changes [2]. Poor governing practices eventually cause corruption, allowing low-quality, environmentally harmful GDP and worsening environmental pollution.[3] Explored thatcorruption in governmental institutions is a major factor in the destruction of water, air, food, and human habitats, which leads to malnutrition, disease, and mortality, as well as economic instability and climate change in developing nations. Even though there have always been climate changes, human-caused climate change has heightened these worries [4]. Human capital is needed to reduce greenhouse gas emissions, and education increases awareness of corruption and environmental problems [5]. Official corruption is anticipated to impact of GDP on CO2emissions nexus in emerging countries with high levels of corruption in Bangladesh. Despite decreasing in the ranks for global sensitivity to environmental pollution, Bangladesh is still extremely sensitive to climate change [6]. Since

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the reform and opening-up, Bangladesh's GDP has been growing. In 2017, the country's GDP increased by 249.72 billion US dollars, and Bangladesh's GDP averaged 49.21 billion dollars, with a record high of 249.72 billion dollars in 2017 and a record low of 4.30 billion dollars in 1960 [7]. More than 60% of China's annual average PM2.5 focuses above the second threshold of the necessary public standard [8].This study aims at exploring the complex effect of corruption on different socioeconomic and environmental aspects in Bangladesh focusing in particular on how corruption affects GDP, energy use, population patterns in urban areas, institutional performance, and human capital. Moreover, the paper aims at explaining the cumulative effect of these factors under the influence of corruption on environmental pollution. To do so the ARDL and NARDL models [9] are used to satisfy the short- and long-run symmetric and asymmetric impact of corruption on the environmental population. It is found that the environmental impacts of corruption are quite asymmetric. Particularly, corruption that comes with economic development is expected to intensify the environmental pollution, but the long-term correlation between corruption and pollution is weakened by human capital. The findings also show that environmental pollution increases with the increase in the rate of corruption. Besides, the human capital index has a direct impact on the environmental population, and this relationship is strongly connected to the institutional quality, especially in the times of GDP growth. The results reveal that the necessities to have policy interventions that can help reduce the negative environmental effects of corruption that are aimed at achieving sustainable economic development.

The remaining parts of the study are structured as follows. Section 2 includes the literature review on GDP growth, human capital, corruption, and environmental pollution. Section 3 describes the econometric model's specification, variables' definitions, and data sources. Section 4 presents the results and discussion of empirical analysis. Section 5 describes the conclusions and future suggestions.

2. Literature Review

The 'Environmental Kuznets Curve' (EKC) is a U-shaped relationship between per capita income and pollution concentration [10]. Trade liberalization, energy consumption, population dynamics, institutional quality, and governance have been environmental detrainments in addition to per capita income [11]. Corruption promotes unethical resource exploitation, management, permitting, and environmental inspections, polluting the environment [12]. Corruption leads to inefficiencies in the trade process, such as favoritism in awarding contracts or customs fraud, resulting in distorted environmental sustainability in Bangladesh [13]. The corruption in high energy consumption, especially if derived from non-renewable sources, contributes to environmental pollution through increased emissions of greenhouse gases and pollutants [14]. Corruption and poor institutional quality, characterized by weak governance, lack of enforcement of environmental regulations, and ineffective management of resources, result in environmental pollution in Bangladesh [15]. Bangladesh's high corruption rate limits human capital index growth, which measures population education and skills, preventing adopting environmentally friendly practices and technologies and developing a workforce that can address environmental issues [16]. Corruption leads to unfriendly policies enforcing strict environmental legislation, diverting resources from eco-friendly efforts [17]. Investments in human capital, such as education and awareness, are crucial for promoting environmental awareness [18]. Corruption and uneven electricity relations make it harder for people to adapt to the stressors brought on by climate change. For already disadvantaged populations, social exclusion imposes additional burdens [19].Higher-educated people notice the negative effects of environmental pollution [20]. Corruption harms the environment and examines how bureaucracy and lobbying groups abuse environmental laws [21]. The economic factors have a greater influence on PM2.5 concentration [22]. There are connections between government rent-seeking, corruption, economic development, and pollution [23]. PM2.5 triggers strong, provocative responses and oxidative pressure; it compromises the lungs' ability to maintain their internal conditions [24]. PM2.5, CO_2, and O_3 are related to more SARS-CoV-2 infections and deaths in London, UK. Natural pollution board professionals should implement key strategies to reduce environmental pollution [25]. According to [26], corruption makes it difficult to execute policies and increases the effects of trade liberalization on the environment. Reduced corruption and increased environmental legislation improve environmental quality [27]. Corruption reduces the socially optimal GDP for environmental damage and delays the Environmental Kuznets Curve (EKC) [28]. Bangladesh's CO2, PM2.5 emissions and water pollution are all impacted by trade liberalization and corruption [29]. In Bangladesh, [30] discovered both short- and long-run EKC, indicating that energy production is good for the environment. Bangladesh's shadow economy and corruption worsen environmental pollution [31]. Corruption reduces the environmental benefits of renewable energy while exacerbating the negative effects of fossil fuels [32]. [33] Explored that the corruption directly lowers CO2 emissions in countries but not those with higher ones. Energy use and environmental quality are two ways that corruption indirectly impacts economic growth and directly impacts energy use and environmental pollution[34]. [35] Found that there is a connection between pollution, economic development, and energy output. Environmental pollution and GDP growth in Bangladesh with a positive input from the human capital index [36]. According to [37] demonstrate how human capital, natural resources, and economic growth influence Bangladesh's environmental quality. The long-run economic growth projections increase the environmental footprint while human capital and natural resources decrease CO2 emissions [38]. A non-linear ARDL technique is used to explore the asymmetric impacts of corruption on environmental pollution and to evaluate both the short- and long-run effects [39].

3. Research Methodology

3.1 Variable Selection and Data Collection

The study has applied a data from 2001 to 2023 as Table 1 represents the data descriptions with crucial dataset information for sample records, metadata data sources', and contact details for dataset maintenance are also provided.

Variables	Symbols	Measurement	Data Sources
Carbon Dioxide	CO_2	Carbon dioxide emissions in metric tons per capita & particular materials PM $_{2.5}$ in kilo tons measure environmental pollution	https://data.worldban k.org.com
Corruption	Corp	The corruption perception index ranges from 0-5, where 0 indicates the highest and 5 indicates the lowest	https://data.worldbank.org.com
Electricity Production	ELE	Total e lectricity production in whole country	https://data.worldbank.org.com
Gross Domestic Product	GDP growth	Log of Gross Domestic Product per capita (Constant local currency unit)	https://www.imf.org.com
Industry	IND	Manufacturing industry	https://data.worldbank.org.com
Government Education Spending	GES	Government expenditures on education as percentage	https://www.imf.org.com
Human Capital	CHP	Human capital of urban population density measured as people per sq. km of urban land area	https://data.worldbank.org.com
Energy Consumption	ENC	Energy consumption used in manufacturing and transportation industry	https://www.imf.org.com

Table 1: Variables details, symbols, and data collection sources

An accepted economic framework for examining economic development and environment is the Environmental Kuznets Curve [40]. [41] Established EKC and became well-known following the [42] report on "Environmental Development." The GDP growth encourages environmental pollution before declining and producing an inverted U-shaped curve. Figure 1 represents the research framework of the independent variables and CO2 emissions to show how alterations in each independent variable are postulated to impact CO2 emissions.

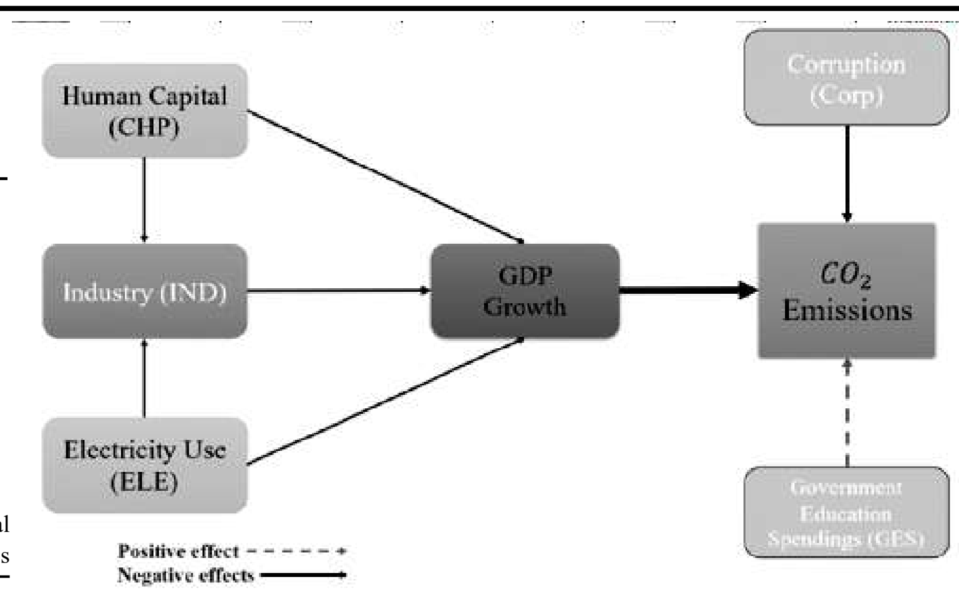

Fig. 1: Theoretical framework of study variables

The study has considered the CO? emissions (Metric tons per capita), and PM2.5 (Annual average exposure to particulate matter, and micrograms per cubic meter) as dependent variables. Whereas corruption (Corruption Perception Index rescaled 0-100; higher values indicate higher corruption), Human Capital (Government expenditure on education (% of GDP)), GDP per capita (Real GDP per capita), Industrialization (Manufacturing value added (% of GDP)), Energy Consumption (Fossil fuel energy consumption (% of total)), and electricity production electricity production (kWh per capita) have been considered as independent variables. Human capital is anticipated to reduce GHG emissions, but corruption is anticipated to exacerbate environmental pollution by obstructive effective environmental regulations [43]. The objectives of the study are to realize the impact of corruption on CO2 emissions. There is a non-linearand inverted U-shaped connection between GDP and GHG emissions in Bangladesh. It seeks to pinpoint the turning moment at which environmental advantages manifest.

3.2 Research Design

3.2.1 Unit root test

The Augmented Dickey-Fuller (ADF) test was used to assess the influence of Corp, ELE, GDP growth, IND, GES, and CHP on EP. The null hypothesis is rejectedindicating that the data is stationary in Equation 1:

$$s_t = \phi s_{t-1} + \varepsilon_t$$

Where s_{t-1} in the ADF (1) process is smaller than 1 indicates that the series is deemed stationary when the coefficient of the lag difference process approaches 1. The variable comprises the unit root process and is non-stationary at the level if $|\phi| = 1$. Because the series in the 3rd scenario is explosive and divergent, $|\phi| > 0$ suggests it never finds equilibrium.

3.2.2 ARDL model

The regression equation of the dependent and independent variables is represented in Equation (2) as follows:

$$lnEP_t = \alpha_0 + \alpha_1 lnCorp_t + \alpha_2 lnCHP_t + \alpha_3 ln(Corp_t * CHP_t) + \alpha_4 lnGDP_t + \alpha_5 lnIND_t + \sum^k \alpha_i X_{it} + \mu_i (2)$$

The interaction run ($Corp_t$* CHP_t) represents the connections between Corp and CHP, the

Environmental Kuznets Curve (EKC) hypothesis is looked at in order to derunine how uncertainly the control variables (IQ, GES, and CHP) are represented by Xt and EP. Cointegration with I(0) or I(1) values are tested using the Bound testing approach [47].The study has used the ARDL model to investigate the relationships between Corp, ELE, GDP, IND, GES, CHP, and EP. Equation (3) represents the regression of the ARDL model:

$$\Delta EP_{2t}=\alpha_0+\sum_{j=1}^{p}\alpha_{1j}\Delta EP_{2t-1}+\sum_{j=1}^{q}\alpha_{2j}\Delta Corp_t+\sum_{j=1}^{r}\alpha_{3j}\Delta ELE_t+\sum_{j=1}^{s}\alpha_{4j}\Delta GDP_t+\sum_{j=1}^{t}\alpha_{5j}\Delta IND_t+\sum_{j=1}^{u}\alpha_{6j}\Delta GES_t+\sum_{j=1}^{u}\alpha_{7j}\Delta CHP_t+\gamma_1 EP_{t-1}+\gamma_2 Corp_t+\gamma_3 ELE_t+\gamma_4 GDP_t+\gamma_5 IND_t+\gamma_6 GES_t+\gamma_7 CHP_t+\varepsilon_t \quad (3)$$

An alternative to factor cointegration is the use of F-statistics for hypothesis testing. The following is the long-run Equation (4), which SBC and AIC will use to resolve slack time:

$$EP_t=\gamma_1 EP_{t-1}+\gamma_2 Corp_t+\gamma_3 ELE_t+\gamma_4 GDP_t+\gamma_5 IND_t+\gamma_6 GES_t+\gamma_7 CHP_t+\varepsilon_t \quad (4)$$

A negative error correction term suggests that the research variables will reach equilibrium. The short-run Equation (5) show a correlation between the study variables.

$$\Delta EP_{2t}=\alpha_0+\sum_{j=1}^{p}\alpha_{1j}\Delta EP_{2t-1}+\sum_{j=1}^{q}\alpha_{2j}\Delta Corp_t+\sum_{j=1}^{r}\alpha_{3j}\Delta ELE_t+\sum_{j=1}^{s}\alpha_{4j}\Delta GDP_t+\sum_{j=1}^{t}\alpha_{5j}\Delta IND_t+\sum_{j=1}^{u}\alpha_{6j}\Delta GES_t+\sum_{j=1}^{u}\alpha_{7j}\Delta CHP_t+\varepsilon_t \quad (5)$$

3.2.3 NARDL Model

[44] developed the NARDL model to study Corp, ELE, GDP, IND, GES, CHP, and EP. [45]described that the model handle nonlinear patterns and asymmetric effects across variables, making it suitable for complex interactions. It separately represents positive and negative changes using dependent variable lag values and differences. Due to its versatility, the NARDL model analyzes real-world data with symmetrical relationships. The NARDL model is more versatile than the ARDL model because it reflects long-run interactions and short-run dynamics [46] Equation 6 shows how ARDL and NARDL model comparisons explain the variables' relationships.

$$\Delta LnEP_t=\alpha+\sum_{i=1}^{p}\alpha_1\Delta LnEP_{t-i}+\sum_{i=0}^{q}a_2\Delta Corp_{t-2}+\sum_{i=0}^{q}a_3\Delta CHP_{t-3}+\sum_{i=0}^{q}a_4\Delta Ln(Corp*CHP)_{t-4}+\sum_{i=0}^{q}a_5\Delta GDP_{t-5}+\sum_{i=0}^{q}a_6\Delta LnIND_{t-6}+\sum_{i=0}^{q}\Psi\Delta X_{t-i}+\delta_1 LnEP_{t-1}+\delta_2 Corp_{t-1}+\delta_3 CHP_{t-1}+\delta_4 Ln(Corp*CHP)_{t-1}+\delta_5 LnGDP_{t-1}+\delta_6 LnIND_{t-1}+\delta_7 X_{t-1}+\varepsilon_t \quad (6)$$

Equation (7)requires the NARDL error correcting model as follows:

$$\Delta LnEP_t=\alpha+\sum_{i=1}^{p}\alpha_1\Delta LnEP_{t-1}+\sum_{i=0}^{q}a_2\Delta Corp_{t-2}+\sum_{i=0}^{q}a_3\Delta CHP_{t-3}+\sum_{i=0}^{q}a_4\Delta Ln(Corp*CHP)_{t-4}+\sum_{i=0}^{q}a_5\Delta GDP_{t-5}+\sum_{i=0}^{q}a_6\Delta LnIND_{t-6}+\sum_{i=0}^{q}\Psi\Delta X_{t-i}+\lambda EC_{t-1}+\varepsilon_t \quad (7)$$

Where 'λ' represents residual adjustments transpire, and EC is error correction. The NARDL model's dynamic flexibility boosts Cointegration test energy with small sample numbers [48]. After using the NARDL model to evaluate short- and long-run symmetric and asymmetric research variables' relationship and formulates Equation (8) as follows:

$$LnEP_t=\alpha_0+\alpha_1 Corp_t\_POS_t+\alpha_2 Corp_t\_NEG_t+\alpha_3 LnGDP_t+\alpha_4 LnIND_t+\alpha_5 LnCHP_t+\sum_{i=6}^{k}\alpha_i X_{it}+\mu_i \quad (8)$$

Where (Corp_POS_t), and (Corp_NEG_t) refers to the partial sum of higher-than-average and lower-than-average corruption, and Equation (9) willbe given as below:

$$\Delta LnEP_t=\alpha+\sum_{i=1}^{p}\alpha_i\Delta LnEP_{t-i}+\sum_{i=0}^{q}\gamma_i\Delta Corp_{POS_{t-i}}+\sum_{i=0}^{q}\gamma_{i2}\Delta Corp_{NEG_{t-i}}+\sum_{i=0}^{q}\Gamma_i\Delta GDP_{t-i}+\sum_{i=0}^{q}\varsigma_i\Delta LnIND_{t-i}+\sum_{i=0}^{q}\Psi\Delta X_{t-i}+\delta_1 LnEP_{t-1}+\delta_2 Corp_{POS_{t-1}}+\delta_2 Corp_{NEG_{t-1}}+\delta_4 CHP_{t-1}+\delta_5 LnGDP_{t-1}+\delta_6 LnIND_{t-1}+\delta_7 X_{t-1}+\varepsilon_t \quad (9)$$

For error correction model for NARDL model Equation (10) is written as follows:

$$\Delta LnEP_t=\alpha+\sum_{i=1}^{p}\alpha_i\Delta LnEP_{t-i}+\sum_{i=0}^{q}\gamma_i\Delta Corp_{POS_{t-i}}+\sum_{i=0}^{q}\gamma_{i2}\Delta Corp_{NEG_{t-i}}+\sum_{i=0}^{q}\Gamma_i\Delta GDP_{t-i}+\sum_{i=0}^{q}\varsigma_i\Delta LnIND_{t-i}+\sum_{i=0}^{q}\Psi\Delta X_{t-i}+\lambda EC_{t-1}+\varepsilon_t(10)$$

The study uses the bound testing method of Cointegration to find a long-run relationship between the variables. The Bound-coefficient test is used to derunine whether the two directions of corruption change are equivalent [$\alpha_1 = \alpha_2$], although equating parameters yields information on the combined significance [$\alpha_1 = \alpha_2 = 0$].

4. Results and Discussions

4.1 Unit Root Test

Statistically, statisticians employ unit root tests to ascertain if a time series variable is stationary or non-stationary. Non-stationary time series show patterns or variations that fluctuate with time, whereas stationary time series have a constant mean and variance. The Augmented Dickey-Fuller (ADF) test is the most often utilized unit root test. The ADF test compares a time series' lagged value to the variation between successive observations in the series. The series may be stationary and lack a unit root if the difference is appreciably different from zero. Table 2 represents the results of unit root tests.

Table 2: Represents the results of the unit root test

Variables	Level	1st Difference	Decision
$lnCO_2$	-2.02	0.0001	I(1)
	-0.5987		
lnGDP	-3.05	-4.05*	I(1)
	-0.4266	-0.051	
lnIND	-3.42	-5.07	
	-0.27873	0.00001	I(0)
lnCorp	-3.09	-9.35*	I(1)
	-0.2008	0.0003	
lnCHP	-5.027*		I(0)
	-0.067		
lnIND	-3.05	-6.02*	I(1)
	-0.6004	-0.0001	
lnENC	-0.67	-6.02*	I(1)
	-0.8944	-0.0002	
lnELE	-4.087	-4.023*	I(1)
	-0.05	-0.0561	
lnGES	-2.0389	-5.092*	I(1)
	-0.589	-0.006	

Notes: '*'represents p-values is significant at 1% level.

The unit root test results demonstrate the stationarity properties of different factors at the two levels and first contrasts. lnCO2, lnGDP, lnCorp, lnENC, lnELE, and lnGES are non-stationary at levels however become stationary after first differencing, making them incorporated of request one, I(1). Interestingly, IND and CHP are stationary at their levels, showing they are coordinated of request zero, I(0). In particular, CO2, GDP, Corp, ENC, and GES show critical stationarity at the primary contrast, proposing these factors have unit roots and just settle in the wake of differencing. Then again, lnIND and lnCHP have critical test insights at the level, meaning they don't need differencing for stationarity. Consequently, the factors display blended requests of reconciliation, with some requiring first differencing (I(1)) and others stationary at the level (I(0)), which is fundamental to consider for any ensuing time series demonstrating. Testing the time series data for stationarity is a need before utilizing NARDL to examine the asymmetric influence of exogenous factors on the ecological footprint [49]. The NARDL models are only used after confirming that all variables have stationarity at level 1st difference and a combination of I(0) or I(1). There are different selection measures used to derunine the most suitable lag length. The Bound test is used to judge the presence of long-run and short-run symmetric and asymmetric relationships between an exogenous variable and ecological footprint [50]. Table 3 represents the Bound test statistically significant variances in how corruption affects environmental pollution.

Table 3: Represents the Bound Test Results

F-statistic (k)	6.078	5.002	7.04	4.01	3.06	3.01	4.00	4.21
Critical value at 10% level	LB	LB	LB	LB	LB	LB	LB	LB
	1.89	1.97	3.00	1.99	1.99	1.87	1.98	1.92
Results of Diagnostic Tests								
R^2	1.03	1.03	1.03	1.03	0.93	0.84	0.91	0.93
Serial Correlation LM Test-$\chi 2$ (p-value)	0.0001	0.0001	0.0003	0.004	0.0001	0.310	0.057	0.209
F-test (p-value)	0.0000	0.0001	0.0005	0.0000	0.0000	0.0002	0.000	0.0004
D-W test	3.097	3.056	3.004	3.005	3.006	3.089	3.008	3.045
Bound Test p-value	-	-	0.045	0.008	-	-	0.034	0.039
Normality test	0.902	0.876	0.978	0.564	0.0000	0.0000	0.0000	0.0000

Notes: '*' represents p-values is significant at 1% level..

The bound experimental results show shifting F-insights across various models, with values going from 3.01 to 7.04, while the basic qualities at the 10% importance level are undeniably ordered as lower bound (LB). Demonstrative tests show high R^2 values, especially for the initial four segments, recommending potential over fitting, while the leftover models have marginally lower R^2. Sequential connection is low across most models, besides in segments 6 to 8, where it is more articulated. F-test p-values are reliably tiny, showing critical model fits. Durbin-Watson (D-W) test values float around 3, recommending potential issues with autocorrelation in residuals. Bound test p-values feature huge Cointegration in models 3, 4, 7, and 8 at the 5% level. In any case, ordinariness tests show non-ordinary residuals in models 5 to 8 (p-values = 0.0000), raising worries about model suppositions.

4.2 ARDL and NARDL Models Short-run Estimates

Table 4 represents that the short-run analysis represents quite interesting output. ARDL and NARDL models are used in econometrics to analyze the relationships between variables in time series data. ARDL models are suitable for co-integrated data, providing insights into both short-run and long-run impacts of variable changes [51]. After adjustments, the long-run estimates demonstrate the equilibrium relationships between variables. These models are essential for understanding the dynamics of variables in different time frames.

Short-Run Estimations								
Variables	**lnCO2 per capita**				**lnPM2.5 per capita**			
Specifications	ARDL		NARDL		ARDL		NARDL	
	With IQ	*Without IQ*	*With IQ*	*Without IQ*	*With IQ*	*Without IQ*	*With IQ*	*Without IQ*
lnGDP(-1)	8.031***	8.244***	2.868***	2.835***	4.495*	0.828	2.808***	2.358*
	-2.864	-2.495	-0.646	-0.193	-2.491	-0.035	-0.684	-2.035
lnGDP(-2)	-2.446***	-2.442***	-	-	-	-	-	-
	-0.686	-0.193						
lnIND(-1)	-4.491***	-4.495***	-0.356***	-0.868***	-2.449*	-0.468	-0.820***	-0.846*
	-0.842	-0.849	-0.284	-0.428	-2.312	-0.492	-0.404	-0.491
lnIND(-2)	2.318***	2.352***	0.002	-	-	-	-	-
	-0.442	-0.424	-0.002					
Corruption	0.282**	0.284***	-	-	0.806	0.449	-	-
	-0.086	-0.068			-0.419	-0.235		
Corp-PS	-	-	0.046	0.0628**	-	-	-0.028	-0.019
			-0.028	-0.02			-0.019	-0.082
Corp-NEG	-	-	-0.044	-0.044**	-	-	0.244	0.019
			-0.035	-0.035			-0.352	-0.062
CHP	-2.686**	-2.495**	-2.194**	-2.446	-0.86	-2.352**	2.496	4.246
	(2.354)	(0.802)	(0.849)	-2.468	-4.31	(2.284)	-4.608	-4.0002

CHP2(-1)	-2.280*** -0.864	-2.400*** -0.468	-	-		-	-	-
ln (Corp* CHP)	-0.235** (0.242)	-0.235*** (0.084)	-	-	-2.086 -0.862	-0.164256	-	-
lnIND(-1)	0.035*** (0.024)	0.084*** (0.024)	0.068*** (0.024)	0.064*** (0.031)	0.242* (0.082)	0.280*** (0.064)	0.244** (0.068)	0.249** (0.062)
lnIND(-2)	-0.049*** (0.035)	-0.046*** (0.020)	-0.049*** (0.035)	-0.049*** (0.035)	-	-	-	-
lnENC	2.310*** (0.462)	2.286*** (0.446)	0.496*** (0.249)	0.444*** (0.249)	2.284 -0.35	0.496 -0.49	0.354*** (0.282)	0.350* (0.620)
lnELE	0.468 -0.498	0.682* (0.449)	0.04 -0.446	0.644 -0.424	4.804* (2.282)	0.842 -2.19	2.849 -2.193	0.468 -2.284
YES	-0.035* -0.049	-0.035*** -0.028	-0.062** -0.031	-0.068** -0.028	-0.492* -0.318	-0.282 -0.358	-0.404* -0.318	-0.352 -0.208
Pol	0.0002 -0.002	-	0.002 -0.002	-	-0.031*** (0.008)	-	-0.020** (0.008)	-

Table 4: Represents the short run Estimates of ARDL & NARDL

*Notes: '***', "**' and '*" represents p-values is significant at 10%, 5%, and 1% levels.*

The results show the effect of different monetary and ecological elements on CO2 and PM2.5 emanations per capita utilizing ARDL and NARDL models, with and without the consideration of level of intelligence as a control variable. lnGDP has a critical and generally constructive result on CO2emissions, proposing that higher financial development increments emanations, however the impact decreases over the long run. lnIND makes blended impacts, reflecting nonlinear effects of industry on both CO2 and PM2.5emissions. Defilement is related with higher CO2emissions, showing more fragile ecological guideline, while corporate shocks (Corp-PS and Corp-NEG) and communication terms with environment arrangements (CHP and ln(Corp * CHP)) uncover nuanced connections where strategy severity relieve emanations relying upon corporate way of behaving. lnENC and lnELE essentially increment PM2.5emissions, recommending that more prominent utilization prompts higher particulate matter contamination. The results reveal that the natural logarithm of CO2 emissions per capita has improved the data's suitability for specific kinds of statistical analysis, indicated by "lnCO2 per capita". In Bangladesh, the short-run asymmetric relationship between corruption, human capital, and environmental pollution is in line with[52], who determined the nonlinear relationship between corruption and environmental pollution in China. [53] found that an increase in renewable energy consumption will reduce CO2 emissions in Bangladesh, and there is a positive short-run relationship between corruption and GDP growth. The results describe positive and negative short-run relationships between environmental pollution proxy CO2 emission and corruption. The sign relation coefficient between environmental pollution and human capital depends on GDP growth and energy consumption methods. The results show that in the short run, there is a positive relationship between corruption levels and GDP growth [54]. GDP growth also tends to increase when corruption increases, and it under certain conditions in the short run, corruption might stimulate economic growth. The relationship did not hold in the short run and also had negative consequences in long-runs of economic stability and sustainability [55]. The relationship between CO2 emissions, which serve as a proxy for environmental pollution, and corruption is negative, and a positive short-run relationship is observed. The impact of corruption on environmental pollution is not straightforward and depends on different factors [56].

4.3 Long-Run Estimates

Table 5 represents the results of ARDL and NARDL models to study long-run relationships between variables in time series data. ARDL assesses relationships between variables that may not be stationary and uses Cointegration tests to check for long-run associations. NARDL extends ARDL by allowing for nonlinear relationships and involves nonlinearity tests. Using time series data, both models help understand how variables affect each other over the long run, either linearly or nonlinearly.

Table 5: Represents thelong run evaluations of ARDL & NARDL

Long Run Estimates								
Variable s	**lnCO$_2$ per capita**				**lnP.M$_{2.5}$ per capita**			
Specifications	ARDL		NARDL		ARDL		NARDL	
	With IQ	*Without IQ*	*With IQ*	*Without IQ*	*With IQ*	*Without IQ*	*With IQ*	*Without IQ*
lnGDP	2.559*	2.112*	0.674**	0.849**	2.206*	0.847	2.453*	2.653**
	-0.496	-0.671	-0.468	-0.429	-0.611	-0.802	-0.296	-0.653
lnIND	-0.536*	-2.071*	-0.460**	-0.429**	-2.046*	-0.429	-0.846*	-0.538**
	-0.429	-0.284	-0.284	-0.268	-0.471	-0.402	-0.592	-0.517
Corruption	0.271***	0.251*	-		0.496***	0.404***		
	-0.053	-0.046		-	-0.253	-0.598	-	-
	-	-	0.051	0.062***	-	-	-0.059	-0.049
Corp_PS			-0.046	-0.028			-0.047	-0.047
	-	-	-0.051*** (0.020)	-0.051*** (0.024)	-	-	0.598	0.071
Corp_NEG							-0.053	-0.071
CHP	-0.494***	-0.298***	-0.811*	-2.202***	-4.112*	-2.498*	-4.294*	-4.678*
	-0.429	-0.253	-0.286	-0.659	-0.496	-0.659	-2.251	-0.811
ln(Corp* CHP)	-0.594***	-0.240*	-	-	-0.532**	-0.678**	-	-
	-0.598	-0.112			-0.46	-0.468		
lnENC	2.006*	2.068*	0.468**	0.849***	0.429**	0.519	0.678*	0.676**
	-0.298	-0.267	-0.253	-0.459	-0.249	0.453	-0.204	-0.514
lnELE	0.716	0.716	0.071	0.628	4.598	0.849	2.471	0.453
	-0.471	-0.4	-0.459	-0.712	-2.2	2.271	-2.868	-2.859
YES	-0.598*	-0.598*	-0.068***	-0.598**	-0.294**	-0.271	-0.262**	-0.267
	-0.071	-0.029	-0.029	-0.071	-0.596	0.268	-0.598	-0.268
Pol	0.0002	-	0.002	-	-0.059**	-	-0.028*	-
	-0.002		-0.002		-0.011		-0.006	
ECT(-1)	-2.251*	-2.596*	-2.046*	-2.011*	-2.271*	-2.053*	-2.594*	-2.286*
	-0.598	-0.598	-0.271	-0.286	-0.598	-0.411	-0.271	-0.229

*Note: Notes: '***', "**' and '*" represents p-values is significant at 10%, 5%, and 1% levels.*

Long-term analyses using the ARDL and NARDL models examine the relationship between CO2 and PM2.5 emissions per capita under calculations that take into account and steer clear of an institutional quality. The results show that GDP has an impact on both emissions, indicating a link between increased pollution and financial development. ENC is often strongly linked to emissions, raising the prospect that increased energy use leads to more significant environmental effects. With enormous coefficients across models, the Blunder Revision Term (ECT) illustrates how quickly things return to equilibrium. [57] proposed that over time, China's ecological pollution is linked to rising degrees of corruption. Although using renewable energy is thought to have a favourable impact on Bangladesh's ecological footprint, this benefit is only noticeable in the short term and is not substantial over the long term. [58] It was shown that increased usage of renewable energy sources results in a greater ecological footprint, although the long-term effects could be more obvious. [59] Investigated the beneficial effects of using renewable energy sources on lowering CO2 emissions and environmental pollutants. Human capital has a negative relationship with emissions of environmental pollutants, which may suggest that government investments in renewable energy and education might draw resources away from polluting businesses while boosting profit growth [60].

4.4 Marginal Effects of Human Capital on Environmental Pollution

Table 6 illustrates how corruption's influence on environmental pollution sharply declines as human capital levels rise. Similarly, with an average level of human capital, the effect tends to decrease by 12%. Human capital improves the environmental performance index and lowers ecological footprints because of greater awareness of and adherence to environmental norms [61].

Table 6: Represents the marginal effects of human capital on environmental pollution

EP	CO_2		$PM_{2.5}$	
	Marginal Effects	Total Effects	Marginal Effects	Total Effects
Average CHP (0.432)	0.056	8%	0.203	41%
15^{th} percentile (0.265)	0.0721	7%	0.461	26%
30^{th} percentile (0.301)	0.0782	9%	0.490	27%
60^{th} percentile (0.418)	0.0982	9%	0.397	38%
80^{th} percentile (0.577)	0.0087	13%	0.096	51%
90^{th} percentile (0.584)	0.0019	13%	0.076	53%

CHP's minimum and complete effects on CO2 and PM2.5 emissions across various percentiles are shown in the table. The peripheral effects reveal that as human resources grow, CO2 emissions will decrease, notably between the 15thand 90thpercentiles, whereas PM2.5 emissions have a mixed pattern, with stronger impacts at lower percentiles. PM2.5 emissions consistently have a greater rate influence than CO2 throughout all percentiles, especially at the 80th and 90th percentiles, when total impacts reach 51% and 53%, respectively, while CO2 stays at 13%. The suggests that expanding human resources can have a greater influence on PM2.5 emissions and require governments to consider how to reduce pollution through human resources. Higher CO2 and PM2.5 emissions were connected to larger positively significant corruption coefficients. Human capital mitigates corruption and environmental population [62]. GDP positively and adversely affects GHG emissions, supporting the Environmental Kuznets Curve (EKC) [63]. The technique reduces pollution during later economic growth by promoting cleaner technology [64]. The strategy provided importance of environmental rules and regulations to reduce the environmental costs of economic growth [65].

4.5 Gyratory Particulars

Figure 2represents the observations made on the Environmental Kuznets Curve (EKC), which shows that GDP grows, environmental pollution ascents first, peaks and then begins to fall. The pattern is depicted by the equation $\alpha_3 \mathrm{Ln}GDPt + \alpha_4 \mathrm{LnIND}t$. The impact is 2%, while the ideal spot is approximately 1%.Economic development and environmental deterioration have a nonlinear relationship, as seen by the nonlinearity of the EKC of CO2 emissions figure. Specifically, the results point to an inverted U-shaped curve, supporting the standard EKC theory. Economic development at lower income levels would result in more CO2 emissions due to the expansion of industrial processes, increased energy consumption, and the usage of fossil fuels. However, at a certain threshold (turning point), a rise in wealth will result in a drop in CO2 emissions. It suggests that higher economic levels are associated with stronger environmental laws, cleaner technology, higher institutional standards, and more public awareness. The tipping point implies that the environmental cost of early development should be offset by a sustainable development policy and a structural change toward more ecologically friendly industries.

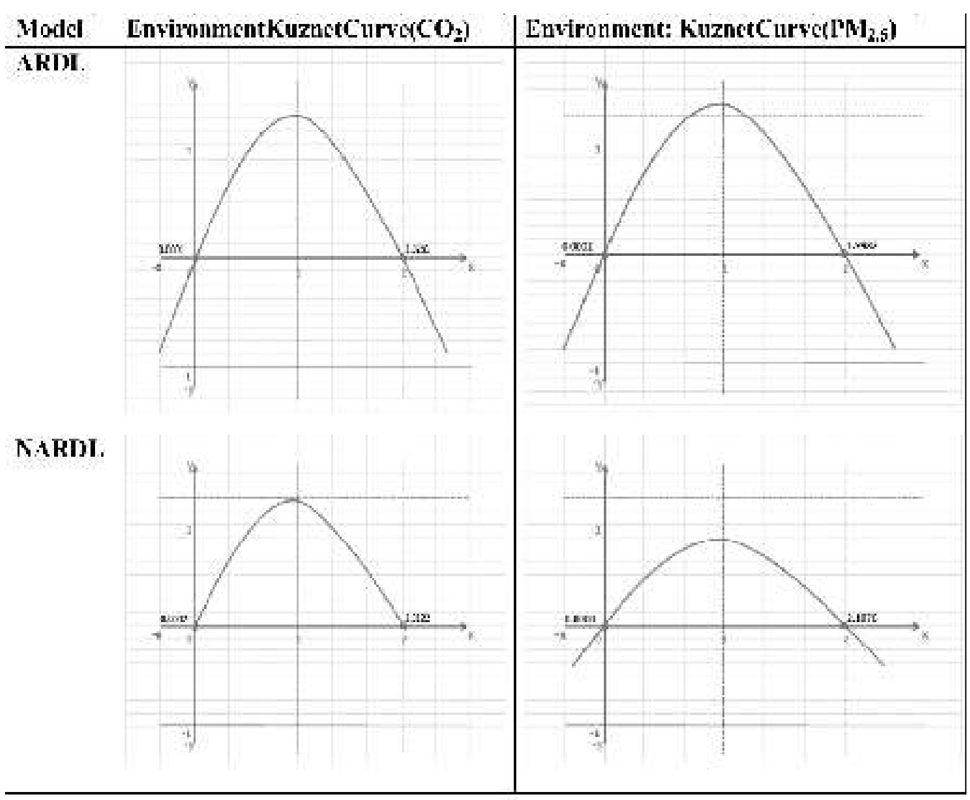

Fig. 2: Represents the ARDL and NARDL models Kuntz curves

Although the size and tipping point may differ from CO2 emissions, the nonlinear trend in the EKC findings of PM2.5 concentrations is comparable. Economic activity during the early stages of development raises PM2.5 concentrations due to industrial output, transportation emissions, and urbanization. PM2.5 concentrations begin to decline if an expected threshold income level is reached. This suggests that environmental regulations have improved, technology has advanced, more energy is being converted to clean energy, and air quality requirements are becoming stricter. The EKC-type association between growth and environmental deterioration is further supported by the inverted U-shape in both CO2 and PM2.5. The long-term equilibrium link between the variables is confirmed by the ARDL result. The two variables are not Cointegration, as indicated by the t-test results being below the upper critical levels. According to the EKC hypothesis, environmental indicators are significantly impacted by economic growth over the long term. Environmental deterioration is positively and statistically significantly impacted by corruption, indicating that institutional inefficiencies and poor governance are to blame for the increased pollution levels. However, over time, human capital has a counteracting effect on the detrimental effects of environmental degradation, thus skill development and education raise environmental awareness and technological adaptation. Some of the variables exhibit short-term volatility, but the ECT is negative and large, indicating that the long-term equilibrium has been reached. The speed of adjustment indicates how quickly equilibrium deviations are restored following a shock. According to the NARDL estimations, there is an asymmetry in the impact of important variables on environmental quality. Environmental deterioration is not equally affected by the positive and negative shocks associated with corruption and human capital. As an illustration, asymmetric institutional impacts are demonstrated by the fact that higher levels of corruption result in higher CO2 and PM2.5 emissions, whereas lower levels of corruption have a larger correcting effect. Similar to human capital, gains in human capital are more effective than losses in reducing environmental deterioration. The asymmetric long-run and short-run coefficients confirm that the direction of change in the explanatory factors affects the environment's reactions. These findings suggest that policy initiatives addressing governance reforms and human capital development may benefit the environment disproportionately. More knowledge and laws promote sustainable behaviours, lowering pollution and supporting environmentally responsible economic growth [66].

4.6 Marginal Effects of Corruption on Environmental Pollution

Because interaction run effects cannot be clearly detected, the technique assesses the marginal impact of corruption on environmental population under different conditions [67]. These marginal impacts are shown in Table 7 using CO2 and PM2.5 ARDL calculations.

Table 7: Represents the marginal effects of corruption on environmental pollution

EP	CO_2		$PM_{2.5}$	
	Marginal Effects	Total Eff ects	Marginal Effects	Total Effects
Average CHP (0.398)	0.045	7%	0.321	40%
15^{th} percentile (0.301)	0.0682	9%	0.398	23%
30^{th} percentile (0.425)	0.0576	7%	0.501	21%
60^{th} percentile (0.521)	0.0810	8%	0.416	34%
80^{th} percentile (0.602)	0.0049	10%	0.067	43%
90^{th} percentile (0.612)	0.0021	11%	0.082	48%

Defilement has minimal and total effects on ecological pollution, namely CO2 and PM2.5 emissions, across various percentiles of the Typical Debasement Discernment List. Negligible CO2 emissions affects peak at 0.0810 and decline to 0.0021 at the 90th percentile, whereas total impacts increase from 7% to 11%. Interestingly, peripheral impacts on PM2.5 are highest at the fifteenth percentile (0.398) and lowest at the 80th percentile (0.067), whereas complete impacts range from 21% to 48%, demonstrating that defilement significantly affects contamination levels at lower percentiles. Human capital improves environmental performance and reduces footprints [68]. Increased environmental compliance is responsible, and Bangladesh has similar results.

4.7 Asymmetric Effects of Corruption on Environmental Pollution

Figure 3 provided more evidence for the importance of the results of the NARDL investigation on how corruption affects CO2 and PM2.5emissions. As indicated in the figure titled Corruption Impact on CO? Emissions, the impact of corruption on CO2 emissions is depicted to be on the rise with an increment in the human capital percentiles of higher classifications. At the 15th percentile, the effect is insignificant, near to zero, yet it steadily increases at the 30th and the 60th percentile, which signifies an enhanced positive relation. This positive trend is more pronounced at the 80thpercentile and peaks at the 90thpercentile where the effect seems the strongest.

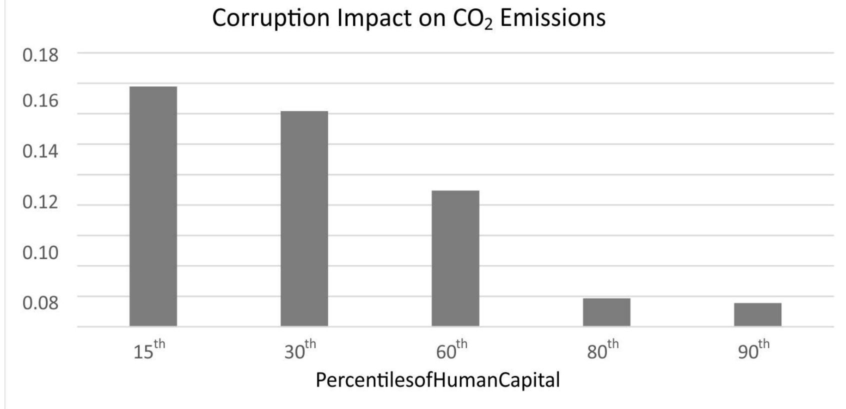

Fig. 3: Represents the human capital impact on CO_2 emissions

The findings indicate that corruption is positively associated with the CO_2 emissions of an increasingly large magnitude with increasing human capital and, therefore, in those nations, where human capital is more developed, corruption can play a more prominent role in environmental degradation.Figure 4 represents the marginal effects of corruption on PM2.5 emissions in the country.

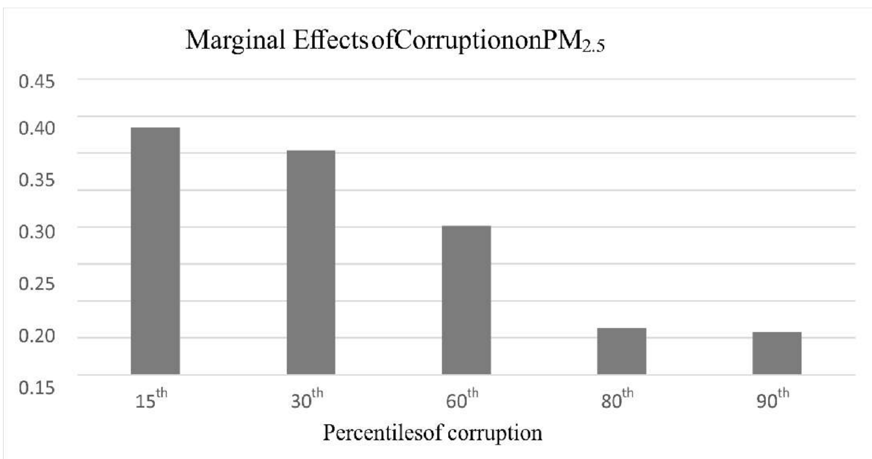

Fig. 4: Represents theMarginal Effects of Corruption on PM2.5

The figure named Marginal Effects of Corruption on PM2.5 shows that the marginal effects of corruption on PM2.5 concentrations also raise steadily with the increase in percentage of corruption. The impact is relatively low at the 15th percentile but the impact increases at the 30th and 60th percentiles indicating that there is a positive relationship that is getting stronger. This trend increases more at the 80th percentile and highest at the 90th percentile. The findings indicate that the contribution of corruption to PM2.5 pollution magnitude is significantly higher with the increasing level of corruption, which means that the worse the air quality in a country, the higher the corruption rates in it. Its emphasis on battling corruption to improving environmental conditions has major ramifications for politicians and campaigners [69].

4.8 Discussions

The study found that economic growth and institutional quality (IQ) harm the environment long- and short-term. The results show that various countries and environmental organizations worry that Bangladeshi enterprises are seen as polluters that transfer economic risks to countries with lax environmental rules [70]. Results show environmental issues rising nations like Bangladesh face. Bangladesh frequently eases environmental laws to attract international investment and economic growth [71]. Corruption increases with GDP growth. The results support the idea that corruption may boost economic growth in the near term. Corruption has positive and negative short-term relationships with CO_2 emissions, a proxy for environmental harm. [72] shows that corruption harms emerging nations' environments. Corruption makes it easier for corporations to harm the environment without penalties, hindering environmental law enforcement. Bangladesh's rapid urbanization increases pollution [73]. [74] Explored that the metropolitan areas consume more energy and resources, increasing PM2.5 and CO_2 emissions. Higher government education investment may reduce fuel emissions. Investment in education boosts human and environmental capital [38]. Higher educated people are more ecologically conscious, advocate sustainable lives, GDP and energy use affect human capital environmental damage. Bangladeshi communities lack environmental justice due to poor water management and law enforcement [75]. Depending on GDP growth and energy use, environmental pollution benefits human capital. Rising energy use will increase pollution, while anti-corruption actions may reduce it [76]. Democracy affects various economic groups differently, but population growth hurts all economies [77]. The short-term imbalance between environmental population, human capital and corruption lowers educational quality, affecting Bangladesh's human capital [78]. GDP growth and energy consumption impact on the environmental pollution-human capital sign association coefficient. Health outcomes and human capital development in Bangladesh are affected by healthcare corruption [79].

5. Conclusions

The study has explored the asymmetric and dynamic relationships between corruption, human capital, economic growth, energy consumption, and industrialization as factors contributing to the environmental situation in Bangladesh as evidenced by CO2 emissions and PM2.5 levels as environmental indicators using data from 2000 to 2023. The study employs the ARDL and NARDL models to provide new information concerning the dynamics between institutional quality and other socio-economic elements of pollution in an immensely vulnerable emerging nation. Corruption contributes significantly to the short term and the long term degradation of the environment. The results reveal that poor quality of institutions undermines environmental laws, distorts distribution of resources among people, and encourages rent-seeking behaviour, which supports the polluting-intense practices. The asymmetric estimates reveal that positive corruption shocks produce stronger negative environmental effects as compared to the beneficial effects caused by corruption reduction. Such an imbalance means that there is a faster accumulation of environmental degradation to the governance decline than a slower recuperation to changes. The theory of Environmental Kuznets Curve (EKC) is confirmed in the case of Bangladesh. The initial effect of economic growth is increased pollution; however, beyond some income level, economic growth contributes towards environmental improvement. Nevertheless, corruption presence delays the EKC turning point which suggests that institutional weakness may increase the duration of the polluting-intensive growth. Development, therefore, cannot ensure environmental sustainability when there is no good governance. The consumption of energy particularly that which depends on fossil fuels has remained a leading source of CO2 and PM2.5 emissions. The findings highlight the ecological cost of the energy system and the industrial growth in Bangladesh. The economic and industrial progress lead to the development of output, there is a lack of environmental regulations and control, which increases the level of pollution. Human capital emerges as a very essential mitigating factor. High levels of education and skills empowerment will reduce the emissions in the long run, and prevent the effects of corruption that increases pollution. Human capital enhances environmental awareness, institutional responsibility, and integrates technology. This mediating position confirms that education investments can help in economic development as well as environmental sustainability. The paper contributes to the body of work since corruption is an issue that is not limited to government matters but rather an issue that is critical to the environment. The role of human capital in the corruption game reveals the importance of institutional-social complementarities in achieving sustainable development. In the case of Bangladesh and other emerging states that have similar structural problems, the long-term environmental improvement is based on parallel improvements in governance, education, and energy reorganization.

5.1 Policy Implications

Policy wise, the results suggest that sustainable development in Bangladesh needs a combined policy that focuses on institutional change, energy shift to clean, and development of human capital. It is important to strengthen initiatives on institutional quality and anti-corruption measures. Rent-seeking and regulatory capture must be checked with transparent environmental surveillance systems, independent regulatory agencies, digital governance, and an increase in the enforcement of environmental regulations. It is essential to speed the process of energy transition to renewable and low-carbon sources. The intensity of economic growth can be lowered by expanding solar and wind power, enhancing the energy efficiency, and encouraging the use of cleaner production technologies. Human capital investment is supposed to be considered as long-term environmental policy instrument. Green production and consumption patterns can be improved by integrating environmental education into the curricula, supporting research, and innovation, and encouraging the development of green skills. Industrial policy needs to be adjusted to the environmental goals so that the development of manufacturing would not negatively affect the ecological system. The structural shift to less carbon-intensive sectors can be achieved with the help of cleaner production standards, pollution taxes, and green financing mechanisms.

5.2 Future Research Suggestions

To interpret the contribution of corruption and human capital towards environmental pollution in Bangladesh, future studies should consider the long-run trends, regional differences, cause and effect, sector studies, cross country studies, and institutions studies. The qualitative study will give a policy evaluation, climate change assimilation, community cognizance, case studies, predictive modeling, interdisciplinary methods, information availability, and policy advocacy.

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