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Impact of Energy Usage, Economic Growth and Structural Industry Changes on Carbon Emissions in Bangladesh

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ABSTRACT

This study examines the dynamic relationship between carbon (CO_2) emissions and energy usage, economic growth, and the changing industry structure in Bangladesh using annual time series data from 1972 to 2020. To this end, the ARDL Bound co-integration approach as well as the ECM method were employed to analyze the dynamics in the long and short run respectively. The findings reveal a strong positive long-run association between CO_2 emissions, economic growth, industry value added and GDP. For agriculture and services value added, no significant long-run relationship could be found. However, both industrial and service sectors show dynamism in the short run indicating that structural industry changes are already reducing CO_2 emissions. Thus, the pressing concerns regarding the increase in emissions and the imperative to achieve its growth potential, Bangladesh ought to foster innovative technological, economic, and social solutions that can harmonize energy-intensive development with a heightened emphasis on clean energy adoption, energy conservation initiatives, and efficiency enhancements.

Keywords: CO_2 Emissions, Energy Usage, Growth, Industry Structure, Bangladesh, ARDL Bound Test, ECM Method
JEL Classifications: O1, O2, Q3, Q4

1. INTRODUCTION

The globe is currently facing a significant problem in the shape of climate change. One of the main causes of this phenomenon is the rising concentration of greenhouse gases, mainly carbon dioxide (CO_2) in the atmosphere (IPCC, 2018). The world's energy consumption has been rising gradually as a result of the global economy's ongoing expansion and the structural changes in industry. This heightened requirement for energy has given rise to a corresponding increase in carbon emissions. As the economy has continued to grow at an accelerated pace, there has been a consistent deterioration in environmental conditions, putting the economic accomplishments at risk (Daizy et al., 2021). Fossil fuel combustion for energy production, transportation, and industrial activities is the primary contributor to global carbon emissions, with the industry sector alone accounting for one-third of total emissions (UNEP, 2020). According to the Intergovernmental Panel on Climate Change (IPCC) 2021 study, the world will most likely warm by 1.5°C (2.7°F) or more during the next two decades. Thus, environmental degradation brought on by CO_2 emissions is becoming more and more apparent, and it now poses an unavoidable threat in Bangladesh. It is already listed as the seventh most susceptible country to the effects of climate change in the Global Climate Risk Index 2021 (Eckstein et al., 2021).

Bangladesh is one of the fastest growing economies in South Asia and globally. In 2022 its real GDP growth rate was 7.2% and is projected to be 6.6% in 2023 (Asian Development Bank, 2023). Rapid income growth has followed with GDP per capita growing from US$401 in 1972 to US$1625 in 2020 at constant prices (World Bank, 2020). However, the country's rapid economic progress has also resulted in a sharp increase in CO_2 emissions, which have soared from 0.05 metric tonnes/capita in 1972-0.51 metric tonnes/capita by 2018 (World Bank, 2020). With Bangladesh's population and economy projected to continue growing, the demand for energy is expected to increase, leading to further emission hikes. While cutting back on energy use would be a good approach to reduce emissions, it could negatively impact the country's economic structure and growth prospects, thereby presenting a significant trade-off for Bangladesh.

Recent economic growth in Bangladesh has been accompanied by structural changes to the economy. Comparable to many other nations throughout the world, Bangladesh has followed a similar pattern of structural change as it transitioned from a traditional agricultural economy to an economy centered on industry and services. The expanding economy of Bangladesh has led to a reduction in the relative importance of the agricultural sector, as the industrial and service sectors have grown significantly. The contribution of agriculture to the country's GDP, which used to be approximately half, has now decreased to 11.63%, while the industrial sector's contribution has grown to 33.32%, and the service sector has become the most substantial contributor, making up 51.30% of GDP by 2021 (World Bank, 2021). This transformation has dramatically increased CO_2 emissions.

Although producing just 0.56 percent of the world's emissions, Bangladesh is extremely susceptible to the effects of climate change. Rainfall in the nation is predicted to increase by roughly 4% year by 2030, with subsequent increases of 2.3% and 6.7% predicted for 2050 and 2070, respectively. The land surface and food production of Bangladesh are seriously threatened by this rise in precipitation, as well as by rising sea levels and coastal erosion. The country may lose 17% of its land area and 30% of its food output as a result of these causes by 2050, (IPCC, 2021). However, more than half (56%) of Bangladesh's population already resides in regions that are extremely vulnerable to the effects of climate change. Thus to investigate the drivers of long-term increases in CO_2 emissions in Bangladesh, this study will focus on energy use, economic growth, and industry composition.

In this study, we will put light on the relationship dynamics among energy usage, changing industrial structure, and economic growth and CO_2 emissions in Bangladesh. In the next section 2 there is an examination of the literature. Section 3 presents and discusses the methodology to be used in the study. Section 4 sets forth and discusses the results. Section 5 contains discussions about the major findings, while section 6 is the conclusion and policy recommendations.

2. LITERATURE REVIEW

During the early 1990s, scientists discovered the greenhouse gas effect and its possible impact on the planet's climate in the future. It became more and more obvious over time that CO_2 emissions have warming consequences, which produce large and long-lasting changes in weather patterns. Economic growth requires the environment as a source of energy and raw materials as well as a sink for economic wastes resulted deterioration of the environmental quality. Regrettably, many nations have prioritized short-term economic gains without adequate environmental protection, leading to severe pollution and resource depletion. Focusing on that, the economic literature has explored the connection between CO_2 emissions and their various drivers through different empirical approaches.

Studies like (Wolde, 2015) for Ethiopia, (Pata, 2018) for Turkey, (Khan and Ullah, 2019) for Pakistan, and (Shikwambana et al., 2021) for South Africa have focused on the environmental pollutants and economic growth nexus and tested the validity of the EKC hypotheses. The EKC hypothesis postulates an inverted U-shaped relationship between per capita income and environmental degradation in the long run with the direction of causality. As per capita income grows environmental degradation increases, but once economic expansion reaches a certain point, it usually slows down (Kuznets, 1955). While these studies have suggested a U-shaped curve, Zhang's (2021) research showed an N-shaped curve. Additionally, Richmond and Kaufman (2006) found no significant link between economic growth and environmental contaminants.

Furthermore, in most empirical research, the association between economic growth, energy usage, and CO_2 emissions has been thoroughly documented (Soytas and Sari, 2009) for Turkey; and (Nguyen and Wongsurawat, 2017) for Vietnam. Also based on panel datasets, researchers like (Mercan and Karakaya, 2015) for selected OECD countries, (Asif et al., 2015) for GCC countries have examined the link between CO_2 emissions, and energy consumption. However, many researchers have examined the long-term relationship between environmental quality and other related macroeconomic variables without using the EKC hypothesis in the estimation model, including (Soytas and Sari, 2009) for Turkey, (Gul et al., 2015) for Malaysia, (Salahuddin et al., 2018) for Kuwait and (Nkengfack and Fotio, 2019) for Algeria, Egypt, and South Africa.

Moreover, emission levels rise when economies undergo structural change in the shift from agriculture to industrial and service sectors. Structural changes are impacting climate change. At the same time, global warming brought attention to of GHG emissions and subsequent environmental degradation in developed, developing and lower developing countries equally. (Shahbaz et al., 2017) confirmed a direct association of industrialization as a proxy of industry value added to GDP with increased CO_2 emissions. González and Martinez, 2012 studied the connection of industrialization with CO_2 emissions on the basis of the classification of industries like manufacturing and steel industries. A very few studies (Sikdar and Mukhupadhyay, 2018; Kim, 2020; Pang et al., 2021) examined the relationship between CO_2 emissions, energy consumption and changing economic structure incorporating other variables like urbanization, trade openness, foreign direct investment.

The methods utilized to examine the causal relationship between CO_2 emissions; energy consumption and economic growth in a multivariate framework have varied as has the choice of control variables. Results have (unsurprisingly) varied with some establishing causality while others failing to establish any.

Looking first at the estimation methods, researchers like (Appiah, 2018; Bah and Azam, 2017; Salahuddin et al., 2018; Pata, 2018) applied the autoregressive distributed lag (ARDL) test to examine the long run relationship between economic growth, pollution emissions and energy consumption. Most studies have observed that energy consumption and economic growth significantly increase CO_2 emissions. Some of the above authors also applied the Toda Yamamoto and Granger causality tests and some others used the vector error correction model (VECM) to examine causality as well. However, (Appiah, 2018) used both the Johansen and Julius-Johansen approach, and ARDL bounds test to verify co-integration between energy consumption, CO_2 emissions and economic growth. Again, authors such as (Pata, 2018; Ali et al., 2016) employed ARDL bounds test and the Error Correction Model (ECM) approach to examine short and long run co-integration among and found a positive association among them.

Both ARDL and Johansen-Juselius maximum likelihood procedure is applied to examine the existence of long run equilibrium relationship among the variables by (Sikdar and Mukhopadhyay, 2018). Whereas (Kim, 2020) used only the ARDL bound test approach to examine the long run association among the variables and confirmed that transformed economy structure from agriculture to industrial and service sectors increases CO_2 emissions.

However, the available empirical evidence for Bangladesh yields a mixed bag of results. Most of the studies examined the nexus between energy consumption, economic growth and CO_2 emissions (Rayhan et al., 2018; Islam et al., 2017). Furthermore, (Rayhan et al., 2018; Islam et al., 2017; Wahid et al., 2017; Shahbaz et al., 2014) incorporated other variables like industrialization, urbanization, trade openness and financial development with the above variables. Among these studies (Rayhan et al., 2018) found significant environmental degradation due to economic growth and energy consumption while trade openness and financial development showed no impact on CO_2 emissions. Shahbaz et al. (2014) scrutinized the relationship between industrialization and CO_2 emissions and applied the ARDL bounds testing approach to discover co-integration in the presence of structural breaks in the data series examined. Daizy et al. (2021) examined the impact of CO_2 emissions on agriculture, globalization, industrialization and electricity consumption over the period 1971-2014. There was no relationship between agriculture and CO_2 emissions but there was one with both electricity and globalization and CO_2 emissions in the long run. A similar but weaker relationship was found between CO_2 emissions and industrialization.

This review of the literature shows that the impact on CO_2 emissions resulting from energy usage, economic growth, and the changing economic structure is still being debated in both the theoretical and applied empirical research. Study of the long run impact of the share of the service and agriculture sector on CO_2 emissions has not been undertaken except in India and China. The bulk of studies, on one hand, have analyzed how economic growth, energy usage, industrialization, urbanization, trade openness, foreign direct investment, and globalization affect environmental quality. Few studies have examined the environmental impact of agriculture value added to GDP on CO_2 emissions. Notwithstanding, only a negligible number of studies have detected the impact of industrialization on CO_2 emissions in Bangladesh, and no study has ever attempted to examine the impact of structural economic changes from traditional agriculture to non-traditional industrial and service sectors. As a result, the present study breaks new ground in analyzing the long run and short run impacts using a co-integration approach of CO_2 emissions on economic growth, energy usage and structural economic changes in Bangladesh.

3. MATERIALS AND METHODS

3.1. Data

Annual time series data from 1972 to 2020 of GDP per capita (GDP) (constant 2015 US$), energy usage (EU) (kg of oil equivalent per capita), and CO_2 emissions (CO_2) (metric tonnes per capita) were utilized in the analysis. The rest of the structural variables are Industry (including Construction) value added (IS) (constant 2015 US$), Agriculture value added (AS) (constant 2015 US$), and Services value added (SS) (constant 2015 US$). The data for GDP per capita, industry, agriculture and services value added come from World Development Indicators (WDI) (World Bank, 2020). Since data for CO_2 emissions and energy use in WDI from 1972 to 2020 is unavailable, data from the BP Statistical Review (2020) is used instead. However, the data for CO_2 emissions are transformed from tons to metric tons per capita and primary energy usage converted from millions of tonnes of oil to kilograms (kg) of oil and then calculated as kg of oil equivalent per capita. Furthermore, all are expressed as natural logarithms, to reduce the effect of heteroscedasticity on the results and enable more stable variance of the data.

3.2. Methodology

When the above specified factors are incorporated in the model, this study develops a framework to analyze the long-run and short-run dynamics of CO_2 emissions– which is a significant development on more recent studies. Employing techniques such as the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) test to check the presence of unit roots, the ARDL bound test along with ECM test for co-integration is implemented to define long and short run connections between the variables respectively.

3.2.1. ADF stationarity tests

Non-stationary data can frequently result in spurious regressions in the form of white noise, which can skew findings. To avoid this, the order of integration of the variables is determined using a unit root test. To check for the existence of unit roots, this study uses the ADF test which is an excellent way to test the sensitivity of the findings as well as ensures a reliable model for determining the order of data integration. The ADF regression model has the following specifications:

For intercept and trend:

$$\Delta y_t = \mu + \delta y_{-1} + \lambda_t + \sum_{i=1}^{p} Q_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

For intercept:

$$\Delta y_t = \mu + \delta y_{-1} + \sum_{i=1}^{p} Q_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

Here y_t resembles each time series variable to be used in this paper. Δy_t stands for first difference of the variable y_t, the intercept term is denoted by μ, the residual term is denoted by ε_t, and lastly the optimum lag length for which the lagged value of variable is significant has been indicated by p.

The ADF's null hypothesis is that $\delta = 0$ against the alternative hypothesis of $\delta < 0$. If the variables do not reject the null, the series is non-stationary, whereas rejection means the series is stationary. Furthermore, a series is an I(0) series if it is stationary at its level. When a series stays stationary after differencing once, it is referred to as an I(1) series.

3.2.2. ARDL Bound co-integration test

The next stage is to check for the presence of a long-run equilibrium relationship after checking that all of the variables are integrated in the same order. It's a useful strategy for uncovering long-term correlations between variables that are generally obscured by noise from short-term variations. Researchers (Alshehry and Belloumi, 2015; Jebli and Youssef, 2017) have traditionally used several co-integration strategies to explore long-run relationships (Phillips and Hansen, 1988; Engle and Granger, 1987; Johansen and Juselius, 1990). When variables are integrated at their lowest level, I(0), or their initial difference, I(1), the aforementioned procedures produce unintended biased results. To overcome this the ARDL model (Pesaran and Shin, 1999; Pesaran et al., 2001) was developed, which can yield unbiased estimates even in the presence of a mixed I(0) and I(1) series. Further, long and short-run variable estimates can both be measured by this model and even if the sample size is small, it can generate statistically significant and consistent results (Narayan and Smyth, 2005).

The ARDL model is used in this study as the co-integration technique. To demonstrate the presence of any co-integration or long-run link among the specified variables, the ARDL model usually employs a simple test known as the bound test. Therefore, the following ordinary least squares (OLS) equation is estimated for the ARDL bounds test approach.

$$\begin{aligned}\Delta lnCO_{2t} &= \propto_o + \sum_{i=1}^{p_1}\beta_{1i}\Delta lnCO_{2t-1} + \sum_{i=1}^{p_2}\beta_{2i}\Delta lnEU_{t-i} \\ &+ \sum_{i=1}^{p_3}\beta_{3i}\Delta lnGDP_{t-i} + \sum_{i=1}^{p_4}\beta_{4i}\Delta lnIS_{t-i} + \sum_{i=1}^{p_5}\beta_{5i}\Delta lnAS_{t-i} \\ &+ \sum_{i=1}^{p_6}\beta_{6i}\Delta lnSS_{t-i} + \gamma_1 lnCO_{2t-i} + \gamma_2 lnEU_{t-i} + \gamma_3 lnGDP_{t-i} \\ &+ \gamma_4 lnIS_{t-i} + \gamma_5 lnAS_{t-i} + \gamma_6 lnSS_{t-i} + U_{t-i} + \sum_{i=1}^{p_5}\beta_{5i}\Delta lnAS_{t-i} \\ &+ \sum_{i=1}^{p_6}\beta_{6i}\Delta lnSS_{t-i} + \gamma_1 lnCO_{2t-i} + \gamma_2 lnEU_{t-i} + \gamma_3 lnGDP_{t-i} \\ &+ \gamma_4 lnIS_{t-i} + \gamma_5 lnAS_{t-i} + \gamma_6 lnSS_{t-i} + U_{t-i} \qquad (3)\end{aligned}$$

Here, Δ operator indicates first-difference of that variable, and all the β coefficients, and γ coefficients have been written to represent the short-run dynamic relationships, and the long-run dynamic relationships respectively. α_0 has been included to represent the intercept term, and the white noise error term has been addressed by u. The p indicates the optimum lag lengths, and the subscript (t–i) beside any variable refers to i^{th} lag of that variable.

The bounds test is evaluated using the F-statistic, which follows an asymptotic distribution, and under a no co-integration null, this test statistic is assumed to be non-standard. During the bounds testing, the presumption of no co-integration in the null (i.e., H_0: All the γ coefficients = 0) is checked against the alternative hypothesis of co-integration (i.e., H_A: Not all the γ coefficients = 0) in order to identify the presence of co-integration. However, the decision depends on the comparison between calculated F-statistics, and the critical value. Two types of asymptotic critical values are commonly used here (Pesaran et al., 2001). One is the upper critical bound (UCB), and other one is the lower critical bound (LCB). Hence, if the calculated F-statistics is below the lower bound critical value then the null hypothesis (H_0) will not be rejected, indicating that no long-run relationship exists between the variables. On the contrary, if the computed F-statistic is greater than the upper bound critical value then H_0 is rejected, which means the variables are co-integrated. If the calculated F-statistic falls between the lower and upper bound critical values the results of the test will be inconclusive.

This estimated F-statistic, however, is quite sensitive to lag order selection. If the lag length used is incorrect, it can lead to misleading findings. As a result, rather than leaping into the bounds test after the ADF test, the ideal number of lags (p) must be determined using lag order selection criteria that will minimize mistakes. To that purpose, AIC criteria were used in this study (Akaike, 1969), and the lag with the lowest AIC value was chosen. At each stage, AIC criteria was used because it produces superior outcomes when the goal is prediction.

Next, because the limits test revealed co-integration among the variables, it is now possible to estimate a conditional ARDL model to capture the model's long-run dynamics. This model can be described in the following way:

$$\begin{aligned}lnCO_{2t} &= \propto_o + \sum_{i=1}^{p_1}\gamma_{1i} lnCO_{2t-i} + \sum_{i=1}^{p_2}\gamma_{2i} lnEU_{t-i} + \sum_{i=1}^{p_3}\gamma_{3i} lnGDP_{t-i} \\ &+ \sum_{i=1}^{p_4}\gamma_{4i} lnIS_{t-i} + \sum_{i=1}^{p_5}\gamma_{5i} lnAS_{t-i} + \sum_{i=1}^{p_6}\gamma_{6i} lnSS_{t-i} + U_t + \sum_{i=1}^{p_3}\gamma_{3i} lnGDP_{t-i} \\ &+ \sum_{i=1}^{p_4}\gamma_{4i} lnIS_{t-i} + \sum_{i=1}^{p_5}\gamma_{5i} lnAS_{t-i} + \sum_{i=1}^{p_6}\gamma_{6i} lnSS_{t-i} + U_t \qquad (4)\end{aligned}$$

Finally, an error correction model is estimated and it provides advantages by capturing the short-run dynamics of a long run relationship. It accomplishes so by determining factors such as the rate at which the system adjusts to equilibrium. The short-run parameters are determined by estimating an error correction model based on the long-run estimates. The ECM can be defined as follows:

$$\Delta lnCO_{2t} = \propto_o + \sum_{i=1}^{p_1} \beta_{1i} \Delta lnCO_{2t-1} + \sum_{i=1}^{p_2} \beta_{2i} \Delta lnEU_{t-i}$$
$$+ \sum_{i=1}^{p_3} \beta_{3i} \Delta lnGDP_{t-i} + \sum_{i=1}^{p_4} \beta_{4i} \Delta lnIS_{t-i} + \sum_{i=1}^{p_5} \beta_{5i} \Delta lnAS_{t-i}$$
$$+ \sum_{i=1}^{p_6} \beta_{6i} \Delta lnSS_{t-i} + \theta ECT_{t-1} + U_t + \sum_{i=1}^{p_5} \beta_{5i} \Delta lnAS_{t-i}$$
$$+ \sum_{i=1}^{p_6} \beta_{6i} \Delta lnSS_{t-i} + \theta ECT_{t-1} + U_t \quad (5)$$

ECT_{t-1} stands for the error correction term, and θ describes the speed at which any short-run deviations in this framework adjust to the long-run equilibrium. In this study, a significant negative ECT_{t-1} is preferred because it implies a convergent correction process from short to long-run equilibrium.

3.2.3. Diagnostic tests

The ARDL model's stability based on residual diagnostic tests such as serial correlation, heteroscedasticity and normality was used. The Breusch-Godfrey Lagrange multiplier examines the residuals for serial correlation (Breusch, 1978). Second, the Breusch-Pagan-Godfrey tests reveal heteroscedasticity in the residuals (Breusch and Pagan, 1979). Finally, the Jarque-Bera test is used to determine whether the residuals are normal (Porter and Gujarati, 2009). Furthermore, the cumulative sum of recursive residuals (CUSUM) and cumulative sum of square of recursive residuals (CUSUMSQ) were used to show if the model parameters are stable.

4. RESULTS

The descriptive statistics show some statistical measures of the variables in Table 1.

Figure 1 shows the time-series plots of the underlying variables, with a rising trend for all of the series. Therefore, the graphic representation implies that these series are linked in some way. However, robust statistical procedures were utilized to verify co-integration among the variables.

4.1. Unit Root Tests

The unit root test was conducted to check the reliability of the bounds test result (Van and Bao, 2018). This is done by using the ADF unit root test which examined the underlying data with the specifications given by (1) and (2). The results are delineated in Table 2. The ADF test results indicates that at 1% level of significance, all variables except industry value added are found to be integrated of order (1). So, industry value added is stationary at I(0). In addition to that, no I(2) variables are present. Since the proposed model has both I(0) and I(1) variables, the appropriate method for modeling the data is the ARDL Bounds test.

4.2. Optimal Lag Selection by VAR

The optimal lag order was selected to estimate the ARDL model utilizing the unrestricted VAR model. All the criterions suggest using lag two for conducting the ARDL model and in this study the optimal lag length (p) is selected based on the Akaike or Schwarz information criterion. In addition, the statistical software Eviews recommends ARDL (LCO2, LEU, LGDP, LIS, LAS, LSS) = ARDL (1, 1, 2, 1, 0, 2) as the most suitable model. Optimum lag selection criteria are shown in Table 3.

4.3. ARDL Estimates and the Bound Tests

Table 4 depicts the ideal ARDL model (1, 1, 2, 1, 0, 2). This model's adjusted R-square, R-square, F-statistic, and Durbin-Watson statistic are all excellent, confirming the model's fitness. After determining the appropriate lag length, the ARDL bounds test was run. Table 5 shows the estimated F-statistic is 4.86, and though not all of the series are I(0), it was compared it to the UCB at a 1% level of significance, and it successfully exceeded the UCB value of 4.68. As a result, the statistical evidence shows that the study variables have a co-integrating relationship.

4.4. Long-run and Short-run Results

The long-run results are demonstrated in Table 6. CO_2 emissions has a positive long-run linkage with economic growth. That implies a 1% increase in economic growth will induce CO_2 emissions to rise by 3.7%. This finding is similar to (Appiah et al., 2019; Pata, 2018; Nkengfack and Fotio, 2019; Bah and Azam, 2017). There is also observed a positive association between CO_2 emissions and share of industry. This result suggests that, keeping other variables constant, a 1% decrease in industrial share will increase CO_2 emissions by 1.54% and this finding matches with (Pata, 2018; Shahbaz et al., 2017). So economic growth has the highest impact on degrading Bangladesh's environment. On the contrary, the results show a strong negative and significant long-run association between energy usage and CO_2 emissions. The coefficient of energy usage shows a 2.38% decrease in CO_2 emissions, presenting a contradiction with the findings of (Ali et al., 2016; Van and Bao, 2018), except the studies of (Thao, 2015; Gokmenoglu and Sadeghieh, 2019) confirmed a significant

Table 1: Summary statistics

	LCO_2	LEU	LGDP	LIS	LAS	LSS
Mean	−1.770006	4.992245	6.501109	23.31973	23.43628	24.45205
Median	−1.940023	4.927675	6.372837	23.27619	23.30656	24.36168
Maximum	−0.446287	5.840642	7.393677	25.14876	24.26615	24.66885
Minimum	−2.943668	4.479001	5.995109	21.36288	22.84464	23.44083
Std. Dev.	0.664496	0.367658	0.411855	0.994787	0.438998	0.650720
Skewness	0.350746	0.715840	0.736914	0.151859	0.410166	0.276950
Kurtosis	2.013408	2.505009	2.319194	1.994039	1.842832	1.909871

Source: Author's calculation.

Figure 1: Representation of time series pattern of all variables (a) Carbon emissions, (b) Energy use (c) Economic growth (d) Industry share (e) Agriculture share (f) Service share

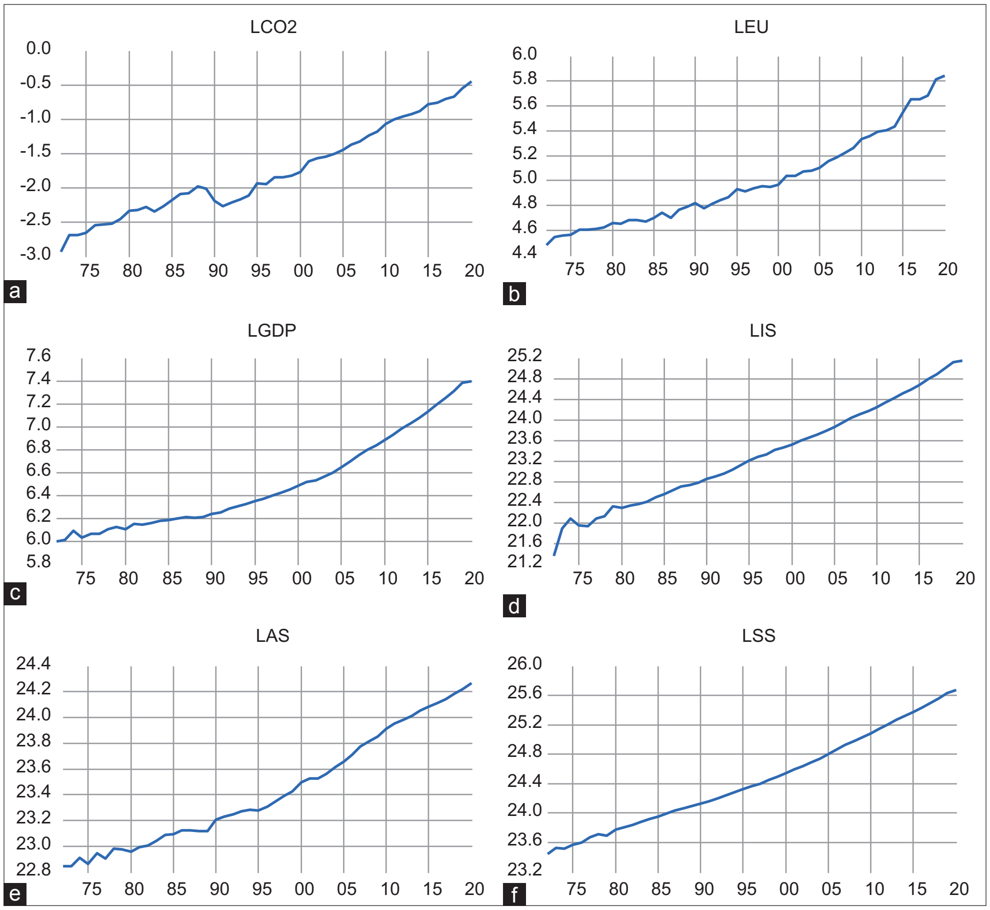


Table 2: Results of ADF stationary test

Variables	Intercept		Intercept and Trend		Outcome
	Level	1st difference	Level	1st difference	
	t-statistics	t-statistics	t-statistics	t-statistics	
LCO_2	0.2905	−6.7924***	−1.3193	−6.9468***	I (1)
LEU	4.7479	−6.8867***	1.8556	−7.1250***	I (1)
LGDP	4.8039	−5.8233***	0.3613	−9.6119***	I (1)
LIS	-0.7382	−10.1847***	−4.0309**	−4.7767***	I (0) I (1)
LAS	1.9241	−9.1146***	−1.4963	−10.3834***	I (1)
LSS	5.5847	−7.8397***	0.3179	−11.5578***	I (1)

Source: Author’s Calculation. 1%, 5%, and 10% significance levels are denoted by ***, **, and *respectively.

Table 3: Optimum lag selection by VAR

Lag	Log L	LR	FPE	AIC	SC	HQ
0	345.9713	NA	2.10e-14	−14.4668	−14.2306	−14.3779
1	688.4956	583.0201	4.61e-20	−27.5104	−25.8571	−26.8882
2	769.2682*	116.8626*	7.39e-21*	−29.4156*	−26.3452*	−28.2602*

*indicates lag order selected by the criterion.
LR: Sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan- Quinn information criterion
Source: Author’s calculation.

negative association of energy usage with CO_2 emissions in the long-run.

The long-run share of the agriculture and service sectors both are statistically insignificant in this study which is similar to (Daizy, et al., 2021) who also found a significant negative association between share of agriculture and CO_2 emissions. Furthermore, (Sikdar and Mukhpadhyay, 2018) also showed a statistically insignificant relationship between the share of industrial, agriculture and services with CO_2 emissions as industrial structure has no influence on environmental degradation. However, (Kim, 2020) showed that industrial composition notably deteriorates the environment in the long run.

After confirming the long run links of the variables, ECM was adopted to identify the short run dynamics of these variables. The short run dynamics are shown in Table 7. The lagged value of the error correction term ECT (−1) is significantly negative at 1% and the coefficient value means that convergence towards equilibrium will take place at the speed of 0.326% which is good. The result is also significant as is clear by its t-value and the related P-value. The results further reveal that short-run energy usage, the share of service sector (lagged) and industrial share increase short-run CO_2 emissions in Bangladesh which are positively significant at 5% and 1% level respectively. This result is like (Appiah, 2018; Bah and Azam, 2017; Salahuddin et al., 2018; Pata, 2018). Whereas economic growth and its 1-year lag both contribute to decrease CO_2 in the short run.

Table 4: ARDL estimation results

Variable Name	Coefficients
LCO_2(−1)	0.6738***(0.0924)
LEU	0.7209**(0.2549)
LEU(−1)	−1.4578***(0.2695)
LGDP	−1.7850**(0.8123)
LGDP(−1)	2.1817**(0.7115)
LGDP(−2)	1.8086**(0.5871)
LIS	0.8639**(0.3019)
LIS(−1)	−0.3613 (0.2192)
LAS	0.0375 (0.3029)
LSS	0.9660*(0.5149)
LSS(−1)	0.5532 (0.7413)
LSS(−2)	−2.0501**(0.7451)
C	−2.5432 (2.3032)
Adjusted R-Squared	0.9955
R-Squared	0.9966
Durbin-Watson Statistic	2.0043
F-Statistics	853.8552

Source: Author's calculation using Eviews. Values in parentheses are standard errors. 1%, 5%, and 10% significance levels are denoted by ***, **, and * respectively.

Table 5: Results of bounds tests

Calculated	10%		5%		2.5%		1%	
F-statistic	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
4.8608***	2.26	3.35	2.62	3.79	2.96	4.18	3.41	4.68

Source: Author's Calculation. 1%, 5%, and 10% significance levels are denoted by ***, **, and * respectively.

Table 6: Estimates of long-run coefficients

Variables	Coefficients	t-statistics	Prob.
LEU	−2.383873	−2.614701	0.0132**
LGDP	3.698464	2.870102	0.0070**
LIS	1.540864	1.924685	0.0601*
LAS	0.115252	0.112172	0.9113
LSS	1.627591	0.955211	0.3462

Source: Author's Calculation. 1%, 5%, and 10% significance levels are denoted by ***, **, and * respectively.

4.5. Diagnostic Tests

All diagnostic checks indicate that the model passed all tests. The results of tests for serial correlation, heteroscedasticity, and normality of residuals are reported in Table 8 and Figure 2.

The error correction model was subjected to stability and reliability testing. Figures 3a and b show that the plots of CUSUM and CUSUMSQ statistics are within the 95% critical bounds indicating all coefficients of the ECM model are reliable and stable.

5. DISCUSSION

The empirical results of the study support a longer period interconnection of CO_2 emissions with economic growth, industrial share and energy usage. GDP per capita growth strongly increases CO_2 emissions. Bangladesh has had tremendous rates of economic growth in the recent past that helped the country graduate from a lower to middle income country via increasing GDP per capita. The link between increasing CO_2 emissions and growing GDP per capita is consistent with most empirical studies. Therefore, GDP per capita increases show a statistically significant impact on the environment and a 3.7% increase in CO_2 emissions results as national income increases by 1%. This is an alarming long-term threat to Bangladesh as it is already extremely vulnerable to climate change. However, the short run effects of GDP per capita are not as dramatic and climate change mitigation and CO_2 emission reduction policies as well as initiatives that were driven largely by economic, energy security and local environmental concerns (Xenarios and Polatidis, 2015) can ameliorate the long run trend.

Table 7: Estimates of short-run coefficients

Variables	Coefficient	t-statistic	Prob.
C	−2.543264	−5.862646	0.0000***
D (LEU)	1.785033	2.197463	0.0244**
D (LGDP)	−2.785073	−4.299311	0.0001***
D (LGDP(−1))	−1.808625	−4.341420	0.0001***
D (LIS)	0.863950	3.953095	0.0004***
D (LSS)	0.963039	2.152271	0.0386**
D (LSS(−1))	2.050105	3.180745	0.0031**
CointEq(−1)*	−0.326154	−5.783902	0.0000***
Adjusted R-squared	0.571147		
R-squared	0.636407		
Durbin-Watson	2.004329		

Source: Author's Calculation. 1%, 5%, and 10% significance levels are denoted by ***, **, and * respectively.

Table 8: Diagnostic test analysis

Types of tests	Test statistics	P-value
Breusch-Godfrey LM test for autocorrelation	0.416220	0.8121
Breusch-Pagan-Godfrey heteroscedasticity test	11.50722	0.3315
Jarque Bera test for Normality	1.031546	0.5970

Source: Author's Calculation

Figure 2: Result of Jarque-Bera normality test

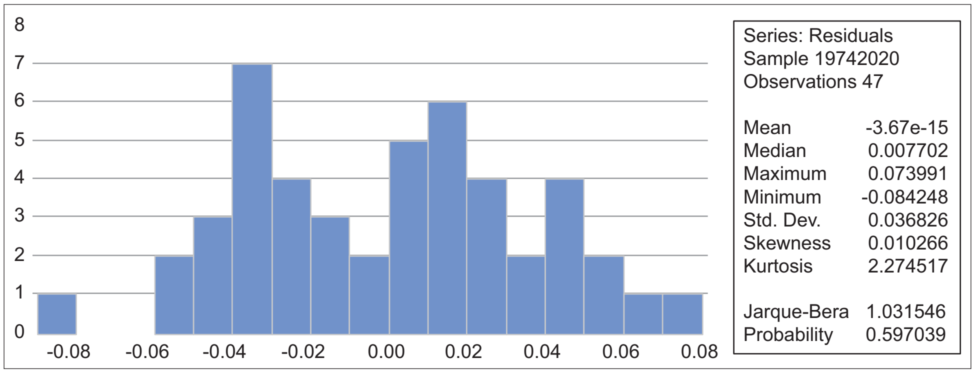
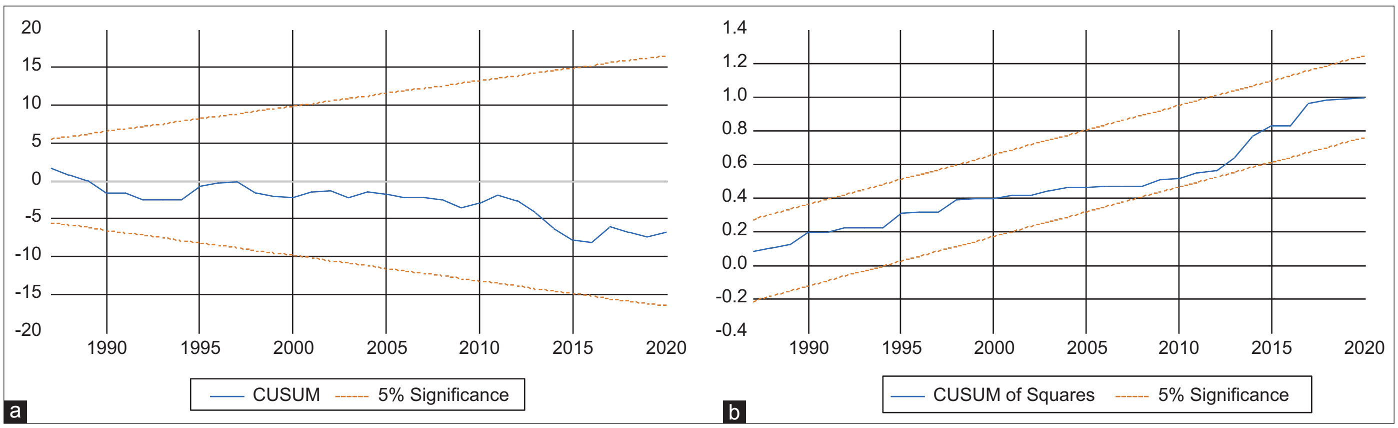


Figure 3: Representation of (a) cumulative sum of recursive residuals, and (b) cumulative sum of squares of recursive residuals



The study results show a negative significant long run association between energy usage and CO_2 emissions which is contradictory to the findings of others. Bangladesh has developed a good policy framework during the last decades, compared to many other developing countries, with initiatives like the new National Environment Policy, a very long-term Delta Plan 2100 along with Vision 2041. In addition, the government successfully introduced affordable renewable energy solutions through a public-private partnership and expanded other renewable energy options (The World Bank, 2021). Therefore, it can be stated that primary energy usage in Bangladesh is still increasing CO_2 emissions in the short run, as in the long run there is a significant improvement in environmental efforts to ameliorate this outcome.

Increasing industrialization has a significant increasing impact on CO_2 emissions in both the long and short run. The continued expansion of services value added has already revealed its short-term environmental impact due to excessive generation of electricity. In contrast, because CO_2 emissions were of interest rather than non-CO_2 GHG emissions, the results found no substantial long-term influence of agriculture value added on CO_2 emissions. As a result, switching from traditional (agricultural) to nontraditional (industry and services) industrial mix increased CO_2 emissions which is similar to the findings of (Wahid et al., 2017), who concluded that Bangladesh's rapid economic transformation from rural to industrialization has a direct impact on rising CO_2 emissions.

6. CONCLUSIONS

The economy of Bangladesh has seen significant structural changes over the past several decades, with a sharp decline in the share of GDP that comes from the agricultural sector. In general, the country's economic growth is characterized by a thriving industrial and service sector, and this trend is likely to continue into the future. However, the changing industrial mix has been endangering the country's growing economy by gradually harming the environment.

This study aimed to understand the long-run and short-run relationship between CO_2 emissions, energy usage, economic growth and industrial structure using data from 1972 to 2020. The results confirmed that both GDP per capita and increasing industrial (including construction) value added to GDP result in more CO_2 emissions. The service sector showed its dynamism in the short run and its growth may cause serious impacts on environment. However, it was revealed that energy usage showed a different outcome than found in other investigations. According to this research, long-term energy use would improve environmental quality since Bangladesh has adopted a number of policies to encourage climate change investments. At the same time there have been new environmental guidelines promoting green financing, fostering green banking and establishing dedicated funds. Bangladesh is also active in seeking grant financing from the international community to improve its capacity to address climate change, particularly compared with other emerging countries in Asia.

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