Poverty, Income inequality and Carbon Emission (CO2e) in Bangladesh: Evidence from ARDL and NARDL model

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Abstract

Many researchers have tried to bring out the relationship between poverty and carbon emission in the environment that to a higher percentage result in environmental degradation in Bangladesh, India, Pakistan, among other countries across the world. Environmental concern remains the topmost factor of concertation by different organizations in the world. In 2021, for instance, many countries were declared susceptible to the increasing environmental degradation that could result in cases of famine, among other factors. Environmental protection is currently the priority of many firms, businesses, and countries in achieving sustainable development goals (SDGs). A significant number of studies has been done on the impact of population growth and poverty on carbon emission in Bangladesh. However, the symmetric and asymmetric impact of income inequality, poverty and population on carbon emissions (CO2e) has not been conducted in Bangladesh. Thus, this study was conducted on the short-run and long-run impact of poverty, income inequality, population and Gross Domestic Product (GDP) per capita on carbon emission in the country. This effect was investigated using Autoregressive Distributed Lag (ARDL) and also the Non-linear Autoregressive Distributed Lag (NARDL) cointegration method in Bangladesh using the 1983 to 2020 yearly data period. Poverty, population density, and GDP per capita raise short-term carbon emissions, whereas economic disparity has minimal influence on long-term emissions. Asymmetric results show economic disparities decrease carbon emissions. The NARDL findings suggest that Bangladesh's economic growth positively influences carbon emissions.

Introduction

Global carbon emissions have increased significantly over the past several decades, and governments and academic scholars throughout the world are keeping an eye on this trend to discover whether there is a link between these economic difficulties and the rise in carbon emissions (Khan and Yahong 2021a). Researching these issues and providing appropriate information to environmental quality protection policymakers is essential. Environmental degradation has long been considered a regular side effect of most economical operations, particularly in developing countries (Baloch and Suad 2018). Faster expansion in the economy leads to a rise in the consumption of fossil fuels for industrialization and supporting economic growth, which has a negative impact on rising nations' environmental quality (Yang et al. 2020). Deteriorating environmental quality is also linked to nations with weak financial institutions. In contrast, countries with strong financial institutions fund green energy and environmentally friendly activities, both of which have the opposite effect. Economic activity may be connected to environmental deterioration, but there are nations in the same stage of growth economically that have varying degrees of environmental quality, which leads me to conclude that this is not the case.

Foreign direct investment (FDI), an expansion in international trade activities, and fossil fuel energy for production boost economic development while worsening environmental quality; The earlier study implies a relationship between wealth distribution and environmental quality (Saelim 2019a). There are several possible explanations for the link between income inequality and environmental degradation or improvement. In Bangladesh, poor individuals will do whatever it takes to get what they need, even if it means causing harm to the environment in the process. As an illustration, abundant natural resources are being utilized to meet their specific requirements (Sarkar et al., 2018). As a result of a lack of educational resources in low-income countries, fossil fuels and other food waste can be used to generate natural resources. Counties and people in these regions are dependent on natural resources because they lack access to modern technologies, renewable energy sources, and environmental protection measures.

Rising carbon dioxide emissions (CO2e) are a severe threat to environmental quality and long-term economic growth in many nations. As environmental deterioration worsens, governments worldwide are feeling the heat to reduce CO2e emissions and prioritize economies with low carbon emissions (Mondal et al., 2010a). To control and limit CO2e emissions, several developing and developed countries have come to accords, including the "Paris Agreement," the "Kyoto Protocol," and the "United Nations Framework Convention on Climate Change" (UNFCCC) (Khan et al. 2018a). Because so many industrialized and wealthy nations have implemented policies to reduce CO2 emissions, the need for further reductions has become apparent. However, as the quality of the environment has deteriorated as a result of economic activity, concerns about sustainable development have grown in importance. The United Nations' Sustainable Development Goals (SDGs) focus on environmental improvement and poverty eradication (Azad et al., 2006). Providing a safe and healthy environment for the human race requires the cooperation of all countries, developed and developing (Baloch et al. 2020a). When it comes to reducing poverty, most less developed countries increase their manufacturing capacity and industrialization level. However, the primary goal of economic activity is to increase economic growth, which leads to a rise in CO2e, which in turn has a negative impact on sustainable development and the well-being of humankind.

As a result, the study believes that in order to close current and future gaps, further study on the impact of poverty on carbon emissions and the role of institutions at the global level is required. A previous study showed the impact on carbon emissions of institutional quality and the regulatory effect of institutions, or that generated an index of institutions and used mixed factors (Grunewald et al. 2017a). There are six metrics that may be used to evaluate institutions: voice and accountability; the rule of law; regulatory excellence; political stability; corruption control; and government efficiency. The state's legal system is represented by the first three indicators, while its political system is represented by the last three. To understand the impact of these six indicators on economic carbon emissions, we combine them with income inequality and other factors. Each environmental quality indicator has a specific function to play. For each of the six variables, we created an indicator of institutional quality and assessed its impact on carbon emissions. The next step is to create an index based on three different legal system measures. Additionally, we create an index based on political indicators. In the model, we also use a variety of indicators specific to each political system.

Sustainable development and economic progress are beneficial to the elimination of severe poverty, particularly if they are not coupled with environmental damage and income disparity. Numerous studies have looked at the relationship between CO2e emissions and wealth disparity and concluded that as the income gap widens, so does the environment's quality. Ultimately, from the perspective of undeveloped nations like Bangladesh, Pakistan, Mumbai, among others, the link between CO2e and wealth disparity could lessen poverty, but at the same time, it promotes environmental degradation (Khan and Yahong, 2021b). However, in many nations, especially emerging countries like South Asia, including Bangladesh, the link between extreme poverty and income disparity and population, economic growth, and environmental degradation has been disregarded. Research on other environmental concerns has received the bulk of attention in industrialized nations, but empirical research on developing economies like Bangladesh have been few, as evidenced by previous literature reviews.

As opposed to rich countries, Less Developed countries LDCs are less likely to meet the goals of the SDGs. To enhance the living conditions of poverty in Bangladesh, this study mainly focused on the country's economy, which is always striving to expand and develop, minimize inequalities of all kinds (especially income inequality), eradicate severe poverty, and manage population growth. Extreme poverty is one of Bangladesh primary causes of high energy production and consumption, which results in high CO2e emissions. As a result, the country's energy supply is mostly derived from fossil fuel sources (Khan et al., 2018b). Bangladesh's environmental deterioration is on the rise as a result of the country's increased use of energy, which releases poisonous and dangerous pollutants into the atmosphere and water supply.

During this period, Bangladesh saw an average of 24702 kt, with a high of 3509 kg in 1972 and a low of 3509 kg in 2018. The most recent tally is 82760 kt, which was from 2018. According to data from 186 countries, the global average for 2018 was 192252 kt (Rahman, 2021). A country comparator or global rankings can be used to observe how the metric has changed over time (World Bank, 2021). To see changes over time, check out the global rankings for that measure or use the comparison by nation tool. According to the latest recent estimates, Bangladesh is expected to generate 0.64 tons of CO2 per person by 2020. (Nwokoro and Chima, 2017). The average annual growth of 5.48 percent from 1971 to 2020 in Bangladesh's CO2 emissions per person was 0.05 tons of CO2 per person. By 2030, if given $175.9 billion, Bangladesh may reduce greenhouse gas emissions by as much as 21.85 percent if it participates in efforts to keep global warming at 1.5 degrees Celsius over pre-industrial levels and avoid catastrophic climate change (Hoque et al., 2014). At this rate, Bangladesh will create roughly 409.4 million metric tons of carbon dioxide equivalent (MtCO2e) by 2030, based on current trends. This may be reduced to 319.94 million tons, according to the most current Nationally Determined Contributions (NDCs) it has made (Uzair Ali et al. 2020).

It was expected that natural gas (63.31 percent), furnace oil (24.72 percent), diesel (4.59 percent), imported 7.63 percent, coal (2.70%), hydro (1.63%), and wind (00.01%) would make up the majority of Bangladesh's 2019 energy supply. According to research, natural gas has been one of Bangladesh's key sources of power in the previous two decades. As a result, the study's goal was to determine the country's energy sector's carbon footprint (Hoque and Das, 2013). Short and long-term pollution cutback techniques (i.e., thermal and solar energy) have been halted for environmental safety, thus incorporating the balance of payment, energy security, economic growth, and environmental sustainability in the overall strategy (Uzair Ali et al. 2020). Power officials are still dealing with the present energy crisis in the form of

June 2017's 15,953 MW power outage. This year's annual report from Bangladesh Power Development states that the country suffered a total of 32 mega kilowatt-hours of load shedding (MKWH).

Global Vision 2041 is a five-year plan established by the government with the following objectives: (1) developing a high-income country; (2) exploiting local natural resources (such as gas and coal); (3) developing high-quality power networks; (4) maximizing the use of renewable energy; and (5) stabilizing the supply of energy. A rapid economic expansion, strong financial health, a plentiful supply of energy, and environmental preservation are all components of the strategy. China and India have reached an agreement on two major power projects, both of which are rated at 1320 megawatts (MW). One project will cost $2 billion, while the other will cost $1.49 billion for India's Rampal coal power station (Khan et al. 2018c). Since coal-fired power plants have a large carbon footprint compared to other forms of renewable energy, they are more environmentally costly to construct, and this could result in significant climate change mitigation expenditures (Khan, 2019a). The current condition of electrical construction in Bangladesh does not match the requirements for long-term sustainability or long-term sustainability through the use of renewable energy sources. According to (Wang et al. 2021a), carbon dioxide emissions are responsible for more than half of global warming. According to Islam and Ghani (2018a), the Earth's environmental changes are similar to the dispersal of humans throughout the planet. Bangladesh was unable to demonstrate a significant reduction in CO2 emissions at the United Nations Climate Change Conference (COP-21). Due to the goal of "affordability" in environmental transition, the greatest reduction in CO2 emissions needs donations from the global climate financing business, which necessitate the identification of advanced technology capabilities and their application (Abdullah et al. 2015a). According to Power System Master Plan, Bangladesh had five primary targets to foster industrial development and decided to open 100 Special Economic Zones by 2030 Vision-2040 in order to attract foreign investment, industrial need, and energy capacity, notwithstanding Bangladesh's commitment to COP-21 regarding climate change. As a result of these erratic pledges, the study began investigating Bangladesh's electricity sector's carbon impact.

Accessible renewable energy sources are an important factor in reducing CO2 emissions from Bangladesh. As of right now, Bangladesh is producing an annual average of 216.75 megawatts (MW) from renewable energy sources. There are 27 gas fields in Bangladesh. With GIIP totalling around 11.91 trillion cubic feet, it is possible to generate low-cost energy (Abid, 2016a). Among the "7" gas fields where the GOB has carried out exploration are Bakhrabad, Rashidpur, Jalalabad, Bibiyana, Kailashtila, Habiganj, and Titas. Bangladesh is located in the northern portion of the country, where there are five coal seams tucked between riverbeds (the Padma and Jamuna). Coal reserves in the country are thought to be 3.3 billion metric tons (Mondal et al., 2010b).

As a result of Bangladesh's reliance on insecticides in its agriculture industry, the country's water supplies are being negatively impacted. In contrast, deforestation and rapid urbanization lead to the destruction of our natural resources (Akbar et al. 2018). Bangladesh and other developing countries have seen their CO2e pollution levels rise rapidly in recent years, prompting concerns about the quality of the environment in these areas. Only 0.70 percent of developing countries' CO2e emissions came from

Bangladesh in 2013. According to the International Energy Agency (IEA), more than as much CO2e was created in 2013 as in the 1990s by Bangladesh, according to the International Energy Agency (IEA) (Mondal, 2019). Carbon dioxide emissions have risen dramatically in recent years and now pose the greatest threat to Bangladesh's environment.

Most recent studies have examined not only whether or not population growth has an effect on CO2e emissions but also the effect of different levels of poverty. Using the findings of this study, the study can better understand the role of absolute and relative poverty in causing environmental degradation. Another reason for using population density and other environmental degradation models in this study was to avoid potential specification bias (Koçak and Ulucak, 2019a). New evidence from NARDL cointegration has been incorporated into the current study (Baek and Gweisah 2013). To do so, they will need to examine how changes in the poverty HCR and income inequality, as well as population and GDP per capita (economic growth), affect CO2e emissions. Apart from that, the study incorporated an ARDL model that looks for both long-term symmetry and short-term ties between variables.

Literature Review

As a result of this study, a conclusion can be made that poverty and economic disparity have a direct correlation with CO2e emissions in Bangladesh. For this reason, the literature review has been separated into three pieces: first, the link between CO2e and poverty is examined; similarly, the second and third sections examine how both income disparity and population growth affect the atmospheric concentration of CO2e.

Relationship between Poverty and CO2e

Since it is one of the core Millennium Development Goals (MDGs), alleviating extreme poverty remains a priority for government officials and policymakers (MDGs). Numerous social and environmental specialists have studied the impact of absolute poverty on CO2e emissions. It's a problem that's been brought up in previous studies, but gathering actual evidence to back up the "poverty–CO2e link" can be difficult (Torras and Boyce, 1998a). The relationship between environmental quality and poverty is increasingly being discussed in current research investigations. Many academics believe that extreme poverty, particularly in the LDCs, is a significant predictor of environmental degradation. To put it another way, poor economic conditions and a large population can lead to poor environmental safety practices that strain natural resources and harm the ecosystem, according to Koçak and Ulucak (2019b). In addition, extreme poverty negatively impacts the land quality and CO2e emissions because poor and needy people waste natural resources (such as chopping down trees) to make ends meet and stay alive. Ecologists who believe in the two-way relationship between environmental degradation and poverty are also out there (Boyce, 1994a). There is a belief that both the rich and the poor contribute to natural resource extraction and environmental destruction, but rich people have a lower influence on the environment than the poor since they are seen as both victims and perpetrators. Few studies have examined the link between environmental deterioration and poverty, but these estimates are still hazy, and most studies have failed to generate a thorough and unambiguous evaluation of the connection between poverty and environmental pollution (Twisa et al. 2020). Table 1 cites the most recent and important studies on these issues. In light of the aforementioned factors and the paucity of prior research, the current inquiry suggests the following four alternatives.

Hypothesis 1 (H1): Poverty has a significant impact on CO_2 emission in Bangladesh

(Table 1)

Income Inequality and Carbon Dioxide Emissions: A Correlation Study

The study of wealth inequality in connection with environmental degradation has arisen as an emergent and hot research phenomenon in the empirical literature as a result of this deficiency of attention. It is possible to divide income inequality and environmental deterioration into two distinct categories. During the first section of the literature review, the Environmental Kuznets Curve (EKC) is discussed, as well as the relationship between environmental deterioration and income inequality (Abid, 2016b). According to the findings of the majority of these studies, an increase in income disparity has a negative impact on the environment's quality. According to Boyce (1994b), disparities in wealth have a negative impact on environmental quality in the United States. Torras and Boyce (1998b) discovered that wealth disparity has a favourable and direct impact on environmental deterioration in both the short and long term. Studies such as (Baloch et al. 2020b), (Khan S. A., 2019b), (Wang et al. 2021b), (Masron and Subramaniam, 2019a), (Grunewald et al. 2017b), and (Khan and Yahong, 2021c) are among the most recent to demonstrate that government policies on environmental issues diverge the poor masses bear the economic as well as the horrific environmental expenses, but the privileged bear simply the economic costs of their lives. It is possible that inequality may have a direct and favourable impact on environmental deterioration, but this will result in climate change and a more polluted planet (Lu, 2017). Following the findings of various research, income disparity has been found to have a negative impact on environmental quality. Increased economic disparity has been proven to be associated with a reduction in environmental deterioration, as demonstrated by Hailemariam et al. (2020a), for instance. According to the marginal propensity to emit, so does environmental deterioration (MPE) when income disparity shifts. Despite their points of view being diametrically opposed, they both recognized that CO_2 emissions and economic disparities are inextricably linked. Table 1 contains citations to the most recent and important works on these subjects. In order to confirm this association, the researchers theorized even further.

Hypothesis 2 (H2): Income inequality has a positive relationship with CO_2 emission in Bangladesh

Population and Carbon relationship

Poverty and economic disparity in the population are used in this study, not only for the sensitive assessment but also for the evaluation of CO_2e's distinct influence. According to previous studies, economic growth and development are severely impacted by rapid population increase (Hailemariam et al. 2020b). As a result, the multiplier effect has an impact on both CO_2 emissions and energy consumption, discouraging both investment savings and research and development (R&D) while motivating the most vulnerable to seek out and use the cheapest forms of energy, such as fossil fuels (Khan, 2019c). Because of this, the study came to the conclusion that Bangladesh's population has a major effect on CO2e emissions and is critical to understanding those emissions. As a result, the study came up with a third possibility.

Hypothesis 3 (H3): Population in Bangladesh has a positive effect on the level of CO2 emission

Materials And Methods

Model

From the preceding studies, this empirical research analyzes poverty, income inequality, population, and GDP per capita to examine the impact of poverty, income inequality, and population on Bangladesh's environmental deterioration. The study used a paradigm for empirical analysis similar to Saelim's (2019b) for analyzing these correlations. The study used a small number of control variables to make sure the study didn't miss any significant CO2e-influencing factors while verifying the influence of poverty, economic disparity, and population growth. To minimize heteroscedasticity, the study changed all variables into logarithmic form. The following empirical model was calculated in the study:

$$\mathrm{LnCO_2et} = \mathrm{B}_0 + \mathrm{B}_1\mathrm{LnPOV}_t + \mathrm{B}_2\mathrm{LnPOP}_t + \mathrm{B}_3\mathrm{LnINEQ}_t + \mathrm{B}_4\mathrm{LnGDP}_t + \mathrm{B}_5\mathrm{LnCONT}_t + e_t$$

Where the dependent variable used in the study is represented by (CO2et), which is the long-term CO2 e per capita, the independent variables used in this study are; LnPOVt, which represents poverty, LnINEQt, which is the Gini coefficient used to measure a nation's income inequality. POPt, as used in the equation, represents the Population density of a country, LnGDPt on the other hand, represents Bangladesh's GDP per capita (Abdullah et al. 2015b). And finally, the controlled variables used in the study (CONTt) include lnINFt, LnLSSt is the logarithm of the number of people who use the most basic water sanitation services available. Furthermore, the little t (t) in the above equation indicates the time in years, whereas the εt denotes the error term or residual in the equation.

The table 2 shows the expected signs, variable description, definitions and source of the data of the variables.

(Table 2)

For this study, we used yearly data from 1983 to 2020. The data were obtained from World Bank. The study used linear methodology imputation (L1) (Khan and Yahong, 2021d) for the missing data.

(Table 3)

In this study, the missing data in the variables were analyzed using the linear imputation (LI) method. Thus, the table 3 represents the descriptive statistics for the variables used in the study; this includes the mean of the variables, standard deviation, number of observations minimum and maximum variable.

Unit Root Tests

Prior to studying the model's long- and short-run dynamics, we conducted unit root tests on each series to determine the degree of stationarity present in each series. The concepts of several tests for stationarity have been proposed in previous research; however, in the current study, the most often used unit root tests, namely the "Phillips–Perron" (PP) and the "Augmented Dickey-Fuller" (ADF), have been included as well. According to the table 4, I also investigated the degree of stationarity at the "level" [I (0)] and the "first difference" [I (1)] of all the variables to determine their level of stationarity. All variables in the log form are stationary at I (1) according to the unit root testing procedures of stationarity used by both the PP and the ADF (1).

(Table 4)

The lag selection test criteria

Lag lengths are critical for analyzing cointegration data. The ideal lag selection criteria are shown in the table 5. For cointegration estimation, all of the optimum lag selection criteria (LR, FPF, AIC, SC, HQ) offer a lag order length of 3 (LR, FPF). As indicated in Fig. 1, lag order selection criteria (under VAR = vector autoregressive) have been created. Small dots in the polynomial graph show that the lag selection of 3 is appropriate for policy implications and decision making.

(Table 5)

Autoregressive Distributive Lag (ADL) using cointegration modelling

Earlier studies have revealed a variety of empirical modelling approaches for investigating the model's long-term behaviour. Even though Johansen and Juselius, as cited by Murad and Mustapha (2010), employed maximum likelihood for multivariate cointegration analysis, Hassler and Wolters (2006a) used modified ordinary least square (OLS) for univariate cointegration analysis. Johansen cointegration approaches, despite the fact that they are widely used, can give two or more cointegration connections and can accept small (minimum of 30) and biased sample sizes, but it is required that all variables of the model(s) are integrated with a single direction (Johansen and Juselius 1990a).

(Fig. 1)

To deal with the problem of Johansen cointegration, Bahmani-Oskooee et al. (2002a) used the ARDL model. Cointegration analysis between the variables of interest was carried out using ARDL methods in the current study. There are various advantages to using the ARDL bounds testing technique over any other method. For starters, the ARDL generates reliable estimates by taking into account the endogeneity of the variables, eliminating serial correlation, and using the appropriate delays. Second, because it is analogous to Johansen's cointegration model, ARDL may be important for studies with a small sample size (Asumadu-Sarkodie and Owusu, 2016a). As the use of the ARDL model does not need all variables to be integrated with the same direction (order), it is unique from Johansen's cointegration technique, which requires all variables to be integrated with the same direction. If the variables are I (0), I (1), or both, we may still use ARDL. Finally, ARDL bounds testing measures the model's short- and long-term dynamics simultaneously (Johansen and Juselius, 1990b).

In the current study, we used a similar technique to examine the impact of poverty and income inequality, as well as population and economic growth, on CO2e emissions, based on the previously described time series data and the advantages of the ARDL model. According to the ARDL model, the study used the following specification;

Unrestricted error correction model (UECM) bounds testing technique is depicted in the equation above, where lnCO2e, POV, INEQ, POPD and GDP indicate their respective difference values in terms of their respective difference values. This model's short-run dynamic connection is represented by coefficients b2, b3, b4, and b5, whereas the model's long-run dynamic relationship is represented by coefficients 1, 2, 3, 4, and 5. In the same way, each variable's lag duration is explained by P. (both dependent and independent variables). In the ARDL bounds testing technique, a joint (mutual) significance test is used to determine if there is any long-term or cointegration link.

The equation below then describes the short-run, which explains the adjustment speed of the equilibrium following various short-run economic shocks to carry out the statistical diagnostic tests for model stability and estimate the short- and long-run coefficients.

NARDL methodology

In contrast to the straightforward ARDL model, the applications of the NARDL technique do not necessitate the integration of all variables (included in the model) in the same r direction. According to Nathaniel (2021a), the study applied the NARDL approach in order to detect asymmetric relationships (non-linear relationships) between the variables; to do so, we utilized the current estimates in the following model:

$$\begin{aligned}\Delta \mathrm{lnCO2et} = {} & \mathrm{b_o} + \mathrm{b_1}\Delta \mathrm{lnPOV}_t^+ + \mathrm{b_2}\Delta \mathrm{lnPOV}_t^- + \mathrm{b_3}\Delta \mathrm{lnINEQ}_t^+ + \mathrm{b_4}\Delta \mathrm{lnINEQ}_t^- + \mathrm{b_5}\Delta \mathrm{lnPD}_t^+ \\ & + \mathrm{b_6}\Delta \mathrm{lnPD}_t^- + \mathrm{b_7}\Delta \mathrm{lnGDP}_t^- + \mathrm{b_8}\Delta \mathrm{lnGDP}_t^- + \varepsilon_t\end{aligned}$$

As stated by Khan and Yahong (2021e), the above equation is used in the study to explain the positive variation in poverty, Gross domestic product per capita, income inequality and population density. And on the other hand represents the negative variation in the GDP per capita, income inequality, population density and poverty.

Using a similar procedure as the ARDL, the resulting stationarity test for), and, all variables do not have a unit root and are stationary even at the I(1) level, as revealed by the resulting probabilities of unit root tests. The lag order selection criteria revealed that the lag of 3 would be suitable for the NARDL methodology technique, as confirmed by the lag order selection criteria. In the following step, we used the NARDL model to analyze the asymmetric relationship between the variables of interest in greater depth.

To determine whether or not variables in the research are cointegrated, the study examined the limits cointegration testing strategy, which used the joint-F significance test, prior to calculating both the long- and short-run analyses (in the long run). These results, as well as the corresponding levels of significance (10, 5, 2.5, and 1 percent), are shown in the table 6, along with the lower I(0) and lower I(1) critical values, respectively.

(Table 6)

Upper bound I(1) values presented (fixed) are fewer than computed F-values, and (with intercept and without trend) are highly significant even at a 1 percent (0.1) level; a similar finding was determined by (Khan and Yahong, 2021f). The long-term relationship between poverty (HCR), income inequality, population density, GDP per capita, and CO2e has been established following the processes outlined above.

Results

ARDL model estimation

Using the ARDL technique, we quantified the link between HCR of poverty, income inequality (Gini index), population density, GDP per capita, and CO2e for Bangladesh. A long-term elasticity may be inferred from coefficient probabilities since most of the variables in the model were changed to log form.

At one percent, the correlation between poverty and CO2e is statistically significant, according to Tables 7 and 8 of the ARDL estimations. These data show that the rising trend of poverty in Bangladesh positively affects CO2e, which negatively impacts the environment. According to the findings of the current study, some major actions must be taken to alleviate extreme poverty, which has a negative impact on environmental quality in Bangladesh and other countries in the region. It is possible that poverty (HCR) has a favourable effect on CO2e emissions because of a variety of causes. One of the indirect mechanisms of CO2e and poverty may be to increase the severity of environmental degradation in terms of CO2e in order to speed up the industrialization process.

Wang et al. (2021c) also determined that income inequality and CO2 emissions have a negative correlation because of reduced economic development discrepancy. In developing nations, reducing economic disparity increases CO2 emissions from secondary businesses. Maintaining these results is the responsibility to increase economic activity and, as a result, decreasing the severity of severe poverty is to encourage and accelerate the process of industrialization (Khan et al. 2018d). The quality of the environment is harmed as a result of this procedure. This study's conclusions have been corroborated by studies conducted by Baloch, Khan, et al. (2020c) and Masron and Subramaniam (2019b) on developing nations; Lu (2017) on a diverse group of Asian countries; and Khan (2019d) on the ASEAN member countries of Southeast Asia. While this study's findings may differ from some others, such as those of Abid (2016c) for African countries, Koçak and Ulucak (2019c) for LDCs, and Islam and Ghani (2018b) for ASEAN countries, because the economic dynamics of these countries and regions are distinct from those of Bangladesh, the results may still be relevant.

(Table 7)

In addition, a new approach was used to investigate the connection between the two variables. It also reveals an alternative scenario and the existence of policymaker disagreements on whether environmental protection events or economic growth in Bangladesh should be prioritized. As a result of this incongruous situation, politicians and government officials find it difficult to prioritize environmental concerns as a top priority when developing a policy (Lu, 2017).

(Table 8)

The relationship between CO2e and the income differential is shown in Tables 7 and 8. According to the data, there is a substantial relationship between CO2e and the Gini index, indicating that economic disparity has a negative impact on environmental degradation. To put it another way, Bangladesh's significant economic gap has a good impact on the natural environment. There is a possibility that lower Gini index values in less developed nations such as Bangladesh are lessening economic rivalry and making it more affordable for the economically disadvantaged to purchase high-carbon emitting and energy-consuming sources. Because of a lack of economic rivalry, fewer environmentally friendly energy sources are developed, resulting in higher levels of CO2e emissions and environmental degradation. As a result of the tiny wealth disparity in developing countries such as Bangladesh, people find it difficult to invest in new and high-emitting technologies that would increase their earnings and, as a result, lower CO2e emissions (Ali et al. 2020).

According to Boyce (1994c), increased income produces a power disparity between the elite and poorer classes in society, which in turn degrades the environment's quality. However, the current study's findings are fascinating and contradicting. Rich individuals make use of the system, while the environmental consequences fall disproportionately on the poor. Increased CO2e and environmental degradation can be caused by a rise in wealth disparity, according to Boyce (1994d). Increasing the income gap between the affluent and the poor prevented wealthy individuals from exploiting natural resources for their own benefit, demonstrating that high-income inequality is ecologically beneficial yet creates a major societal dilemma. Uddin et al. (2020) for the G7, (Wang et al. 2021d) for China, Kounetas (2018) for European countries, Grunewald et al. (2017c) for Third World nations, and Demir et al. (2019) for Turkey's results are all compatible with this study's conclusions. Because this inconsistency is different from Bangladesh, we feel that this study's conclusions are not comparable, and this study used a variety of different research approaches.

In models (1), (2), (3) and (4), the positive and significant coefficients for density have been altered. These studies link population increase to Bangladesh's worsening environment. This might be because more people need more resources, which puts more pressure on Earth's natural resources, causing them to decline faster. People deforest and lose biodiversity to manage a rising population. Bahmani-Oskooee et al. (2002b) and Islam and Ghani (2018c) have found similar results for ASEAN states. Khan and Yahong (2021g) and Hassler and Wolters (2006b) have different outcomes for Asian and Chinese emerging states. The aforementioned study found a link between environmental degradation and human population expansion. Densely inhabited areas are thought to benefit from enhanced infrastructure and ecological transmission.

According to the data in Tables 7 and 8, there is a statistically significant relationship between GDP per capita and environmental degradation in Bangladesh, indicating that GDP per capita increases CO2e both in the short and long term. Furthermore, the conclusions of this study are equivalent to those of Khan (2019e) for BRICS economies, Malik et al. (2020a) for Pakistan, Lu (2017) for developing nations, Khan and Yahong (2021h) for Pakistan, and Zhang et al. (2014) for China, among other researchers. According to the conclusions of this study, economic expansion and economic activity in developing countries such as Bangladesh contribute to poverty reduction, but at the expense of a high environmental cost in the form of environmental degradation.

The following is the outcome for the control group: Khan (2019f) and Malik et al. (2020b) found similar results for Pakistan, where inflation has a negative and statistically significant impact on CO2e over the long term. Environmental deterioration in Bangladesh was not significantly affected by the value-added component of the country's GDP or, at the very least, basic sanitation services (as a percentage of the overall population). Therefore, industries and GDP value-added shares, as well as even the most basic sanitary facilities, have no impact on CO2 emissions in the country of Bangladesh. The presence of the marginal propensity to emit (MPE) hypothesis between these two variables, as well as the extended trade-off between them, are the explanations for the antagonistic link between income inequality and CO2 emissions (Nathaniel S. P., 2021b). A shift from an agricultural to a more industrialized economy is taking place in Bangladesh right now, which has resulted in an increase in greenhouse gas emissions. It is anticipated that the country's emission rate will decrease as the country transitions to a more service-oriented economy in the future.

According to the same findings, raising the income of the poor will increase energy and CO2 emissions, according to studies conducted by the OECD (Organization for Economic Co-operation and Development) and China (Wang et al. 2021e). Income inequality and CO2 emissions have a negative correlation because of reduced economic development discrepancy. In developing nations, reducing economic disparity increases CO2 emissions from secondary businesses.

Diagnostics test and stability for the model

To summarize the empirical findings for each model, Table 7 gives the results of the diagnostic tests, which include both model diagnostics and model stability tests. After much deliberation, it was decided to use the Jarque–Bera test to determine whether or not the data was normally distributed. This test indicates statistical insignificance and fails to reject the hypothesis that the data is normally distributed if the Chi-square test value is greater than 5 percent. By combining ARCH with the Breusch–Pagan (BP) test, heteroscedasticity was examined; however, the resultant probability value of the Chi-square test was statistically insignificant, indicating that the null hypothesis of homoscedasticity could not be ruled out.— Ploberger and Krämer (1992) conducted an additional stability analysis on all models by combining the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residual squares (CUSUMSQ) in order to offer robust findings from the models. As illustrated in Fig. 2, the graphical outcomes from the CUSUM and CUSUMSQ tests represent the models' dynamic stability.

(Fig. 2)

Estimating NARDL model

As shown in the table 9, no statistically significant trend can be observed based on F-values (7.99) that are bigger than the bottom and upper bounds of the constant (intercept), 0(1) and I(I), even at a 1% significance level. Thus, the study established a long-run among the variables (CO2e, PD, LPOV_pos, LPOV_neg, LGINI_pos, LGINI_neg, LGDP_pos and LGDP_neg).

(Table 9)

Detailed results of both the long-run non-linear ARDL and the short-run non-linear ARDL long-run are shown in tables 10 and 11. The NARDL coefficients, as well as the relationship between poverty and HCR, are both statistically significant and positively correlated. According to Tables 7, 8, and 9, the short- and long-run NARDL findings agree with the long- and short-run ARDL results in both the short and long runs. Because of their asymmetrical relationship with CO2 emissions, which are directly connected to poverty, negative shocks in the partial sum of poverty HCR have no effect on CO2 emissions (positive shocks in the partial sum of poverty HCR).

(Table 10)

(Table 11)

Statistically significant impacts of poverty on CO2e are shown in both the short and long term, while long-term effects of poverty on CO2e are statistically positive and statistically significant at the 5 percent level. Short-term NARDLs show statistically significant and positive effects of GDP per capita (positive shocks) in both the short- and medium-term NARDLs, suggesting that GDP per capita has a favourable effect on environmental degradation in both time periods. Inequality (positive shocks) has exhibited a consistent and statistically significant negative impact on CO2e emissions over the course of history. In contrast to a reduction in population density, both short-term (positive) and long-term (negative) population density shocks increase CO2e. A graphical representation of CUSUMSQ and CUSUM results for NARDL is illustrated in Fig. 3, as it suggests that all models are dynamically stable.

(Fig. 3)

According to previous research, the outcome of this study is consistent with the outcome of this study. Because natural resources are related to environmental degradation, increasing natural resource extraction and unsustainable consumption increase CO_2 emissions in Bangladesh (Zaidi and Ferhi 2019).

Discussion And Conclusion

The current study studied the relationship between poverty, income inequality, and CO_2e emissions in Bangladesh using time-series monthly data spanning the years 1983 to 2020 in order to achieve the study's stated objectives and the Sustainable Development Goals (SDGs). The ARDL and NARDL approaches were used in the current investigation in order to obtain data that were both unbiased and dependable in nature. The following are the conclusions of the current research: When it comes to carbon dioxide emissions in Bangladesh, the Human Capital Ratio (HCR) is the most important predictor, whereas the Gini coefficient (which measures economic disparity) has just a minor impact. Bangladesh's high population density and the country's low GDP per capita have a negative impact on the country's environmental quality.

According to research, extreme poverty is a significant contributor to environmental degradation in Bangladesh; as a result, authorities should develop measures to eradicate extreme poverty without jeopardizing the quality of the environment. This study looked at a few critical, long-term, medium-term, and short-term effects for policymakers across the long, medium, and short terms. Researchers discovered that, in addition to high population density and extreme poverty, increased GDP per capita also contributes to environmental deterioration, which in turn results in a rise in CO_2 emissions. Policymakers may be able to draw inferences from this study on how to minimize the severity of severe poverty, which has the potential to have a large impact on the population and CO_2e levels in the environment.

For long-term policy implications, an all-encompassing strategy that promotes economic growth and development that benefits the poor is one that protects environmental quality while simultaneously maximizing opportunities that benefit the poor, as described in the preceding paragraph. As a result, the government and related authorities should develop and implement a comprehensive policy to ensure that the advantages of all productive and economic activities are allocated to those who are most in need. In addition to having a detrimental impact on environmental quality, Bangladesh's economy is growing and developing, which means that authorities must consider both economic growth and environmental quality when making choices. The government of Bangladesh should establish environmental control legislation. The use of environmentally friendly energy should be promoted to achieve sustainable economic growth and accomplish the Millennium Development Goals (MDGs). Rules designed to safeguard the environment encourage innovation, which results in increased energy efficiency and, as a result, decreased CO_2 emissions.

It is only possible to target Bangladesh's low-income and impoverished population for short-term policy consequences if the government confirms that their demands will not result in significant CO2 emissions (Asumadu-Sarkodie and Owusu, 2016b). While relying on economic growth as a short-term policy, Bangladesh's government should also address the existing situation in order to create short-term work opportunities for the impoverished. Furthermore, in order to provide immediate support to the underprivileged, authorities should create microfinance programs and provide assistance through social safety nets as quickly as possible. Although greater income disparity is not a significant predictor of CO2 emissions, policymakers and the government should strive to preserve an equitable income distribution in order to foster economic stability, improve environmental quality, and manage CO2 emissions.

To counteract the negative effects of increasing economic insecurity on environmental degradation and the consequent increase in demand for a better environment, more equitable income distribution can help cut CO2 emissions by reducing people's financial anxiety. Individualism lessens, and social consciousness rises as a result of a well-balanced economic distribution, which is vital to promoting quality environmental awareness. Political power distribution can be balanced by more fair wealth distribution, but the decline in the influence of higher-ups and elite groups will keep environmental protection measures from slackening. Through a more equitable distribution of revenue and power, traditional energy companies may have less influence on lawmakers. Because environmental requirements are becoming increasingly stringent, the policies should be developed accordingly. Efforts to lessen income disparity may be made through educating low-income populations about the environmental impact of their behaviours, such as burning fossil fuels and chopping down trees. Equality in income distribution is something that the government should work to achieve. In addition, government spending on human capital and infrastructure can help alleviate wealth disparity.

The utilization of renewable energy has been shown to have a negative and significant impact on CO2 emissions. According to these findings, government authorities support renewable energy generation by providing financial incentives such as tax breaks and low-interest loans to businesses and individuals. As a result of the detrimental effects of fossil fuels, the government should raise research and development funding to stimulate the adoption of renewable energy sources. By utilizing renewable energy sources, it is feasible to limit the growing CO2 emissions that are being produced (Omojolaibi and Nathaniel, 2020). To produce and use renewable energy sources (such as solar, wind, tidal, and hydropower) in a sustainable manner, laws and legislation must be in place to control their use. It is believed that strengthening links with industrialized countries that have a history of producing clean energy will encourage international corporations to invest in environmentally friendly technologies. The Pakistani government must strengthen environmental restrictions and encourage enterprises to use renewable energy and ecologically beneficial practices to protect the environment. Renewable energy sources exist in Bangladesh, but the nation must make significant investments in them to avoid further environmental degradation.

A significant contributor to environmental degradation is the depletion of natural resources. The conservation of natural resources and the reduction of their use are two important goals that should be pursued in the future. It is vital to educate people about environmentally friendly products, as well as to reduce excessive deforestation and land degradation, in order to control natural resource exploitation and improve environmental quality. Because of the current state of affairs, which is outmoded and inefficient, policymakers should prioritize technological innovation and the efficient use of natural resources. To deal with energy-producing companies, natural resources must be taken into consideration by policymakers.

We must undertake inclusive policy measures that can regulate population growth and ensure that a scenario may alleviate severe poverty levels without degrading environmental quality or economic growth. Economic development and poverty alleviation are also two key focuses of the study's empirical findings. Following up on what we discussed previously, it is imperative that Bangladesh's government take a few essential actions to ensure that their policies on poverty alleviation and population density reduction impact the country's environment. As important as this study is for policymakers, there are a few caveats. Using the most often used Gini index as an indicator of income inequality is unimportant; hence alternative indices for income inequalities, such as the Theil index and Palma ratio, should be utilized in future studies to increase their significance. Future studies might test the validity of this study's findings by comparing them to other indexes of income inequality. The last focus of this research was on Bangladesh's population density and economic growth in connection to poverty and income disparity.

Declarations

Competing interests:

The authors declare no competing interests.

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Tables

Table 1: List of past Literature Review in a table format

References	Country	Period	Methodology	Result
				Recent studies on poverty and environmental degradation
(Masron and Subramaniam, 2019)	50 developing counties	2001 - 2014	GMM	According to the study's conclusions, poverty is the most significant contributor to environmental deterioration in the world.
(Islam and Ghani, 2018)	ASEAN nations	1995-2014	Johansen cointegration test and Granger causality test	The poverty level in Malaysia has a detrimental influence on the country's energy usage.
(Khan, 2019)	ASEAN Countries	2007-2017	GMM	The data reveal that poverty has a positive and substantial link with increased environmental\degradation
				Recent studies on Income inequality and environmental degradation
(Wang, Uddin, and Gong, 2021)	Pakistan	2019-2021	ARDL	Increased exploitation and unsustainable use of natural resources in Pakistan would increase CO2 emissions. Traditional resource usage and dependence on fossil fuels have increased environmental stress. Pakistan's natural resources are polluting due to unrestricted exploitation and a low percentage of clean, renewable energy sources.
(Baloch, Khan, Ulucak, and Ahmad, 2020)	Pakistan	1966-2011	ARDL bound testing method	According to the findings of the study, CO2 emissions rise as economic disparity increases.
(Grunewald, Klasen, Martínez-Zarzoso, and Muris, 2017)	158 nations	1980-2008	FE, OLS and GFE	According to the researchers, the data imply that the association between CO2 emissions and wealth disparity is favourable in middle-income developing nations.
(Masud, Kari, and Saifullah, 2018)	ASEAN 5	1985-2015	Panel regression analysis and Granger causality test	The findings demonstrate that there is a bidirectional link between environmental sustainability and wealth disparity in the United States.
				Recent studies on poverty, income inequality and population
(Khan and Yahong, 2021)	Pakistan	2021	ARDL and NARDL Co-integration	According to the study's findings, considerable steps must be taken to alleviate Pakistan's chronic poverty, which harms the environment. Poverty (HCR) may help the environment by releasing CO2e for several reasons. On one side, reducing poverty may contribute to higher CO2 emissions as a result of industrialization, hastening the environmental degradation process.

Where: GMM, generalized method of moments; DK, Driscoll Kray (DK); OLS, ordinary least square; EKC, Environmental Kuznets curve; ARDL, autoregressive distributive lag; FE, fixed effect; GFE, grouped fixed effect.

Table 2: Variable's description

Variables	Description	Measurement	Expected sign
CO_2e	Carbon emission	CO_2e measures in per capita metric tons	
POV	Poverty	Poverty is the percentage of the total population living below $1.90 a day	+
INEQ	Income inequality	INEQ is the GINI index that is estimated by the world bank	±
PD	Population	PD is the No. of people per square kilometre	+
IND	Industry	The industry is the total percentage of the value added to the GDP, including construction	+
INF	Inflation	Inflation is measured by the CPI of the country (yearly)	±
LSS	Sanitation	Population with access to at least the most basic sanitation services (total percentage of the population)	-
GDP	Gross Domestic Product	GDP per capita that is measured at a fixed/constant 2015 US$	+

Data source: World banks.org

Table 3: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CO2e	38	.2481237	.1435453	.09561	.5526987
INF	38	7.287729	3.81194	2.007174	19.72242
LSS	38	26.19423	16.7273	-1.36049	54.1647
INEQ	38	31.33763	2.397669	25.88	33.46
IND	38	23.5878	2.743297	19.60082	29.64868
GDP_con201~S	38	813.2399	344.6465	470.9053	1625.672
PD	38	987.9333	184.4468	661.7691	1265.187
Poverty	38	43.76053	21.08865	14	83.5

Table 4: Unit test for stationarity

Methodology			Methodology		
Variable At level	ADF t-stat	PP t-state	Var 1^{st} difference	ADF t-stat	PP t-state
CO_2e	3.826	3.676	$d1CO_2e$	-4.010	-4.099
POV	-1.719	-1.479	d1POV	-11.767	-14.636
INEQ	-2.828	-2.397	d1INEQ	-2.678	-2.879
GDP	9.886	11.026	d1GDP	-1.860	-1.814
INF	-3.933	-4.283	d1INF	-6.805	-7.121
PD	-9.583	-5.293	d1PD	0.336	-0.396
IND	0.807	0.843	d1IND	-5.295	-5.305
LSS	3.920	2.222	d1LSS	-1.146	-1.333

According to the above STATA output results, the null hypothesis is H0, which means either there is a unit root or no stationarity. The importance levels are indicated by the letters *, **, and ***. (10, 5, and 1 percent, respectively).

Table 5: Optimal selection criteria

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-594.755				345687	35.4562	5.5786	35.8153
1	-98.0338	993.44	64	0	3.40E-06	10.002	11.1043	13.2343
2	20.9005	237.87	64	0	2.60E-07	6.7706	8.85269	12.876
3	335.083	628.36*	64	0	1.30E-12	-7.94606*	-4.8841*	1.03254*
4	.	.	64	.	-6.e-109*	.	.	.

In the above table, AIC, HQIC, FPE, LR and SBIC represent the selection criteria, and * represent the study optimal lag selection criteria

Table 6: Cointegration for NARDL bound test

Bound Test		H0: No cointegration			Decision
Sig.			Level: I(0)	1st Difference: I(1)	
F-stat	9.650*****	0.1	2.1	2.98	
k	4	0.05	2.45	3.39	
		0.025	2.67	4.01	
		0.01	3.7	4.57	Cointegrated

*, **, ***, and **** shows the level of significance at 10, 5, 2.5, and 1%, respectively.

Table 7: Long-run ARDL diagnostics and stability

	Model 1	Model 2	Model 3	Model 4
LPOV	0.10322*** (0.0980)	0.0896*** (0.125)	0.1433*** (0.0912)	0.0582*** (0.0879)
LINEQ	−0.0299 (0.9161)	−3.0299*** (1.8571)	−0.0574** (0.9162)	−3.0299 (1.8571)
PD	0.063*** (0.0060)	0.015** (0.0119)	0.0743* (0.0622)	0.0110*** (0.0023)
LGDP	0.577*** (0.790)	1.435*** (0.721)	0.6581*** (0.883)	2.245** (0.433)
LINF		−0.0552** (0.029)		
LIND			−0.7484 (0.7423)	
LLSS				0.7484 (0.7623)
Constant	−5.2651***	−5.511***	−7.321***	−6.213***
ARDL bound test				
F-statistic	10.72***	15.031***	12.678***	9.612***
Model Sel.	1, 3, 1, 1, 0, 4	1, 3, 2, 2, 1, 4	1, 1, 1, 0, 2, 3	1, 0, 0, 2, 3, 4
		4	1	0
Statistics				
R-Sq.	0.998	0.999	0.998	0.997
Adjusted R-Sq.	0.995	0.996	0.996	0.995
F-Stat.	361.134***	417.890***	521.106***	632.437***
Diagnostic tests				
Normality test				
Jarque–Bera test	0.418	0.032	0.613	0.441
Heteroscedasticity				
Breusch–Pagan test	0.385	0.392	0.303	0.360
ARCH	0.690	0.123	0.776	0.559
Model stability				
CUSUM test	Yes	Yes	Yes	Yes
CUSUMSQ	Yes	Yes	Yes	Yes

The standard errors are indicated by parenthesis. *, **, and *** The levels of significance are represented by the numbers 10%, 5%, and 1 percent.

Table 8: Short-run ARDL model

	Model 1	Model 2	Model 3	Model 4
LPOV	0.124*** (0.0980)	0.116*** (0.125)	0.157*** (0.0912)	0.0142*** (0.0979)
LINEQ	−0.135 (0.9161)	−2.211*** (1.8571)	−0.141** (0.9162)	−2.030 (1.8571)
PD	0.0533*** (0.0060)	0.125** (0.0119)	0.0092* (0.0622)	0.032*** (0.0023)
LGDP	0.456*** (0.790)	0.843*** (0.721)	0.562*** (0.883)	2.001** (0.433)
LINF		−0.120** (0.029)		
LIND			−0.672 (0.7423)	
LLSS			0.005	
			(0.078)	
Coint-Eq.	–4.22*** (1.161)	−4.190*** (0.913)	−4.998*** (0.897)	−5.002*** (1.323)

The standard errors are indicated by parenthesis. *, **, and *** The levels of significance are represented by the numbers 10%, 5%, and 1 percent.

Table 9: NARDL cointegration bound test

Bound Test		**H0: No cointegration**		**Decision**	
Sig.			**Level: I(0)**	**1st Difference: I(1)**	
F-stat	7.990*****	0.1	1.9	2.16	
k	4	0.05	2.9	3.01	
		0.025	3.1	2.98	
		0.01	3.9	4.78	Cointegrated

*, **, ***, and **** shows the level of significance at 10%, 5%, 2.5% and 1% respectively.

Table 10: Model diagnostics

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	coef.	F-stat	P>F	coef.	F-stat	P>F
LPOV	0.233	.06687	0.839	0.157	.3025	0.680
PD	0.005	4.353	0.285	0.000	.	.
LGDP	0.427	.6459	0.569	-86.211	.6343	0.572
LIND	-1.959	19.38	0.142	-0.925	.2296	0.716
	Long-run asymmetry				Short-run asymmetry	
	F-stat	P>F			F-stat	P>F
LPOV	.1219	0.786			6.23	0.243
PD	4.353	0.285			.5011	0.608
LGDP	.6309	0.573			2.619	0.352
LIND	2.158	0.380			.3468	0.661
Cointegration test statistics:	t_BDM =					-3.3416
	F_PSS =					3.9342
Model diagnostics	**stat.**			**p-value**		
Portmanteau test up to lag 15 (chi2)			47.72			0
Breusch/Pagan heteroskedasticity test (chi2)			2.383			0.1227
Ramsey RESET test (F)	.			.		
Jarque-Bera test on normality (chi2)			3.508			0.1731

Standard errors are in parenthesis. *, **, and *** represent the level of significance at 10, 5%, 1%, respectively.

Table 11: Short-run NARDL model

	Coefficient	**t-statistics**	**Prob.**
d(LPOV_POS)	0.233***	0.669	0.839
d(LPOV_NEG)	−0.157*	0.303	0.680
d(LINEQ_POS)	−0.90***	0.630	0.006
d(LINEQ_NEG)	N/A	N/A	N/A
d(LNGDP_POS)	0.427***	0.646	0.056
d(LGDP_NEG)	-86.210	0.634	0.716
d(PD_POS)	0.005*	4.350	0.285
d(PD_NEG)	N/A	N/A	N/A
Coint Eq.	-2.470	-1.770	0.000

Standard errors are in parenthesis. *, **, and *** represent the level of significance at 10, 5%, 1%, respectively.

Figures

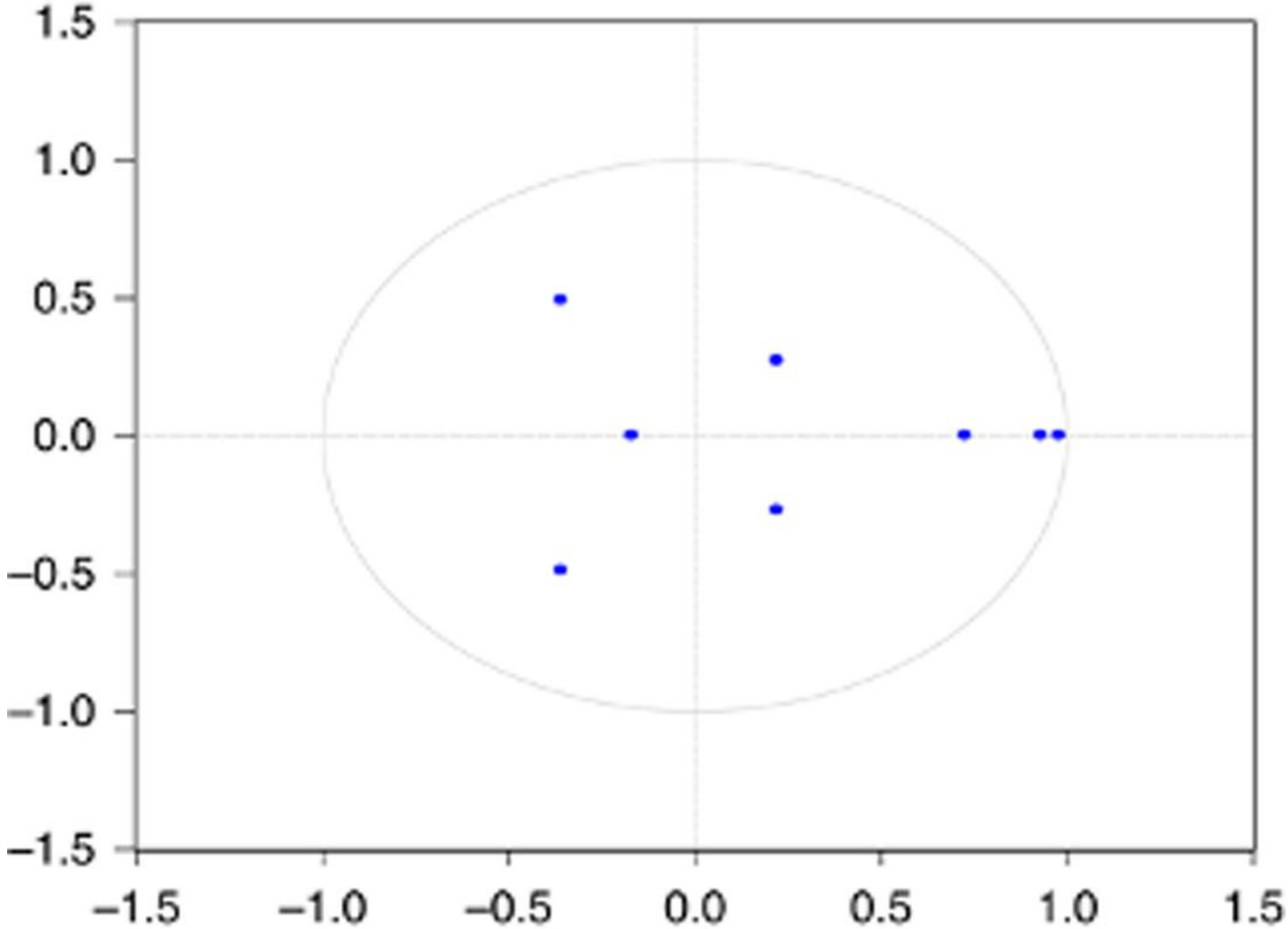
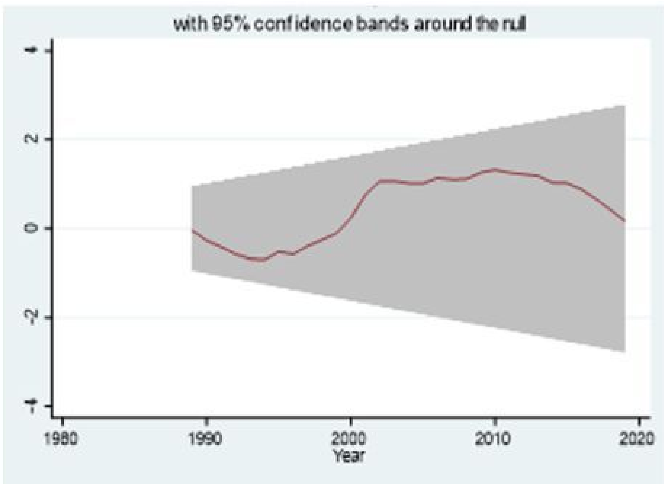
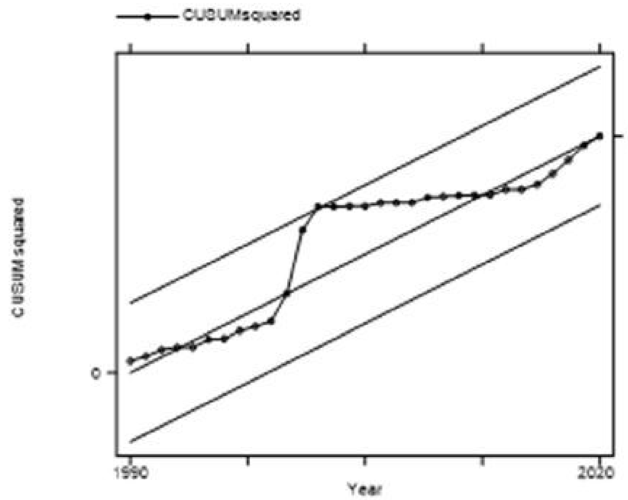


Figure 1

Polynomial graph for optimal selection



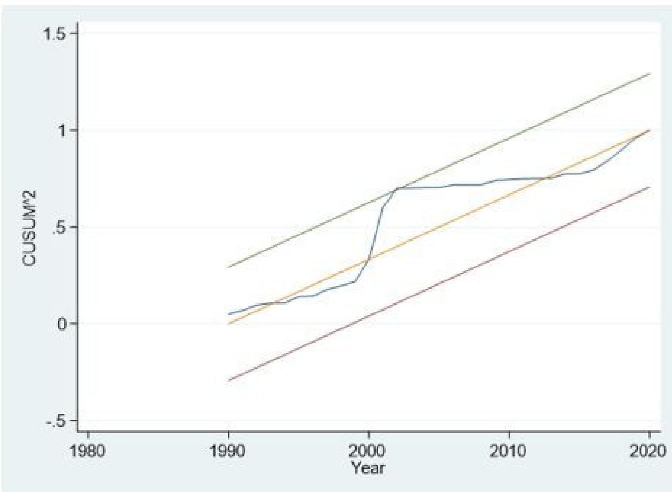


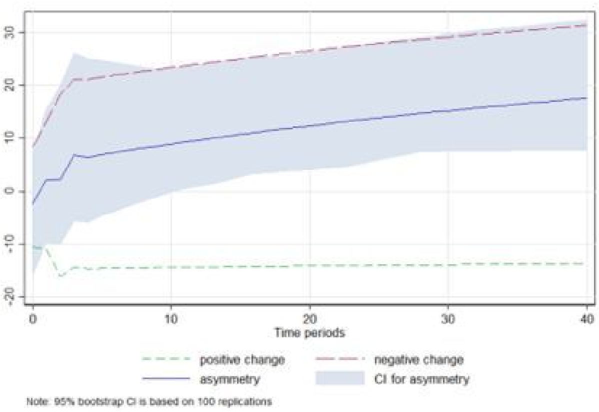
2.1

2.2

Figure 2

CUSUM and CUSUM-square graphs for ARDL





3.1

3.2

Figure 3

NARDL's CUSUM and CUSUM-square graphs