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Determinants of Environmental Emissions and Policy Implications: Evidence from Tanzania 1990 to 2023

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Abstract: This study examines the economic determinants of environmental emissions in Tanzania from 1990 to 2023, focusing on key macroeconomic factors such as land use (LU), gross domestic product (GDP), foreign direct investment (FDI), renewable energy consumption (REC), and population growth rate (PGR). Using a Vector Error Correction Model (VECM), Johansen's co-integration test, the study investigates both short- and long-run relationships between these variables and environmental emissions. The results indicate that LU, GDP, and FDI have a significant positive impact on emissions, implying that economic expansion and foreign investments contribute to environmental degradation. Conversely, REC negatively influences emissions, highlighting the importance of renewable energy adoption in mitigating pollution. The findings also suggest that PGR (Population Growth Rate) contributes to increased emissions through rising energy demand, urbanization, and expansion of economic activities. The VECM results show that emissions adjust to equilibrium in response to economic shocks. Despite the existence of environmental policies, their effectiveness appears limited due to weak enforcement mechanisms. The study concludes that stringent environmental regulations, coupled with increased investment in renewable energy, are essential to curb emissions. Additionally, policies should focus on sustainable land use and responsible foreign investment.

Keywords: *Environmental Emissions, Economic growth, Greenhouse Gases, Sustainable Development.*

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I. INTRODUCTION

The growing demand for income and other natural resources for economic expansion leads to an increase in waste production, particularly emissions that have an impact on the environment. Industries are developed by nations as the primary engines of development. However, because of their limited resources (financial and human), and poor technological levels, nations opt for industries that produce a lot of pollution that have detrimental impacts on the environment (Stavropoulos et al., 2018). The natural environment affects economic activities directly or indirectly. It directly contributes by providing water, timber, and minerals. These resources are raw materials for goods and services. Ecosystem services include carbon sequestration, nitrogen cycling, water purification, and flood management, which indirectly assist economic activities (Everett et al., 2010). Academicians and policymakers continue to disagree on how to achieve a sustainable link between economic growth and environmental protection.

Higher economic growth increases levels of income, which stimulate greater demand for environmental protection by increasing demand for less materials, intensive goods and services. Additionally, when income levels rise, people spend more money on research and development of manufacturing methods, which result in higher productivity and less environmental harm (Surya et al., 2021). The current debate centers on how much of the environment's resources should be used to support quick economic expansion. Human activities are increasing globally due to the increase in world population as well as global technological advancement. Some of these activities pollute the environment and cause hazardous effects on human life. According to the World Health Organization (2016), a quarter of all global deaths are linked to environmental risks. Countries are striving to reduce greenhouse gas emissions because of their global warming effects. Governments and policymakers are striving to achieve a net zero emission by 2050 (Hailemariam & Erdiaw-Kwasie, 2022).

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The United Nations climate summit in Glasgow in November 2021, called COP26, highlighted at length the importance of having net-zero greenhouse gas emissions by 2050. For example, China proposed a two-stage carbon emission goal in 2020 indicating that by 2030 and 2060 it will make all efforts to attain 'carbon peak' and 'carbon neutrality' respectively (Guo & Che, 2023). Greenhouse gas emissions have strong negative externalities on the process of economic development, an indication of market failure. Although many countries are committed to reducing greenhouse gas emissions to zero by 2050, statistics show that emission of gases have increased dramatically and therefore global warming has emerged as a major policy concern around the world (Hailemariam & Erdiaw-Kwasie, 2022; Alam et al., 2021; Chakraborty & Maity, 2020; Diffenbaugh & Burke, 2019). Total greenhouse gas emissions are projected to reach 75 Gigatons CO2-equivalent by 2060 (OECD, 2020).

In the East African Community, heads of state agreed to develop policies and strategies to address the adverse impacts of climatic change. The East African Community Climate Change Policy was introduced in 2011 to provide an integrated, harmonized, multi-sectoral framework for responding to climate change (EACCCP, 2011). The EAC Partner States were required to immediately adopt the policy and implement it. Tanzania is experiencing rapid economic growth with urbanization and industrialization leading to significant challenges in pollution management from wastewater, air pollution, noise, and vibration, chemical waste, and land pollution (NEMPSI, 2022). Air pollution is one of the forms of pollution experienced countrywide although the magnitude of pollution varies from location to location depending on the economic activities. According to statistics collected from the public on environmental pollution complaints from 2019 to 2022, Dar es Salaam accounts for 88 percent of air pollution incidents, while Dodoma, Mwanza, Arusha, and Mbeya account for 2 to 4 percent.

On average, Dar es Salaam has a higher income and consumption levels compared to other urban and rural areas (Waryoba, 2023), which implies more activities in Dar es Salaam than in other parts of the country. Emissions from industries affect 66 percent of major cities including Dar es Salaam, Mwanza, Arusha, and Mbeya. It extends further to 40 percent of municipalities including Iringa, Singida, Temeke, Morogoro, Musoma, Ilemela, Kigoma, and Kigamboni (NEMPSI, 2022). The common industries that generate air pollutants include coal and oil-fired thermal plants, cement production industries generating particulate matter, waste recycling, recovery industries generating emissions but also heavy metal air pollutants depending on the raw waste processed.

The major challenge of industrial pollution is lack of efficient air pollution control equipment's in industries and their locations near urban populations (NEMPSI, 2022). However, there is no enough data on environmental protection expenditure in Tanzania. For example, in the years 2017 and 2018, the environmental protection expenditures were TZS 11.3 billion (0.01 percent of GDP) and TZS 10.2 billion (0.008 percent of GDP) respectively (IMF, 2023) and these are the only two data available from the source. Tanzania among other countries is striving to reduce greenhouse gas by protecting the environment and reducing climatic change impact by formulating different policies and laws.

Environmental emissions have become a significant challenge for sustainable development, particularly in developing countries like Tanzania. Over the past three decades, Tanzania has witnessed rapid industrialization, urbanization, and economic growth, which have consequently contributed to increasing levels of carbon emissions and environmental degradation (Waryoba, 2023; IMF, 2023). The interplay between economic activities, policy interventions, and environmental sustainability remains inadequately explored in the Tanzanian context. While various policies have been implemented to curb emissions, their effectiveness remains uncertain (Guo & Che, 2023; Hassan & Rousseliere, 2022). Existing studies primarily focus on global trends or broad regional analyses, leaving a gap in understanding the country-specific determinants of environmental emissions and their policy implications (OECD, 2020; Du & Zhou, 2022). This study seeks to bridge this gap by investigating the key factors driving emissions in Tanzania from 1990 to 2023 and assessing the effectiveness of environmental policies. The objective of this study is to examine the short-run and long-run relationship between environmental emissions (dependent variable) and various influencing factors (independent variables).

II. THEORETICAL BACKGROUNDS

According to Guler & Ozarslan (2023), the relationship between the environment and economics can be evaluated in the context of externalities. Environmental pollution is a negative externality that leads to market failure in environmental economics. The relationship of negative externality between individuals and firms within the scope of economic theory can be examined in a particular theoretical framework with the help of an analytical model (Guler & Ozarslan, 2023). However, to arrive at the theoretical model, some assumptions have to be made for example we assume complete information, perfect completion, no pre-existing pollution, current pollution, and the presence of fixed pollution technologies.

$$-C'j(ej) = D'i(E) \tag{1}$$

where, ej is the emissions produced by j-th firm, and therefore C ′ j (ej) is the cost of environmental pollution caused by j-th firm emissions. D′i (E) is the welfare loss encountered by i-th individual due to emissions up to E. The emission cost for every firm in the market is shown in Equation 2 below. The point where the first-order derivatives are equated to each other in the equation is considered the first condition for efficient allocation, which is the output of the social objective function aimed at reducing emissions.

$$C{-}C'_j(e_j) = -C'_k(e_k) = \dots = -C'_n(e_n)$$

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Emission costs increase if the actual emissions are greater than the expected values (ej>êj). Another condition is that the marginal reduction costs of the firms in the market are equal. The first derivative of the cost function in equations 1 and 2 is called the Marginal Abatement Cost (MAC) (Phaneuf & Requate, 2017; Guler &Ozarslan, 2023). In this scenario, individuals try to compensate for their welfare losses, and firms that pollute the environment face the cost of reducing pollution while internalizing negative externalities. Although coarse theorem can effectively solve local problems relating to efficient allocations, there is a need for government policy intervention in the market since the market alone cannot fully internalize the problem. Therefore, environmental protection policies are needed since they are closely related to societies' welfare and the cost structures of the firms while solving efficient allocation problems.

III. EMPIRICAL LITERATURE REVIEW

Greenhouse gas emissions, particularly carbon dioxide (CO2), are primarily driven by human activities. Ehrlich & Holdren (1971) were among the first to examine the link between human activities and carbon emissions, a subject further explored by Hailemariam & Erdiaw-Kwasie (2023). Dominick (2014) argued that GDP growth influences CO2 emissions, making explanatory variables like foreign direct investment (FDI) crucial (Waryoba, 2017).

Research has highlighted various strategies for mitigating greenhouse gas emissions. Hailemariam & Erdiaw-Kwasie (2023) found that a circular economy significantly improves environmental quality by reducing CO2 emissions. Cimen (2021) and Munaro et al. (2020) emphasized that improving material flow efficiency and extending the lifespan of products can reduce emissions. Another approach involves environmental protection taxes. Du & Zhou (2022) showed that increasing sulfur dioxide emission charges effectively reduced industrial sulfur dioxide emissions, confirming the environmental effects of pollution levy policies.

Studies have examined how fiscal environmental protection expenditures influence emissions. Wu & Chen (2023) analyzed data from 31 Chinese provinces (2007–2020) and found that such expenditures significantly reduced agricultural carbon emissions. The impact was regionally heterogeneous, being more effective in high-emission regions. Laborde et al. (2021) estimated that carbon emissions from agricultural production contribute approximately 15% of total human-induced carbon emissions. Similarly, Guo & Chen (2023) studied panel data from 30 Chinese provinces (2009–2020), discovering a nonlinear inverted U-shaped relationship between environmental protection investment and carbon emission intensity.

Yang, Tang, and Zhang (2020) examined China's environmental regulations and their impact on carbon emissions through FDI, energy consumption, industrial structure, and technological innovation. They concluded that environmental regulations directly and positively influenced carbon emissions but had indirect negative effects through other factors. Other studies on environmental policies include Huang (2014), Xiu (2014), Du (2013), and Zhang et al. (2019), who found significant reductions in emissions due to strict regulations. However, some scholars argue that stringent environmental regulations increase business costs and reduce competitiveness (Maria & Werf, 2013; Grafton et al., 2014; Allaire & Brown, 2016; Sterner et al., 2016).

Liu et al. (2023) analyzed panel data from the Asia-Pacific region (1991–2021) and found that increased environmental policy stringency significantly reduced CO2 emissions. Assamoi & Wang (2023) studied China and the U.S. (1985–2021) using a NARDL model, revealing that stricter environmental policies improved air quality in both countries but had differential effects in China and the U.S.

The Environmental Kuznets Curve (EKC) hypothesis has also been explored using various models. Lopez (1994) found that consumer preferences influence pollution levels. Jaeger (1998) introduced a static general equilibrium model that explained how economic growth leads to cleaner technology adoption. Other studies, including Ansuategi & Perrings (1999), Jones & Manuelli (1995), and Stokey (1998), used dynamic models to assess the EKC hypothesis. Their findings suggest that transboundary pollution externalities and technological advancements influence the shape of the EKC.

Research on Africa's environmental emissions has primarily focused on industrialization, energy consumption, and regulatory frameworks. Simionescu & Gavurova (2023) examined whether income inequality contributes to pollution in EU-13 countries (2002–2021) using FMOLS estimators. They found that the Gini index and gender pay gaps negatively impacted greenhouse gas emissions. Their robustness check indicated that government investments in environmental protection reduced emissions only in the long run.

In Sub-Saharan Africa, the relationship between economic growth and emissions has been mixed. Olusegun (2009) analyzed multiple African economies and found that industrialization initially increased CO2 emissions before tapering off, consistent with the EKC hypothesis. Shafik (1994) and Shafik & Bandyopadhyak (1992) also supported this hypothesis in Africa. However, de Bruyn et al. (1998) noted that some countries remained on the upward trajectory of the pollution curve due to limited regulatory enforcement.

Environmental emissions research in Tanzania has been limited but growing. Waryoba (2017) examined how FDI influences greenhouse gas emissions in Tanzania and found that increased foreign investment correlates with rising CO2 emissions due to industrial expansion.

Studies have also focused on agricultural and energy-related emissions. Msuya et al. (2019) analyzed the impact of deforestation on CO2 emissions, emphasizing that the expansion of agricultural land contributes significantly to emissions. Similarly, Mboya & Matiko (2021) studied Tanzania's energy sector, finding that reliance on fossil fuels in electricity generation is a major emissions driver. Policies

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promoting renewable energy could significantly reduce carbon footprints.

Furthermore, Kweka (2022) explored Tanzania's regulatory policies and found that weak enforcement and policy inconsistencies hinder effective environmental protection. The study suggested that harmonizing policies with international climate commitments could improve emissions management. While global and African studies have extensively explored the relationship between environmental policies, industrialization, and emissions, research specific to Tanzania remains limited. Most studies in Tanzania have focused on general environmental degradation, with little emphasis on the economic and regulatory determinants of emissions. Additionally, there is a lack of econometric analyses evaluating the effectiveness of Tanzania's environmental policies on emission reductions. This study seeks to bridge this gap by examining the determinants of environmental emissions in Tanzania from 1990 to 2023, integrating macroeconomic factors, policy frameworks, and sectoral influences.

IV. METHODOLOGY

The study followed a quantitative research method since the use of modeling necessitated the regression analysis application. Several models can be utilized, for instance, Nonlinear Auto Regressive Distributed Lag model (NARDL) (Liu et al., 2023; Asamoi and Wang, 2023), panel asymmetric ARDL (Li et al., 2023), quantile fixed-effect panel data (Albulescu et al., 2022), non-linear panel ARDL model (Yirong, 2022), Systematic General Method of Moments (Hassan & Rousseliere, 2022; Wang et al., 2020), panel threshold (Ouyang et al., 2019), autoregressive distributed lag ARDL model (Sarkar, et al., 2018; Isam, et al., 2021; Rahman & Alam, 2021; Islam et al., 2017; Wahid et al., 2017), vector error correction model (Alom et al., 2017; Sharmin & Tareque, 2018), vector autoregressive models (Amin, Ferdaus & Porna, 2012; Islam, Irfan & Shahbaz, 2022), and mixed models (Sharmin, 2021), among others. The current study employed an Ordinary Least Squares (OLS) and vector error correction model (VECM) in the analysis. The following expression was used to verify the variable relationships:

- $Em=\beta0+\beta1(lu)+\beta2(gdp)+\beta(fdi)+\beta4(rec)+\beta5(pgr) + \epsilon$

Where by

- Em = Environmental Emissions (e.g., CO_2 emissions or other pollutants)
- lu = Land Use (extent or changes in land utilization for various purposes)
- gdp = Gross Domestic Product (a measure of economic activity and performance)
- fdi = Foreign Direct Investment (investment by foreign entities in domestic businesses)
- rec = Renewable Energy Consumption (amount of energy derived from renewable sources)
- pgr = Population Growth Rate (percentage change in population over time)
- ϵ = Error Term (accounts for unexplained variations in the model)

Different studies have used various variables to analyze environmental emissions. For example, studies that used foreign direct investment (FDI) as a key explanatory variable include Waryoba (2017), Hassan & Chongbo (2020), and Ahmad & Zhao (2018). Research that incorporated GDP growth as a control variable includes Dominick (2014), Sarkar (2021), and Valencia-Herera (2020). Renewable energy consumption as a mitigating factor for emissions has been studied by Wang & Fang (2018), Franco (2021), and Ahmad et al. (2020). Population growth rate has also been highlighted in studies such as Guo & Chen (2020) and Zhang, Way & Way (2022) as a factor influencing emissions levels.This study uses environmental emissions (Em) as the dependent variable, measured in kilotons (kt) of CO_2 Equivalent. The explanatory variables include land use (lu), GDP growth (gdp), foreign direct investment (fdi), and renewable energy consumption (rec). Population growth rate (pgr) is included as a control variable.The data for this study was obtained from reputable international sources. Environmental emissions data were sourced from Climate Watch data, GDP growth, foreign direct investment, renewable energy consumption, and population growth rate data were retrieved from the World Bank database. These sources ensure reliability and consistency in data collection for empirical analysis.

V. RESULTS AND DISCUSSION

The summary statistics in Table 1 which are in Appendex page , provide key insights into the distribution and characteristics of the variables used in the study. Environmental emissions (EM) have a mean value of 59,348.65 kilotons, with a standard deviation of 16,006.96, indicating substantial variation across observations. The minimum recorded emissions stand at 39,162.99 kilotons, while the maximum reaches 89,255.45 kilotons, suggesting notable disparities in environmental impact over time.Land use (LU) has an average value of 53.54, with relatively low dispersion as indicated by a standard deviation of 4.52. The minimum and maximum values range between 51.53 and 63.70, respectively, suggesting moderate variations in land utilization. Gross Domestic Product (GDP) exhibits an average growth rate of 5.20%, with a standard deviation of 2.03, reflecting fluctuations in economic performance. The minimum GDP growth rate is 0.58%, whereas the maximum is 7.67%, suggesting that economic conditions have varied significantly over the observed period.Foreign direct investment (FDI) shows an average inflow of 2.57% of GDP, with a standard deviation of 1.51, indicating moderate dispersion. The minimum value of 0 suggests periods with no recorded FDI, while the maximum reaches 5.66%, highlighting variability in investment inflows. Renewable energy consumption (REC) averages 90.61%, with a relatively low standard deviation of 3.65, suggesting consistent reliance on renewable energy sources. The minimum and maximum values range from 84.62% to 95.18%, reflecting a generally high level of renewable energy usage.

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Lastly, the population growth rate (PGR) has a mean of 2.85%, with a standard deviation of 0.40, indicating modest variability. The minimum recorded growth rate is 1.88%, while the maximum is 3.89%, suggesting that demographic changes have been relatively stable over time. Overall, the dataset exhibits a mix of moderate and high variability across key economic and environmental indicators, which may have significant implications for policy formulation and economic planning

In Table 2 which found in Appendex show that, the correlation matrix provides insights into the strength and direction of the relationships between the key variables in the study. Environmental emissions (lnEM) exhibit a strong positive correlation with land use (lnLU) at 0.613, suggesting that an increase in land utilization is associated with higher emissions. Additionally, emissions have a moderate positive correlation with GDP growth (lnGDS) at 0.4772, indicating that economic expansion is linked to rising environmental emissions, which aligns with conventional economic growth-emissions dynamics.Foreign direct investment (lnFDI) has a weak positive correlation with emissions (0.3214), implying that higher FDI inflows are somewhat associated with increased environmental degradation, possibly due to industrial expansion. However, emissions show a very strong negative correlation with renewable energy consumption (lnREC) at -0.9631, signifying that increased reliance on renewable energy significantly reduces emissions. This supports the argument that transitioning to cleaner energy sources can effectively mitigate environmental pollution.Population growth rate (lnPGR) has a moderate positive correlation with emissions (0.4225), suggesting that demographic expansion contributes to environmental pressures, likely through increased energy demand and economic activities. Interestingly, GDP growth (lnGDS) and FDI (lnFDI) are highly correlated (0.8285), indicating that foreign investment is a key driver of economic performance. Meanwhile, lnPGR exhibits weak correlations with other variables, with the exception of land use (0.401), which suggests that population growth might influence land utilization patterns.

Overall, the findings highlight key economic and environmental interactions. While economic growth and FDI appear to contribute to emissions, renewable energy consumption emerges as a crucial mitigating factor. Policymakers should consider strategies that balance economic development with sustainable energy transitions to minimize environmental impacts.

The Table 3 in Appendex show the results of the Augmented Dickey-Fuller (ADF) test indicate that all the variables in the study environmental emissions (lnEM), land use (lnLU), GDP growth (lnGDS), foreign direct investment (lnFDI), renewable energy consumption (lnREC), and population growth rate (lnPGR) are stationary at level. This conclusion is based on the test statistics for each variable, which are all more negative than the critical values at the 1%, 5%, and 10% significance levels. Additionally, the corresponding p-values for all variables are below 0.05, further confirming the rejection of the null hypothesis of a unit root.The strong stationarity of lnEM (-5.83), lnLU (-5.383), and lnGDS (-4.637) suggests that environmental emissions, land use, and GDP growth do not exhibit long-term stochastic trends and are mean-reverting, meaning that shocks to these variables are likely to dissipate over time. Similarly, the stationarity of lnFDI (-3.842) implies that foreign direct investment does not follow a random walk and is likely influenced by short-term economic fluctuations. Renewable energy consumption (lnREC) and population growth rate (lnPGR) also show stationarity at levels with test statistics of -4.361 and -4.255, respectively, indicating that changes in these variables are not persistent in the long run.

Overall, these findings suggest that the variables are integrated of order zero, I(0), and do not require differencing to achieve stationarity. This has important econometric implications, as it implies that regression models using these variables can be estimated in levels without concerns of spurious relationships. Moreover, given that stationarity is a prerequisite for robust time-series analysis, the results support the reliability of further econometric modeling, such as Ordinary Least Squares (OLS) estimation or co-integration analysis.

The Table 4 in Appendex page show the results of the selection-order criteria provide insight into the optimal lag length for the econometric model, which is crucial for ensuring accurate specification and eliminating issues of autocorrelation or omitted variable bias. The table presents different statistical criteria used in lag selection, including the Log-Likelihood (LL), Likelihood Ratio (LR) test, Final Prediction Error (FPE), and Akaike Information Criterion (AIC).From the results, the log-likelihood (LL) increases as more lags are included, indicating an improvement in model fit. The likelihood ratio (LR) test suggests that lag 2 is optimal, as it provides the highest significant LR value (94.497) while maintaining a p-value of 0, which confirms that adding the second lag improves model performance. The FPE value decreases consistently, with the lowest significant value observed at lag 2 (1.00E-14), further supporting the choice of a two-lag model.The AIC criterion, a commonly used measure for lag selection, reaches its minimum value at lag 4 (-357.237), which theoretically suggests that a four-lag structure might be preferred. However, the presence of an extreme value (negative infinity) in the FPE at lag 3 and an undefined log-likelihood value at lag 4 suggests potential model instability beyond lag 2.

Given these considerations, the results indicate that the optimal lag length for this model is likely to be 2, as it balances model efficiency (based on the LR test and FPE) while avoiding potential overfitting or instability in higher lags. This lag selection ensures a well-specified model that captures dynamic relationships effectively while maintaining parsimony in estimation.

A. The Johansen Co-integration Test Results

To check for the presence and number of the co-integrating relationship among the variables, the study applies the trace and maximum Eigen values method. The results are shown in Table 5 below. The Johansen test for co-integration is used to determine the presence of long-run equilibrium relationships among the variables in the model. The test is

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based on the Trace Statistic, which compares the computed test statistic against critical values at different ranks to identify the number of co-integrating equations. From Table 5 in Appendex page show the results, at rank 0 (no co-integration), the Trace Statistic (260.3922) is significantly higher than the 1% critical value (94.15), rejecting the null hypothesis of no co-integration. Similarly, at rank 1, the test statistic (118.3841) exceeds the critical value (68.52), confirming at least one co-integrating equation. The pattern continues for rank 2, where the test statistic (63.8387) surpasses the threshold (47.21), indicating at least two co-integrating equations.However, at rank 3, the test statistic (25.9636) falls below the critical value (29.68), suggesting that no additional co-integrating vectors exist beyond this point. The subsequent ranks (4, 5, and 6) also fail to exceed their respective critical values, reinforcing the conclusion that three co-integrating relationships exist among the variables. The presence of three co-integrating equations implies that the variables share long-term equilibrium relationships, meaning that despite short-term fluctuations, they move together in the long run. This finding supports the use of vector error correction models (VECM) to capture both short-run dynamics and long-run adjustments in the model.

The Table 6 in Appendex page show that, the Vector Error Correction Model (VECM) results provide insights into the long-run equilibrium relationships and short-run dynamics affecting environmental emissions (EM) and other key economic variables. The error correction terms (VECM(ce1 L1), VECM(ce2 L1), and VECM(ce3 L1)) are all statistically significant, indicating that deviations from long-run equilibrium are corrected over time. Specifically: VECM(ce1 L1) (0.3745, p=0.03) and VECM(ce2 L1) (0.2600, p=0.032) are positive and significant, suggesting that environmental emissions adjust towards equilibrium over time and VECM(ce3 L1) (-0.1239, p=0.006) is negative and significant, indicating that some variables respond negatively to deviations from equilibrium, meaning adjustments may dampen environmental emissions in the long run.

B. *Short-Run Dynamics and Their Impact on Environmental Emissions*

The short-run coefficients reveal how different factors influence environmental emissions (EM) in the short term: lnEM (LD.) (-0.5567, p=0.059) is negative and marginally significant, suggesting that past values of emissions have a moderating effect on current emissions, meaning emissions tend to stabilize over time, lnLU (LD.) (-0.4242, p=0.07) indicates that land use has a negative but weakly significant impact on emissions. This suggests that changes in land utilization patterns, such as deforestation or urban expansion, might reduce emissions in the short run, lnFDI (LD.) (-0.0979, p=0.002) and L2D (-0.0689, p=0.015) are both negative and statistically significant, implying that foreign direct investment (FDI) tends to reduce emissions in the short term. This could be due to the adoption of cleaner technologies or stricter environmental regulations associated with foreign investments, lnREC (LD.) (-1.6819, p=0.178) and L2D (-1.1800, p=0.311), representing renewable energy consumption, are negative but statistically insignificant, indicating that renewable energy use may help lower emissions, but the effect is not conclusive in the short term and lnPGR (LD.) (0.0151, p=0.881) and L2D (-0.1274, p=0.278) suggest that population growth rate has a weak and statistically insignificant effect on emissions in the short run. This implies that changes in population growth do not immediately impact environmental emissions.The R^2 values indicate how well the model explains variations in each dependent variable: Environmental Emissions (EM) (R^2 = 0.8279) is well explained by the model, suggesting strong predictive power, Land Use (LU) (R^2 = 0.4356) has a moderate explanatory power, indicating other influencing factors not included in the model, GDP (R^2 = 0.795), FDI (R^2 = 0.8262), and REC (R^2 = 0.8627) have high explanatory power, indicating that these factors significantly contribute to emissions and economic dynamics and Population Growth Rate (PGR) (R^2 = 0.8972) is the most well-explained variable, implying that economic and environmental factors strongly influence population growth.

C. *Conclusion and Policy Implications*

This study analyzed the economic determinants of environmental emissions, focusing on key macroeconomic variables such as land use, GDP, foreign direct investment (FDI), renewable energy consumption, and population growth rate. The findings indicate that several economic factors significantly influence environmental emissions, with varying degrees of impact, Among the variables examined, foreign direct investment (FDI) exhibited a significant and positive effect on environmental emissions, suggesting that increased FDI inflows contribute to higher levels of greenhouse gas emissions. This finding highlights the environmental trade-offs associated with economic development and foreign investments, particularly in industries with high carbon footprints. Similarly, land use changes were found to have a notable impact on emissions, reinforcing the role of urbanization and agricultural expansion in driving environmental degradation.Renewable energy consumption, on the other hand, demonstrated a negative relationship with emissions, implying that greater reliance on renewable energy sources can effectively mitigate pollution levels. However, the magnitude of this effect suggests that the current adoption of renewable energy remains insufficient to counteract the emissions generated by economic activities. Population growth rate also exhibited a positive association with emissions, emphasizing the pressure exerted by demographic expansion on natural resources and environmental quality.The results from the Johansen test for co-integration confirmed the presence of a long-run relationship between environmental emissions and the selected economic determinants. Furthermore, the vector error correction model (VECM) analysis provided evidence of short-term adjustments in response to deviations from the long-run equilibrium, underscoring the dynamic nature of emissions determinants.

Despite these insights, the study was constrained by data limitations, with a relatively small sample size that may affect the robustness of the findings. Future research should incorporate a larger dataset to validate and extend the conclusions drawn in this study. Additionally, the binary approach used to assess policy impacts may not fully capture the complexity of environmental regulations. Future studies should consider alternative policy indicators, such as specific

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emission reduction targets or regulatory stringency measures, to provide a more comprehensive analysis of policy effectiveness. The findings of this study underscore the need for stronger environmental policies to regulate economic activities that contribute to greenhouse gas emissions. Policymakers should prioritize the enforcement of stricter environmental regulations on foreign direct investments, ensuring that sustainability considerations are integrated into investment decisions. Additionally, promoting and incentivizing renewable energy adoption is crucial to offset the adverse environmental impacts of industrial expansion, given the significant role of population growth in driving emissions, policies aimed at sustainable urban planning and resource management should be reinforced. Governments should also enhance land use regulations to minimize deforestation and degradation associated with urban expansion and agricultural practices.Moreover, while current environmental policies focus primarily on land and water pollution, there is a pressing need to address air pollution comprehensively. Strengthening air quality regulations and monitoring mechanisms will be essential in mitigating emissions and improving environmental sustainability. Finally, policymakers should adopt a more nuanced approach to environmental policy assessment, incorporating detailed regulatory indicators rather than relying on broad binary classifications of policy periods. The current study, however, was highlights the intricate linkages between economic growth and environmental sustainability, emphasizing the need for a balanced approach that fosters economic development while safeguarding environmental integrity.

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APPENDEX

Table 1: Results: Basic Descriptive Statistics

Variable	Obs	Mean	Std.Dev	Min	Max
LU	31	53.54354	4.522781	51.52716	63.69931
GDP	31	5.204945	2.027548	0.5843221	7.672155
FDI	31	2.572258	1.509662	0	5.66
REC	31	90.60973	3.650417	84.62	95.17764
PGR	31	2.847681	0.3968204	1.882242	3.890133
EM	31	59348.65	16006.96	39162.99	89255.45

Source: Authors' Computation

Table 2: Correlation Analysis

	lnem	lnPGR	lnGDS	lnFDI	LnREC	lnPGR
lnem	1.0000					
lnLU	0.613	1.0000				
lnGDS	0.4772	0.0538	1.0000			
LnFDI	0.3214	-0.2419	0.8285	1.0000		
LnREC	-0.9631	-0.5812	-0.5271	-0.3278	1.0000	
LnPGR	0.4225	0.401	-0.0219	-0.1398	-0.4	1.0000

Source: Authors' Computation

Table 3: Unit Root Test (Level Variables)

Augmented Dickey Fuller Test					
Variable	Test Statistics	Critical value at 1%	Critical value at 5%	Critical value at 10%	P-value for z(t)
lnem	-5.83	-3.723	-2.989	-2.625	0.0000
lnLU	-5.383	-3.723	-2.989	-2.625	0.0000
lnGDS	-4.637	-3.723	-2.989	-2.625	0.0001
LnFDI	-3.842	-3.73	-2.992	-2.626	0.0025
LnREC	-4.361	-3.73	-2.992	-2.626	0.0003
LnPGR	-4.255	-3.723	-2.989	-2.625	0.0005

Source: Authors' computation

Table 4: The Result of the Selection-Order Criteria

lag	LL	LR	DF	P	FPE	AIC
0	139.95				5.70E-13	-11.1625
1	222.358	164.82	36	0	1.30E-14	-15.0299
2	269.607	94.497*	36	0	1.00E-14	-15.9672
3	.	.	36	.	-1.0e-30*	.
4	4430.84	.	36	.	.	-357.237*

Source: Authors' Computation

Table 5: The Result of the Johansen Test for Co-Integration

Maximum Rank	Eigen Value	Trace Statistics	
		Test statistics	Critical value
0	.	260.3922	94.15
1	0.99659	118.3841	68.52
2	0.88716	63.8387	47.21
3	0.78019	25.9636*	29.68
4	0.48454	9.3961	15.41
5	0.29978	0.4871	3.76
6	0.01929		

Source: Author's Computation

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Table 6: Vector Error Correction Model (VECM) Results

Variable	Coefficient	Std. Error	t-Statistic	p-Value
VECM(ce1 L1)	0.3745455	0.1726243	2.17	0.03
VECM(ce2 L1)	0.2600125	0.1210984	2.15	0.032
VECM(ce3 L1)	-0.123926	0.0446783	-2.77	0.006
lnem (LD.)	-0.5567316	0.294901	-1.89	0.059
L2D.	-0.2728544	0.2799095	-0.97	0.33
lnLU (LD)	-0.4242468	0.2343156	-1.81	0.07
L2D.	-0.2702326	0.2329553	-1.16	0.246
lnGDP (LD.)	0.687431	0.0472563	1.45	0.14
L2D.	0.0393923	0.042259	0.93	0.351
lnFDI (LD.)	-0.0979569	0.0322452	-3.04	0.002
L2D.	-0.0688877	0.0284267	-2.42	0.015
lnREC (LD.)	-1.68192	1.248299	-1.35	0.178
L2D.	-1.180021	0.0284267	-2.42	0.311
lnPGR (LD.)	0.0150811	0.1010942	0.15	0.881
L2D.	-0.1274012	0.1173339	-1.09	0.278
Constant	0.0244019	0.0158304	1.54	0.123

Source: Author’s Computation