IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(4), 152-165.

Analysis of the Economic and Environmental Factors Affecting CO_2 Emissions in Egypt: A Proposed Dynamic Econometric Model

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Received: 04 January 2025 **Accepted:** 18 April 2025 **DOI:** https://doi.org/10.32479/ijeep.19222

ABSTRACT

Developing nations have environmental issues due to their dependence on non-renewable energy sources for economic development. This paper analyzed the interplay between CO_2 emissions and five economic variables, namely land under cereal production (LAND), manufacturing (MANUF), trade openness (TRADE), GDP per capita (GDPPC), and foreign direct investment (FDI) in Egypt from 1990 to 2022. The autoregressive distributed lag (ARDL) model is used to examine both short-term and long-term relationships. The results indicated that the ARDL(1,1,2,2,0, 0) is the optimal model, which has the lowest Akaike information criterion (AIC) value. The variables of MANUF and GDPPC negatively affected CO_2 emissions, but the TRADE and LAND variables had positive long-term effects. The lagged periods of TRADE and LAND variables have significantly affected CO_2 levels. The results of the error correction model indicate that the speed of return to long-run equilibrium after a short-run deviation occurs within about 4.5 years based on the value of the error correction term.

Keywords: ARDL Model, Climate Change, Economic Activities, Land Under Cereal Production
JEL Classifications: C1, C32, C58, E6, Q43, Q54

1. INTRODUCTION

Economic expansion is an essential determinant of a nation's prosperity; nonetheless, it frequently leads to environmental degradation. The interdependence between economic advancement and environmental well-being is clear: economic expansion can adversely affect the environment, whereas environmental deterioration can impede economic development. Environmental degradation, influenced by resource depletion and natural calamities, presents considerable threats to economic stability (Azam et al., 2016; Abonazel et al., 2025; Ebrahim et al., 2025).

A key factor contributing to environmental degradation is global warming, predominantly exacerbated by CO_2 emissions (Nguyen and Le, 2018). The Industrial Revolution marked a shift from organic to inorganic manufacturing techniques, predominantly dependent on non-renewable energy sources like fossil fuels, which intensify global warming through the emission of greenhouse gases (GHGs) into the atmosphere. This predicament has emerged as a critical concern for policymakers and environmental advocates, as economic activities in both developed and developing nations consistently elevate GHG emissions (Adebayo and Beton Kalmaz, 2021). Carbon dioxide, primarily emitted via fossil fuel combustion, cement production, and alterations in land use, is acknowledged as the primary contributor to global warming due to its heat-retaining characteristics. Developing nations, in their quest for enhanced living standards, frequently prioritize swift economic growth, resulting in urbanization and increased energy use. This advancement frequently relies on non-renewable energy sources, leading to increased carbon dioxide emissions. Consequently, achieving a balance between economic advancement and environmental sustainability has emerged as an urgent challenge, particularly for developing countries (Adebayo and Beton Kalmaz, 2021).

Sustainable development, a framework emphasizing growth that meets current needs without compromising future generations, has received heightened focus since the 1970s (Jalil, 2010). Unsustainable practices, such as excessive reliance on fossil fuels and deforestation, have significantly contributed to climate change, resulting in a notable increase in global CO_2 emissions throughout the decades (El Ouahrani et al., 2011; Ebrahim et al., 2025). The consequences of unmanaged emissions include biodiversity loss, increased health risks, and disturbances to ecosystems and agricultural systems (Stern, 2007; Bekhet and Othman, 2017). Urbanization, a crucial driver of economic and social transformation, has increased energy consumption and CO_2 emissions. With more than fifty percent of the world population residing in urban areas, a figure expected to rise, cities have transformed into hubs of energy-intensive activity. Urban lifestyles, marked by high consumption rates, lead to increased energy needs, hence exacerbating emissions (Ji and Chen, 2017).

Empirical studies consistently demonstrate a positive correlation between urbanization and CO_2 emissions, with the residential, transportation, and industrial sectors as primary contributors (Bekhet and Othman, 2017). The ongoing exploitation of natural resources and disregard for ecological health have led to substantial repercussions, including climate change driven by greenhouse gas emissions. Carbon dioxide is essential in amplifying the greenhouse impact (Jeon 2022). Energy, a crucial element of economic advancement and daily existence, is intrinsically linked to environmental outcomes, highlighting the necessity for sustainable energy policy (Wang, 2022). These simultaneous developments allow Egypt to reevaluate the principal elements leading to environmental degradation and the interactions among essential indicators, such as independent variables including industrialization, trade, urban population, and area designated for wheat farming.

Our paper aims to present an efficient econometric model (ARDL model) suitable for explaining and identifying the economic and environmental factors affecting CO_2 emissions in Egypt based on the period from 1990 to 2022.

The paper is organized into multiple sections: Section 2 examines pertinent literature and underscores significant findings from previous research. Section 3 delineates the ARDL model framework. Section 4 addresses empirical study. Section 5 concludes the study by summarizing its principal results and implications.

Figure 1 effectively visualizes the global distribution of CO_2 emissions in 2022, highlighting the significant contributions of major economies like China, the United States, and India. It underscores the need for global cooperation in reducing emissions, with a focus on transitioning to sustainable energy sources and supporting developing nations in their growth without exacerbating climate change. China, the US, and India are the most elevated producers of CO_2 all around the world. They have high modern action, thick populaces, and high energy use. European nations, the Center East, and a few Asian nations (e.g., Germany, Japan, and Saudi Arabia) have moderate outflows, which show their modern base and energy use. African and South American nations, as well as little nations, will generally have low emanations. This is regularly because of lower industrialization and energy utilization.

Figure 2 provides valuable insights into the trends and disparities in per capita CO_2 emissions across four countries (United States, China, India, and United Kingdom). It underscores the need for global cooperation in addressing climate change, with developed nations leading in emission reductions and developing nations

Figure 1: World distribution of CO_2 emissions in 2022

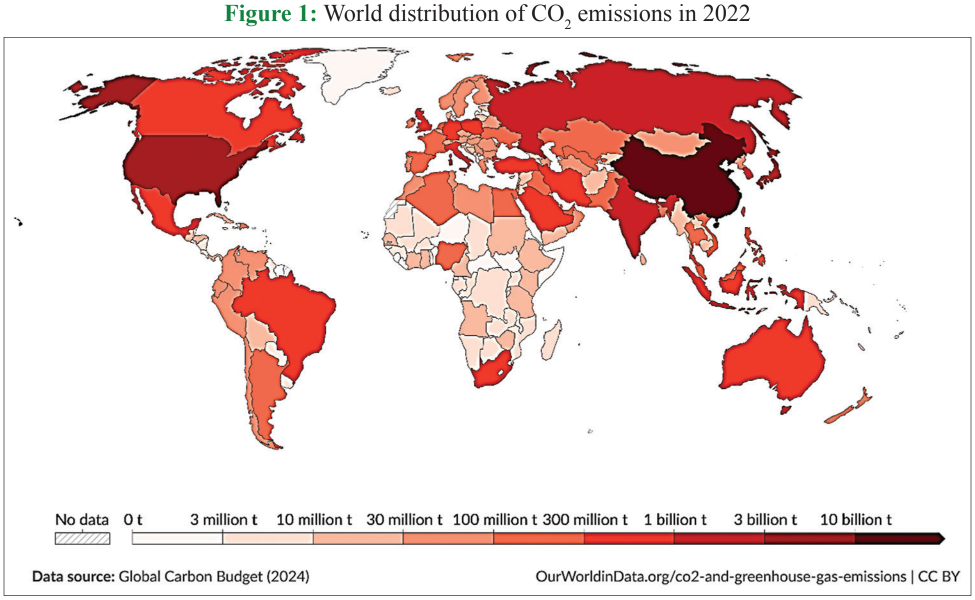
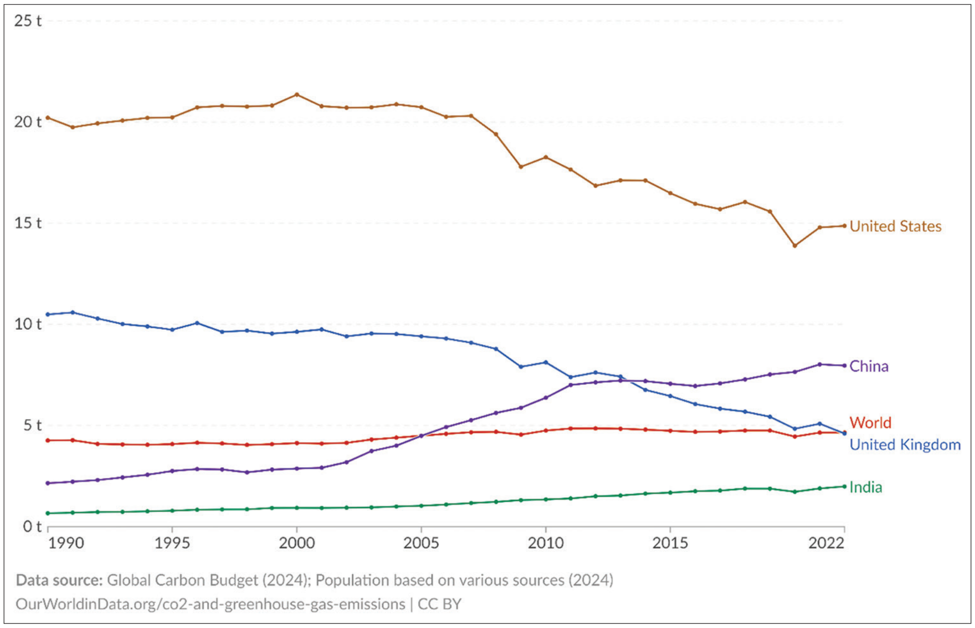


Figure 2: Per capita CO_2 emissions trend across four countries from 1990 to 2022



transitioning to cleaner energy pathways. The United States has historically been the largest per capita emitter, though its emissions have been declining. China has seen a dramatic rise in per capita emissions, reflecting its role as the world's largest emitter in absolute terms. India, despite its large population, has much lower per capita emissions compared to the US and China, highlighting the disparity in energy consumption and development levels. The United Kingdom serves as an example of successful emission reduction, likely due to proactive climate policies.

2. LITERATURE REVIEW

This section concentrates on applied research concerning CO_2 and the economic variables influencing it, with particular emphasis on applications utilizing the ARDL model.

Pachiyappan et al. (2021) investigated the correlation among CO_2 emissions, GDP, energy utilization (ENU), and population growth (PG) in India from 1980 to 2018 by contrasting the "vector error correction model" (VECM) with the "autoregressive distributed lag" (ARDL) methodology. The research demonstrated a sustained equilibrium relationship among the variables. Granger causality analysis revealed short-term bidirectional causation between GDP and ENU, while unidirectional causality was identified from CO2E to GDP, CO2E to ENU, CO2E to PG, and PG to ENU. Variance decomposition study indicated that 58.4% of future variations in CO2E are ascribed to alterations in ENU, 2.8% to modifications in GDP, and 0.43% to changes in PG. The ARDL test results indicated that a 1% increase in population growth results in a 1.4% increase in CO_2 emissions.

Karedla et al. (2021) investigated the influence of trade openness, economic growth, and industrial activities on CO_2 emissions in India. The research utilized the ARDL limits testing methodology, examining data from 1971 to 2016, concentrating on variables including GDP, manufacturing output, trade openness, and CO_2 emissions. The findings indicated a sustained correlation between CO_2 emissions and the analyzed parameters. Trade openness was specifically found to diminish CO_2 emissions, although GDP and manufacturing activity exerted a large and beneficial influence on CO_2 emissions in the long term. These findings underscore the intricate relationship between economic development, industrial growth, and environmental consequences in India.

Abbasi et al. (2021) analyzed the determinants of economic growth in Pakistan from 1972 to 2018. The study employed the dynamic ARDL simulations method to examine the impact of both positive and negative fluctuations in energy consumption, industrial expansion, urbanization, and carbon emissions on Pakistan's economic growth. The frequency-domain causality (FDC) test was utilized to evaluate long-term, medium-term, and short-term associations. The results demonstrate that power consumption and industrial value-added substantially affect economic growth in both the short and long term. Simultaneously, carbon emissions and urbanization were observed to positively influence economic growth in the short run. The research indicates that energy consumption, industrial growth, urbanization, and CO_2 emissions all favorably influence Pakistan's economic development. The FDC test further substantiates the presence of causality over long-term, medium-term, and short-term intervals.

A study by Aslam et al. (2022) investigated the connections between Malaysian trade, energy consumption, economic growth, and carbon dioxide emissions. In order to evaluate both long-term and short-term cointegration correlations between the variables, the researchers examined annual data from 1971 to 2016 using the Granger causality method and the ARDL bound testing strategy, which takes structural breaks into account. The results showed that there are substantial long-term correlations between CO_2 emissions (CO2L), industrial activity (IND), trade (TR), and GDP. With an estimated error correction term of -0.952, 95.2% of the variation in CO_2 emissions from short-run to long-run equilibrium is adjusted each year. Furthermore, a unidirectional causal association between trade openness and industrial activity was found at a 1% significance level, whereas a bidirectional causal relationship between trade openness and CO_2 emissions (CO2L) was shown by the Granger causality test.

Raihan et al. (2023) investigated the determinants of CO_2 emissions in Egypt from 1990 to 2019, emphasizing economic growth, fossil fuel energy consumption, renewable energy utilization, tourism, and agricultural production. Employing the Dynamic Ordinary Least Squares (DOLS) approach, in conjunction with alternative estimators such as Fully Modified Least Squares (FMOLS) and Canonical Cointegrating Regression (CCR). Economic expansion, fossil fuel energy consumption, and tourism were found to elevate CO_2 emissions, hence exacerbating environmental degradation. Furthermore, the utilization of renewable energy and enhancements in agricultural production diminish CO_2 emissions, hence elevating environmental quality. The Granger causality test was employed to identify causal links among these variables. The research underscores the significance of shifting to a low-carbon economy in Egypt through the advancement of renewable energy, sustainable tourism, and climate-resilient agriculture. These strategies are crucial for mitigating emissions and guaranteeing long-term environmental sustainability.

Azazy et al. (2024) examined the complex interactions between CO_2 emissions and key variables, including industrial output, international commerce, urban demographic changes, and area designated for grain cultivation in Egypt from 1990 to 2021. It delineates an advanced methodology for estimating the ARDL model using three robust estimation techniques and compares these with the traditional ordinary least squares (OLS) method to determine the best accurate estimation technique. The empirical findings indicate that variables related to industrial production and commerce negatively affect CO_2 emissions, while the urban population and land allocated for grain cultivation exhibit a positive long-term effect. Furthermore, the lagged impacts of trade and land variables were determined to significantly affect CO_2 levels. The ECM indicates that economic adjustments transpire over an anticipated duration of 25 months. The investigation determines that robust estimating strategies regularly surpass the non-robust OLS method.

Tufaner and Sozen (2024) conducted a study to examine the correlations among carbon dioxide (CO_2) emissions, industrial growth, and the utilization of renewable energy. Their research concentrated on data from 38 OECD member nations covering the period from 1997 to 2019. The research revealed that industrial growth is a significant driver of CO_2 emissions in both the short and long term, as determined using ARDL analysis. Conversely, CO_2 emissions diminish throughout both intervals as the proportion of renewable energy in the total energy composition increases. Additionally, the Dumitrescu-Hurlin causality test revealed a unidirectional causal relationship, indicating that industrial growth is influenced by CO_2 emissions, whereas CO_2 emissions are influenced by the utilization of renewable energy. These findings illustrate the essential role of renewable energy in reducing carbon emissions and fostering economic development.

Baz and Zhu (2025) investigated the influence of climate mitigation technology, energy consumption, and environmental regulations on CO_2 emissions in 19 OECD nations, demonstrating that fossil fuels elevate emissions, but environmentally focused technologies and more stringent environmental policies diminish them. Renewable energy exhibits an unexpected correlation with increased emissions, perhaps because of integration difficulties. A unidirectional causality suggests that environmental technology, the adoption of renewable energy, and the rigor of policies affect emissions, but not vice versa. The findings underscore the necessity of investing in green technologies, stringent regulations, and joint initiatives to improve environmental quality and economic productivity, pushing governments to prioritize research, education, and sectoral transitions for sustainable development.

3. METHODOLOGY

This section provides the statistical background of the ARDL model used in our empirical study.

3.1. ARDL Framework

The ARDL model serves as an indispensable resource within the context of econometric studies for dynamic unconstrained single-equation regression analysis. It primarily investigates long-term associations among integrated variables and reevaluates these associations through the lens of an error correction framework. Generally, ARDL models initiate with a comprehensive and expansive dynamic configuration, which is subsequently streamlined by diminishing complexity and modifying variables via the implementation of both linear and nonlinear constraints. A notable advantage of the ARDL model over prior co-integration methodologies is its capacity to conduct co-integration analysis on variables exhibiting mixed integration orders, such as I(0) and I(1). By integrating both contemporaneous and lagged values of independent variables, alongside lagged values of the dependent variable, the ARDL model is adept at resolving issues related to correlation (Abonazel et al., 2021; Sallam et al., 2025).

The ARDL is a statistical model that integrates the temporal properties of time series data with the influence of independent variables. It is composed of stochastic regression that includes a time series involving the explanatory variables' past and current values and variable substitutes, among them lags. That's why you may be able to tackle several econometric problems like misspecification and come up with the most appropriate interpretable model (El-Sheikh et al., 2022).

The general formula of the ARDL (p, q_1,…q_k) model is given by

$$y_t = \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{k} \sum_{h=0}^{q_j} \psi_{jh}\ x_{j,t-h} + \varepsilon_t \qquad t = 1,...,T, \qquad (1)$$

Where ε_t is the stochastic error term of the model, p is the number of lags of the dependent variable (y), q_k is the number of lags of the k[th] independent variable (x), and α, φ_i, ψ_{jh} (for $i = 1,\ldots,p$; $h = 0,\ldots,q_j$; $j = 1,\ldots,k$) are the model parameters that we will estimate.

Based on the econometric literature, the statistical assumptions of the ARDL model are the following (El-Sheikh et al., 2022; Abonazel et al., 2021; Sallam et al., 2025): Firstly, the error terms e_t are assumed to have a zero mean ($E(\varepsilon_t)=0$), constant variance ($var(\varepsilon_t) = \sigma^2$), and no autocorrelation ($cov(\varepsilon_t, \varepsilon_s) = 0$, for all $t \neq s$, where $t, s = 1,2,\ldots,T$). This confirms that the errors are unbiased, homoscedastic, and independent over time. Secondly, the error terms must be uncorrelated with the explanatory variables at each time point ($cov(\varepsilon_t, x_{jt}) = 0$) for $t = 1,\ldots,T; j = 1,\ldots,k$. Lastly, the error terms are assumed to follow a normal distribution ($\varepsilon_t \sim N(0,\sigma^2)$, which is crucial for hypothesis testing and constructing confidence intervals. Together, these assumptions make sure that the ARDL model's OLS estimation method gives accurate and reliable parameter estimates (Hill et al., 2011).

In our study, we can develop the ARDL(p,q_1,q_2,q_3,q_4,q_5) model equation as follows:

$$CO2EM_t = \alpha + \sum_{i=1}^{p}\phi_i CO2EM_{t-i} + \sum_{h=0}^{q_1}\psi_{1h}\ MANUF_{t-h} + \sum_{h=0}^{q_2}\psi_{2h}\ TRADE_{t-h} + \sum_{h=0}^{q_3}\psi_{3h}\ LAND_{t-h} + \sum_{h=0}^{q_4}\psi_{4h}\ GDPPC_{t-h} + \sum_{h=0}^{q_5}\psi_{5h}\ FDI_{t-h} + \varepsilon_t; \qquad t = 1,\ldots,T, \tag{2}$$

where CO2EM is the dependent variable of the model and refers to CO_2 emissions in Egypt, while the five independent variables are defined as follows: MANUF refers to manufacturing, TRADE refers to trade, LAND refers to land under cereal production, GDPPC refers to the gross domestic product per capita, and FDI refers to foreign direct investment, see Table 1 for more details about the studied variables of our empirical study.

3.2. Short-Run and Long-Run Relationship

3.2.1. Long-run relationship

For the ARDL(p,q_1,q_2,q_3,q_4,q_5) model in Equation (2), the long-run equation is

$$CO2EM_t = \theta_0 + \theta_1 MANUF_t + \theta_2 TRADE_t + \theta_3 LAND_t + \theta_4 GDPPC_t + \theta_5 FDI_t + e_t \tag{3}$$

where $\theta_0 = \frac{\alpha}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run intercept, $\theta_1 = \frac{\sum_{j=0}^{q1}\psi_{1j}}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run coefficient of MANUF, $\theta_2 = \frac{\sum_{j=0}^{q2}\psi_{2j}}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run coefficient of TRADE, $\theta_3 = \frac{\sum_{j=0}^{q3}\psi_{3j}}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run coefficient of LAND, $\theta_4 = \frac{\sum_{j=0}^{q4}\psi_{4j}}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run coefficient of GDPPC, $\theta_5 = \frac{\sum_{j=0}^{q5}\psi_{5j}}{1-\sum_{i=1}^{p}\phi_i}$ is the long-run coefficient of FDI, and e_t is the error term.

3.2.2. Short-run relationship

The error correction model (ECM) inside the ARDL framework is a crucial tool for analyzing short-term dynamics and long-term equilibrium relationships among variables. The ECM measures the speed at which a dependent variable returns to its long-term equilibrium after a short-term perturbation, as represented by the error correction term (ECT). This expression, derived from the long-run cointegration relationship, denotes the proportion of the disequilibrium corrected in each period. An unpleasant and significant ECT confirms the existence of a stable long-term relationship, while the short-term coefficients reflect immediate effects of independent factors. The ARDL-ECM methodology is particularly advantageous as it may be applied regardless of whether the variables are integrated of order zero [I(0)] or one [I(1)], making it a versatile approach for time series analysis. Equation (2) facilitates the derivation of the ECM equation as illustrated by Pesaran et al. (2021):

$$\Delta\ CO2EM_t = \alpha_0 + \sum_{i=1}^{p-1}\beta_i \Delta\ CO2EM_{t-i} + \sum_{h=0}^{q_1-1}\gamma_{1h}\ \Delta\ MANUF_{t-h} + \sum_{h=0}^{q_2-1}\gamma_{2h}\ \Delta\ TRADE_{t-h} + \sum_{h=0}^{q_3-1}\gamma_{3h}\ \Delta\ LAND_{t-h} + \sum_{h=0}^{q_4-1}\gamma_{4h}\ \Delta\ GDPPC_{t-h} + \sum_{h=0}^{q_5-1}\gamma_{5h}\ \Delta\ FDI_{t-h} + \lambda ECT_{t-1} + \varepsilon_t \tag{4}$$

where $\Delta CO2EM_t$ is the first difference of the dependent variable $CO2EM_t - CO2EM_{t-1}$, representing short-term changes, ($\Delta MANUF_{t-h}, \ldots, \Delta FDI_{t-h}$) are the first differences of the independent variables, representing short-term changes, β_i are the coefficients for lagged differences of $CO2EM_t$, ($\gamma_{1h}, \gamma_{2h}, \ldots, \gamma_{5h}$) are the coefficients for lagged differences of ($MANUF_t$, $TRADE_t$, $LAND_t$, $GDPPC_t$, FDI_t), respectively, λ is the speed of adjustment

Table 1: Descriptive statistics of the six variables (dependent variable is CO_2 emissions)

Variable	Abbreviation	Mean	Median	Max.	Min.	SD
CO_2 emissions	CO_2EM	146.59510	152.13300	218.92900	76.62900	51.72466
Manufacturing	MANUF	33.32579	32.71143	39.89033	27.40605	3.28808
Trade	TRADE	46.95684	45.25563	71.68063	29.85697	10.75246
Land under cereal production	LAND	2899846	2911543	3623430	2283426	319045
Gross domestic product per capita	GDPPC	2.28223	2.24497	5.17381	−1.62452	1.66462
Foreign direct investment	FDI	2.14356	1.50925	6.87634	−0.20454	1.78155

Max. is the maximum value, Min. is the minimum value, and SD is the standard deviation coefficient (must be negative and statistically significant for cointegration), and ECT_{t-1} is the ECT, representing the deviation from the long-run equilibrium in the previous period. The ECT is calculated as follows

$$ECT_{t-1} = CO2EM_t - \theta_0 - \theta_1 MANUF_{t-1} - \theta_2 TRADE_{t-1} - \theta_3 LAND_{t-1} - \theta_4 GDPPC_{t-1} - \theta_5 FDI_{t-1} \quad (5)$$

3.3. Selection Criteria

To select the better ARDL model suitable to our data, we estimate all possible combinations of lag lengths (p,q_1,q_2,q_3,q_4,q_5) within the maximum lag range. Then use information criteria to compare the estimated models and select the one with the best fit. The most common criterion is the Akaike Information Criterion (AIC) (Akaike, 1973):

$$AIC = -2L + 2k \quad (6)$$

where k is the number of parameters and L is the maximum value of the likelihood function for the model. Lower AIC indicates a better model.

4. EMPIRICAL STUDY

4.1. Data Source

The date of the five independent variables (manufacturing, trade, land under cereal production, GDP per capita, and foreign direct investment) for Egypt from 1990 to 2022 was obtained from the World Bank site (https://data.worldbank.org), while CO_2 emissions data was obtained from the International Energy Agency (IEA) site.

4.2. Descriptive Statistics

Table 1 provides descriptive statistics for the variables used in our study, covering the period from 1990 to 2022. The mean CO_2 emissions (CO2EM) are 146.59510, with a median of 152.13300, indicating a slightly skewed distribution. Manufacturing (MANUF) has a mean of 33.32579 and a median of 32.71143, showing relatively stable values over time. Trade (TRADE) has a mean of 46.95684 and a median of 45.25563, suggesting consistent trade activity. Land under cereal production (LAND) has a mean of 2899846 and a median of 2911543, with a large standard deviation of 319045, indicating variability in land use. Gross domestic product per capita (GDPPC) has a mean of 2.28223 and a median of 2.24497, with a range from −1.62452 to 5.17381, reflecting economic fluctuations. Foreign Direct Investment (FDI) has a mean of 2.14356 and a median of 1.50925, with a range from −0.20454 to 6.87634, indicating diverse investment levels. These statistics offer a comprehensive overview of the variables' distributions and central tendencies, aiding in understanding their behavior over the specified period.

Table 2 displays the results of the Jarque-Bera (JB) test for the normality of each variable (Jarque and Bera, 1980). For CO_2 emissions (CO2EM), the Jarque-Bera statistic is 3.426355 with a P = 0.180292, indicating that the distribution is not significantly different from normal. Manufacturing (MANUF) has a Jarque-Bera statistic of 0.866064 and a P = 0.64854, suggesting a normal distribution. Trade (TRADE) has a statistic of 1.704905 and a P = 0.426368, also supporting normality. Land use (LAND) has a statistic of 1.032731 and a P = 0.596685, indicating no significant departure from normality. GDP per capita (GDPPC) has a low statistic of 0.366486 and a high P = 0.832566, strongly supporting normality. However, Foreign Direct Investment (FDI) has a high statistic of 12.74142 and a low P = 0.001711, indicating that its distribution significantly deviates from normality.

Table 2: Jarque-Bera test of the six variables

Variable	Jarque-Bera	P-value
CO_2EM	3.426355	0.180292
MANUF	0.866064	0.64854
TRADE	1.704905	0.426368
LAND	1.032731	0.596685
GDPPC	0.366486	0.832566
FDI	12.74142	0.001711

Figure 3 provides a visual representation of the time series data for various variables (CO_2 emissions, Manufacturing, Trade, Land under cereal production, GDP per capita, and FDI) over the period from 1990 to 2022. This graphical depiction allows for an intuitive understanding of trends, patterns, and potential anomalies in the data over time. Observing these plots can help identify any significant changes or fluctuations that may be relevant for further analysis. For instance, one might notice periods of rapid growth or decline in CO_2 emissions, manufacturing activity, or trade. The main conclusion from this figure is that the series are non-stationarity except for GDPPC.

Figure 4 shows the first-differenced time series data for the same set of variables. Taking the first difference is a common technique used to address non-stationarity in time series data. By plotting the differenced data, we can assess whether the transformation has successfully stabilized the mean and variance of the series, making them more suitable for econometric modeling. The plots in Figure 4 should ideally show less pronounced trends and more stable behavior compared to the original data in Figure 3, indicating that the differencing process has effectively removed any unit roots present in the original series.

4.3. Multicollinearity Test

Table 3 displays the correlation matrix for the five independent variables, providing insights into the relationships between them.

From Table 3, we note that Manufacturing (MANUF) has a weak positive correlation of 0.05474 with Trade (TRADE) and a moderate positive correlation of 0.709262 with Land use (LAND). Trade has a weak negative correlation of −0.334014 with Land use. GDP per capita (GDPPC) has weak correlations with other variables, ranging from −0.176232 to 0.171269. Foreign Direct Investment (FDI) shows moderate correlations with Trade (0.543341) and Land use (0.289165), and a strong positive correlation with GDP per capita (0.626309). These correlations help identify potential multicollinearity issues and guide the selection of variables for

Figure 3: Time series graphs of the six variables from 1990 to 2022

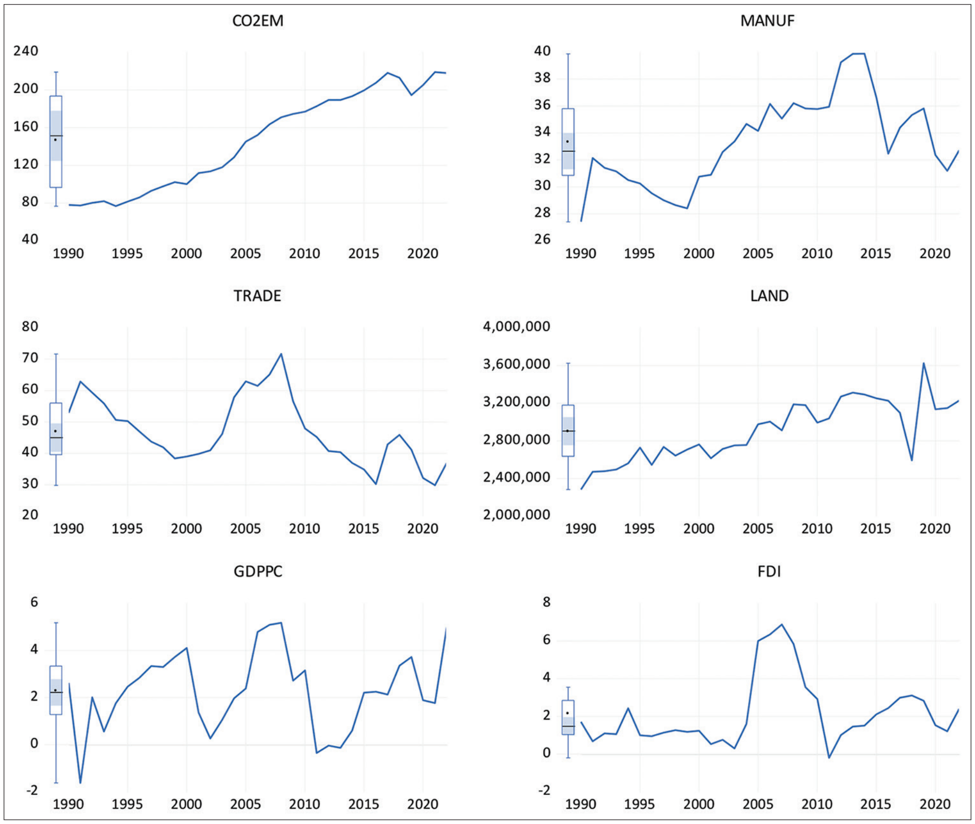
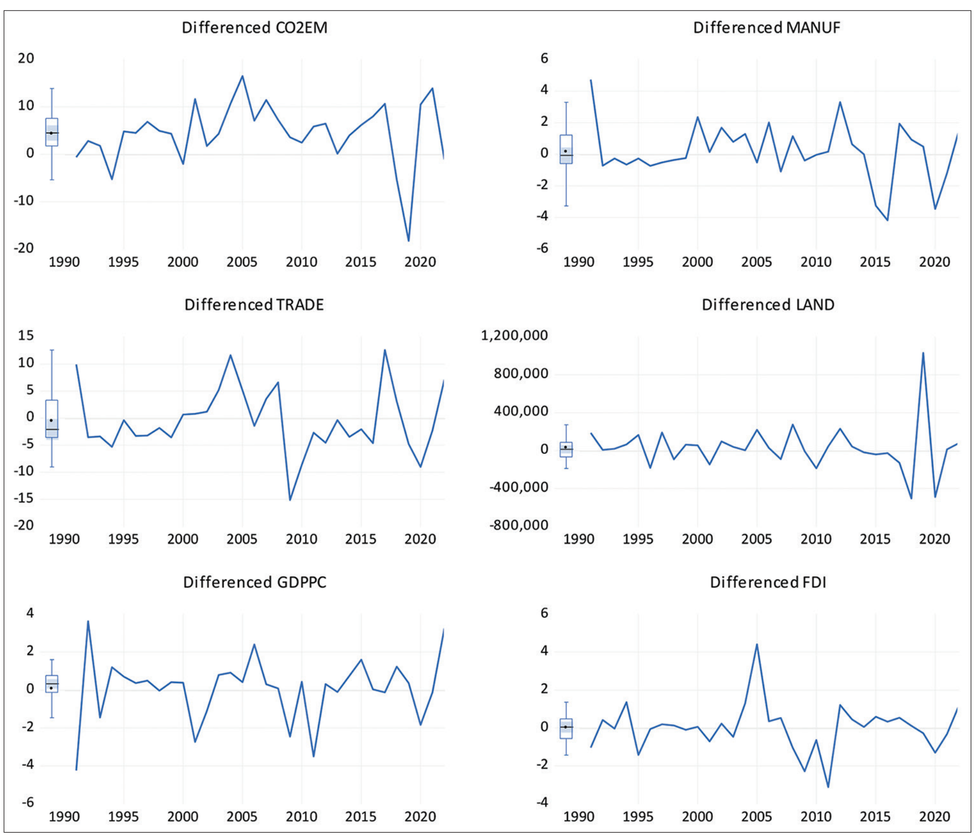


Figure 4: Time series plots of variables from 1990 to 2022 after taking the first difference



modeling. Figure 5 presents a heatmap of the correlation matrix for the five independent variables (Manufacturing, Trade, Land under cereal production, GDP per capita, and FDI). The heatmap visually represents the pairwise correlations between these

Table 3: Correlation matrix of the five independent variables of our study

Variable	MANUF	TRADE	LAND	GDPPC	FDI
MANUF	1	0.05474	0.709262	−0.176232	0.320246
TRADE	0.05474	1	−0.334014	0.171269	0.543341
LAND	0.709262	−0.334014	1	0.112154	0.289165
GDPPC	−0.176232	0.171269	0.112154	1	0.626309
FDI	0.320246	0.543341	0.289165	0.626309	1

variables, with colors indicating the strength and direction of the relationships. A high positive correlation (close to +1) suggests that two variables move together in the same direction, while a high negative correlation (close to −1) indicates that they move in opposite directions. This visualization is particularly useful for identifying potential multicollinearity issues, where two or more independent variables are highly correlated with each other. Such issues can affect the reliability of regression coefficients and their standard errors, so it is crucial to address them before proceeding with model estimation. Since all correlations are less than 0.8, we can conclude that there is no multicollinearity problem (Abonazel, 2025). This means that we can use all these variables together in a single regression model without any side effects on estimation efficiency.

Figure 6 displays the Variance Inflation Factor (VIF) values for the five independent variables. VIF is a measure used to quantify the severity of multicollinearity in a regression model. A VIF value greater than 5 indicates a level of multicollinearity. By examining the VIF values in Figure 6, we can see that all variables have VIF values <5 (Abonazel, 2025). This indicates the absence of multicollinearity.

4.4. Stationarity Test

Table 4 presents the results of the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981) for stationarity of each variable.

From Table 4, the test evaluates whether the variables are stationary or integrated of a certain order. CO_2 emissions (CO2EM) have a t-statistic of −0.25911 at the level with a P = 0.9204, indicating non-stationarity, but become stationary after first differencing (t-statistic = −4.799805, P = 0.0006), classified as I(1). Manufacturing (MANUF) and Trade (TRADE) also display similar patterns, becoming stationary after first differencing (t-statistics = −5.680349 and −4.410778 respectively, both with $P < 0.001$). Land use (LAND) follows the same trend, with a t-statistic of −7.260339 and a P = 0.0001 after first differencing. GDP per capita (GDPPC) is already stationary at the level (t-statistic = −3.001014, P = 0.0455), classified as I(0). Foreign Direct Investment (FDI) becomes stationary after first differences (t-statistic = −4.633706, P = 0.0008). These results are necessary for determining the appropriate order of integration for each series.

4.5. Model Selection

The ARDL model was estimated to be using EViews v.13 with automated lag selection based on the lowest AIC. Figure 7 shows the selected model, ARDL(1,1,2,2,0,0), had an AIC value of 5.656.

Table 5 presents model selection criteria (AIC, BIC, and HQ) for various ARDL models. These criteria are used to compare and select the best-fitting model, with lower values indicating a better balance between goodness-of-fit and model complexity. Model 1 (ARDL [1,1,2,2,0,0]) has the lowest AIC value (5.655868),

Table 4: Unit root (ADF) test for each variable

Series	Level				Integrated order
	Original data		First difference		
	t-Statistic	P-value	t-Statistic	P-value	
CO_2EM	−0.25911	0.9204	−4.799805	0.0006	I (1)
MANUF	−2.154494	0.2260	−5.680349	0.0001	I (1)
TRADE	−2.492604	0.1269	−4.410778	0.0015	I (1)
LAND	−1.493711	0.5230	−7.260339	0.0001	I (1)
GDPPC	−3.001014	0.0455	-	-	I (0)
FDI	−2.632758	0.0974	−4.633706	0.0008	I (1)

Figure 5: Heatmap of the correlation matrix for the five independent variables.

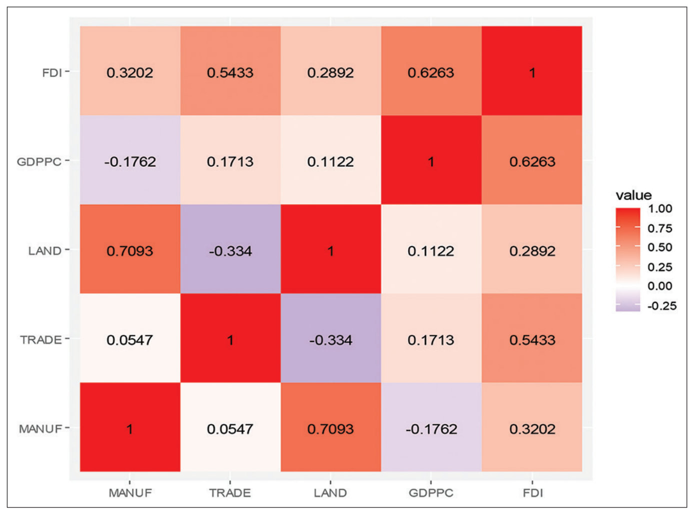


Figure 6: VIF values of the five independent variables.

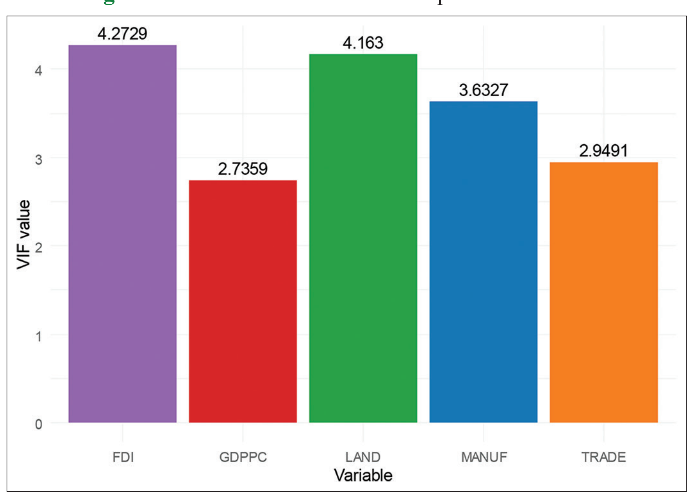


Figure 7: AIC values for the top twenty ARDL models

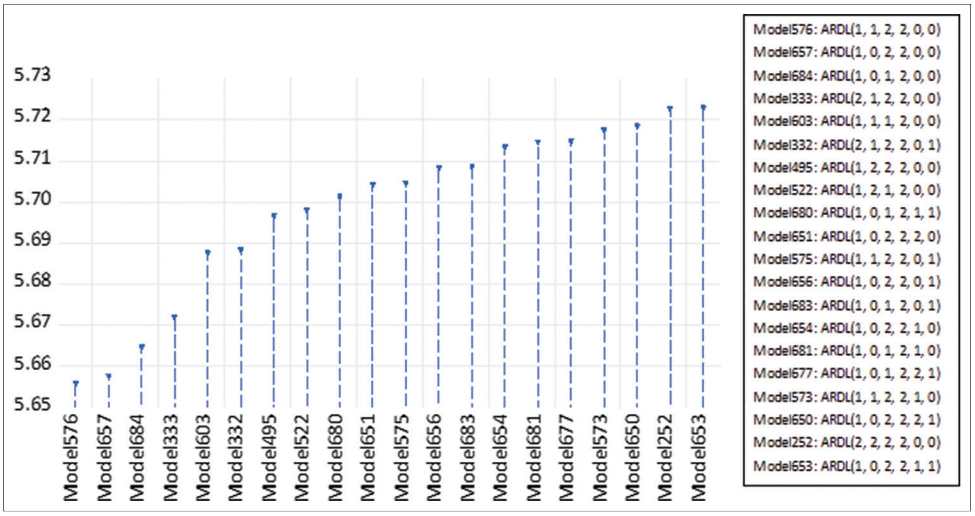


Table 5: Model selection criteria for various ARDL models

Model	AIC*	BIC	HQ	Specification
1	5.655868	6.216347	5.83517	ARDL (1,1,2,2,0,0)
2	5.657701	6.131473	5.822061	ARDL (1,0,2,2,0,0)
3	5.664709	6.171775	5.814127	ARDL (1,0,1,2,0,0)
4	5.671937	6.279122	5.866181	ARDL (2,1,2,2,0,0)
5	5.687526	6.201299	5.851887	ARDL (1,1,1,2,0,0)
6	5.688339	6.342231	5.897524	ARDL (2,1,2,2,0,1)
7	5.696532	6.303717	5.890776	ARDL (1,2,2,2,0,0)
8	5.698053	6.258532	5.877355	ARDL (1,2,1,2,0,0)
9	5.701288	6.261766	5.88059	ARDL (1,0,1,2,1,1)
10	5.704228	6.311413	5.898472	ARDL (1,0,2,2,2,0)
11	5.704551	6.311736	5.898795	ARDL (1,1,2,2,0,1)
12	5.70825	6.268729	5.887552	ARDL (1,0,2,2,0,1)
13	5.708448	6.22222	5.872808	ARDL (1,0,1,2,0,1)
14	5.713383	6.273862	5.892685	ARDL (1,0,2,2,1,0)
15	5.714562	6.228334	5.878922	ARDL (1,0,1,2,1,0)
16	5.714759	6.321944	5.909002	ARDL (1,0,1,2,2,1)
17	5.717463	6.324648	5.911707	ARDL (1,1,2,2,1,0)
18	5.718381	6.372273	5.927567	ARDL (1,0,2,2,2,1)
19	5.722645	6.376537	5.931831	ARDL (2,2,2,2,0,0)
20	5.722854	6.33004	5.917098	ARDL (1,0,2,2,1,1)

AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion, HQ: Hannan-Quinn Criterion, and * means that the selection of the best model is based on AIC

suggesting it is the most preferred model based on this criterion. It also has relatively low BIC and HQ values, further supporting its suitability. Model 2 (ARDL(1,0,2,2,0,0) has the lowest BIC value (6.131473), which is often preferred for its stricter penalty on model complexity, especially in larger datasets. Its AIC and HQ values are also competitive. Model 3 (ARDL [1,0,1,2,0,0]) has the lowest HQ value (5.814127), making it a strong candidate if the focus is on minimizing the Hannan-Quinn Criterion. Models 4 to 20 show progressively higher AIC, BIC, and HQ values, indicating they are less favorable compared to the top three models. However, they may still be considered if specific lag structures are theoretically justified. In summary, the choice between these models should consider the specific objectives of the analysis and the trade-offs between fit and complexity, so we select AIC here in our analysis. AIC is a model selection criterion that is suitable for our data. Therefore, Model 1 is the best choice for our analysis based on AIC.

Table 6: The OLS estimation results of the selected ARDL (1,1,2,2,0, 0) model

Variable	Estimate	Standard error	t-value	P-value
$CO2EM_{t-1}$	0.780283	0.025811	30.23099	0.0001
$MANUF_t$	−1.6499	0.449432	−3.671078	0.0016
$MANUF_{t-1}$	−0.510039	0.522722	−0.975736	0.3415
$TRADE_t$	0.73132	0.118642	6.164108	0.0001
$TRADE_{t-1}$	−0.111776	0.220234	−0.507532	0.6176
$TRADE_{t-2}$	−0.251876	0.156712	−1.607255	0.1245
$LAND_t$	1.38E-05	3.92E-06	3.526674	0.0023
$LAND_{t-1}$	3.34E-05	4.30E-06	7.776266	0.0001
$LAND_{t-2}$	1.70E-05	2.89E-06	5.875957	0.0001
$GDPPC_t$	−2.736628	0.489705	−5.588322	0.0001
FDI_t	0.753833	0.88631	0.85053	0.4056
Constant	−89.14481	22.42851	−3.97462	0.0008

Table 6 presents the OLS estimation results of the selected ARDL(1,1,2,2,0,0) model with specific lag structures for each variable. The coefficient for CO_2 emissions from the previous period ($CO2EM_{t-1}$) is 0.780283, indicating a positive relationship with current CO_2 emissions, which is statistically significant (P = 0.0001). Manufacturing activity ($MANUF_t$) has a negative and significant impact on CO_2 emissions, with a coefficient of −1.6499 (P = 0.0016), suggesting that higher manufacturing levels are associated with lower emissions. Trade ($TRADE_t$) shows a positive and significant effect, with a coefficient of 0.73132 (P = 0.0001), implying that increased trade is linked to higher CO_2 emissions. Land use ($LAND_t$) also shows a positive and significant relationship, with coefficients for $LAND_t$, $LAND_{t-1}$, and $LAND_{t-2}$ all being statistically significant. GDP per capita ($GDPPC_t$) has a negative and significant impact (−2.736628, P = 0.0001), while Foreign Direct Investment (FDI_t) does not show a significant relationship (P = 0.4056).

Table 7 provides various goodness-of-fit measures for the ARDL(1,1,2,2,0,0) model. The R^2 = 0.996793 indicates that approximately 99.68% of the variation in the dependent variable is explained by the independent variables, reflecting a very high level of explanatory power. The adjusted R^2 = 0.994936 adjusts for the number of predictors in the model and remains very high, confirming the model's robustness. The standard error (SE) of the estimated model is 3.569284, which gives an idea of the average deviation of the observed values from the predicted values. Information criteria such as the Akaike info criterion (5.65540) and Schwarz criterion (6.222344) provide measures of model complexity and fit, with lower values indicating better models. The F-statistic of 536.8016 and its associated P = 0.000001 indicate that the model as a whole is statistically significant. These measures collectively suggest that the ARDL(1,1,2,2,0,0) model fits the data well and is reliable for making inferences.

4.6. Diagnostic Tests

4.6.1. Checking normality

In econometric modeling, checking for normality is a key diagnostic test that makes sure the residuals of the chosen ARDL model are normally distributed. This is a key assumption for the OLS estimation method. Normality is typically assessed using graphical methods and formal statistical tests. Graphical methods include plotting a histogram of the residuals or a Q-Q (quantile-quantile) plot, where a straight line indicates normality. One formal test for normality is the JB test.

The JB test was employed to evaluate the normality of the residuals from the ARDL(1,1,2,2,0,0) model, as presented in Table 8. The JB-statistic is equal to 0.471323, accompanied by a P = 0.790048. Given that the P-value significantly exceeds conventional thresholds for statistical significance (e.g., $\alpha = 0.05$), we cannot reject the null hypothesis of normality. This finding implies that the residuals of the ARDL model are consistent with a normal distribution. Figures 8 and 9 confirm this result. The adherence to normality is crucial for ensuring the robustness and reliability of econometric analyses, as it underpins the validity of various inferential statistics and hypothesis tests. Consequently, the normality of residuals supports the credibility of the ARDL model's findings and strengthens the empirical evidence presented in our study.

The histogram in Figure 8 illustrates the distribution of residuals from the ARDL(1,1,2,2,0,0) model. The green bars represent the frequency distribution of the residuals, while the red curve depicts a normal distribution for comparison. The histogram appears to be roughly symmetrical around its mean, with no significant skewness. This symmetry is consistent with a normal distribution. The peaks of the histogram align closely with the red normal curve, indicating that the residuals are distributed similarly to a normal distribution. Additionally, the tails of the histogram do not show extreme values or outliers, further supporting the normality assumption. The red normal curve fits well over the histogram, suggesting that the residuals follow a normal distribution.

The Q-Q plot in Figure 9 visually assesses the normality of the residuals of the ARDL(1,1,2,2,0,0) model. The plot compares the quantiles of the observed residuals against the quantiles of a theoretical normal distribution. The data points generally align closely with the reference line, indicating that the residuals are approximately normally distributed. However, there are slight deviations at the tails, suggesting some minor departures from perfect normality. These findings corroborate the results of the Jarque-Bera test and histogram analysis, collectively supporting the assumption of normality for the model's residuals. This normality is crucial for ensuring the validity of statistical inferences and hypothesis tests derived from the ARDL model.

4.6.2. Checking stability

Checking the stability of an econometric model is essential to ensure that the estimated parameters remain consistent and reliable over time, which is critical for making valid inferences and predictions. Stability is often assessed using tests such as the CUSUM (cumulative sum of recursive residuals) test and the CUSUM of squares test. These tests plot the cumulative sum of

Table 7: Goodness-of-fit measures of the ARDL (1,1,2,2,0, 0) model

Measure	Value
R^2	0.996793
Adjusted R^2	0.994936
Standard error of the model	3.569284
Akaike info criterion (AIC)	5.65540
Schwarz criterion (BIC)	6.222344
F-statistic	536.8016
P-value of F-statistic	0.000001

Table 8: Normality test for the residuals of the ARDL (1,1,2,2,0,0) model

Test	JB value	P-value
Jarque-Bera test	0.471323	0.790048

Figure 8: Residuals distribution of the ARDL(1,1,2,2,0,0) model

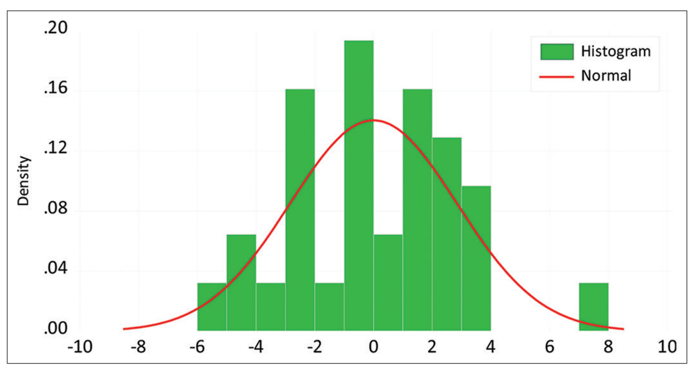
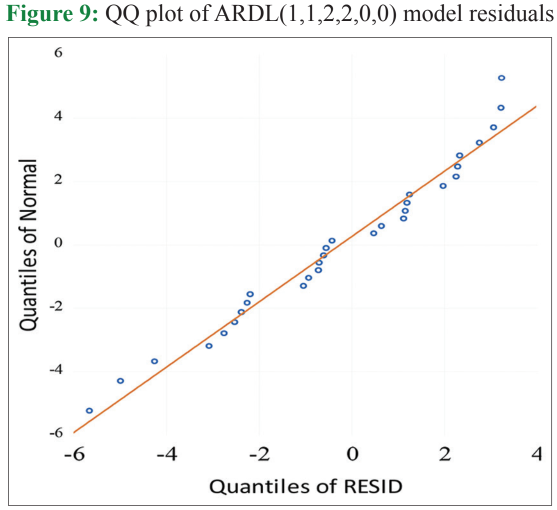


Figure 9: QQ plot of ARDL(1,1,2,2,0,0) model residuals



recursive residuals or their squares against time, with confidence bounds. If the plotted line stays within the confidence bounds, the model is considered stable; if it crosses the bounds, it suggests structural instability or parameter non-constancy over time. Ensuring model stability is crucial because instability can arise from changes in economic policies, external shocks, or shifts in relationships between variables, leading to unreliable estimates and forecasts. The CUSUM and CUSUM of squares stability tests, as depicted in Figures 10 and 11, evaluate the structural stability of the ARDL(1,1,2,2,0,0) model over time.

Figure 10 represents the CUSUM stability test. The blue line represents the cumulative sum of recursive residuals. The dashed red lines indicate the 5% significance bounds. The CUSUM line remains within the 5% significance bounds throughout the entire sample period, suggesting that there are no significant structural breaks or parameter instability in the model.

Figure 11 represents CUSUM of squares stability test. The blue line represents the cumulative sum of squares of recursive residuals. Similar to the CUSUM test, the dashed red lines denote the 5% significance bounds. The CUSUM of squares line also stays within the 5% significance bounds, further confirming the stability of the model parameters over time.

Both the CUSUM and CUSUM of squares tests provide strong evidence for the stability of the ARDL(1,1,2,2,0,0) model. The results indicate that the model's parameters have remained consistent and reliable throughout the period analyzed, without any significant shifts or instability. This stability is crucial for ensuring the robustness and reliability of the model's predictions and inferences.

Figure 10: CUSUM stability test of ARDL(1,1,2,2,0,0) model

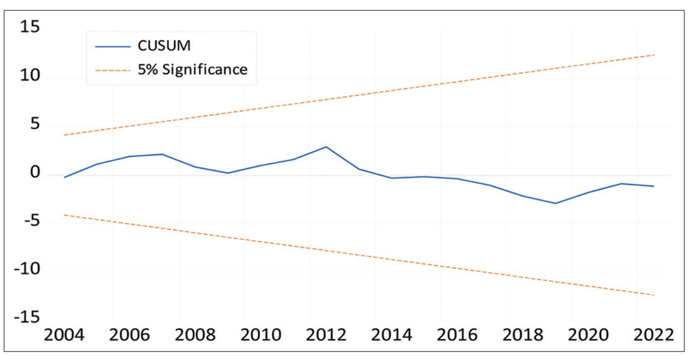
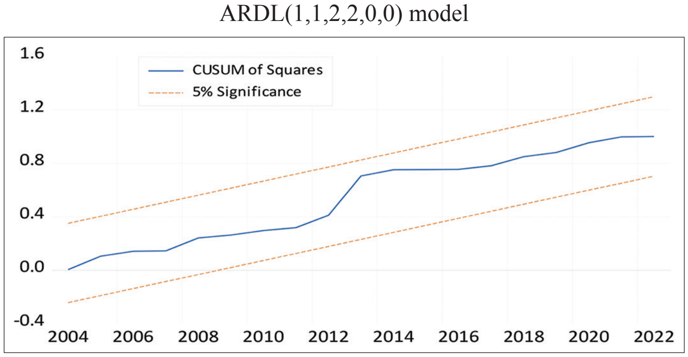


Figure 11: CUSUM of squares stability test of ARDL(1,1,2,2,0,0) model



4.6.3. Checking serial correlation and heteroscedasticity

Figure 12 presents the autocorrelation (AC) and partial autocorrelation (PAC) plots of the residuals from the ARDL(1,1,2,2,0,0) model. The AC plot illustrates the correlation between the residuals at various lags, with most of the bars falling within the dashed significance bounds, indicating that there is no significant serial correlation among the residuals. Similarly, the PAC plot shows the direct correlation between residuals at a given lag, controlling for shorter lags, and again, the coefficients are mostly within the significance bounds. These graphical analyses suggest that the residuals are not serially correlated, which is an important assumption for ensuring the reliability of the econometric model.

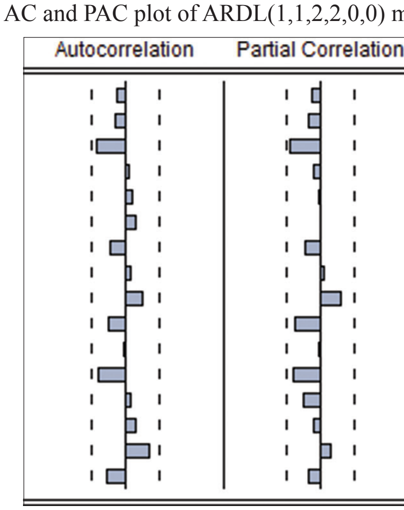
Table 9 provides statistical evidence on the presence of serial correlation and heteroskedasticity in the ARDL(1,1,2,2,0,0) model residuals. The Lagrange Multiplier (LM) test for serial correlation yields a Chi-squared value of 1.032076 and a P = 0.5969. Given that the P-value exceeds the conventional significance level of 0.05, we cannot reject the null hypothesis of no serial correlation, confirming the findings from the AC and PAC plots. Additionally, the Breusch-Pagan-Godfrey test for heteroskedasticity produces a chi-squared value of 14.11498 and a P = 0.2267, which also does not allow us to reject the null hypothesis of homoskedasticity. These results collectively support the validity of the model's assumptions, ensuring that the inferences drawn from the ARDL model are robust and reliable.

Figure 13 presents a dot plot of the ARDL(1,1,2,2,0,0) model residuals, accompanied by a boxplot. The dot plot visually represents the distribution of residuals over time, with each point corresponding to a residual value at a specific year. We can note that the points of the residuals are distributed randomly, so this indicates that the residuals of the ARDL(1,1,2,2,0,0) model are homoskedastic as shown by the Breusch-Pagan-Godfrey test in Table 9.

4.7. F-Bounds Long-Run Test

The F-Bounds Long-Run Test is a key component of the ARDL framework, used to test for the presence of a long-run cointegration relationship among studied variables. This test involves comparing

Figure 12: AC and PAC plot of ARDL(1,1,2,2,0,0) model residuals



the calculated F-statistic from the selected ARDL model against two sets of critical values provided by Pesaran et al. (2001): one for the case where all variables are I(0) and another for the case where all variables are I(1). If the computed F-statistic exceeds the upper critical value, it indicates the presence of a long-run cointegration relationship, regardless of the integration order of the variables. Conversely, if the F-statistic falls below the lower critical value, no cointegration exists. When the F-statistic lies between the two bounds, the test is inconclusive. The F-Bounds test is particularly advantageous because it does not require pre-testing for the order of integration, making it robust and widely applicable in empirical research.

Table 10 indicates a long-run relationship, as the F-statistic value of 15.155 exceeds the upper bounds (5.761 and 4.193) at significant levels of 1% and 5% in the case of a finite sample (n = 30) that is close to the actual sample (n = 31), confirming the long-run relationship between the studied variables.

The results of the ARDL(1,1,2,2,0, 0) model in the long run, as presented in Table 11, reveal significant relationships between various economic factors and the dependent variable (CO_2 emissions). The manufacturing (MANUF) has a negative and highly significant impact on CO_2 emissions, with a coefficient of −9.83057 and a P = 0.0004, indicating that an increase in manufacturing activity is associated with a decrease in CO_2 emissions. Conversely, trade (TRADE) exhibits a positive and significant effect, with a coefficient of 1.673377 and a P = 0.0057, suggesting that higher levels of trade contribute positively to CO_2 emissions. Land (LAND) also shows a positive and highly significant effect, with a small but statistically significant coefficient of 0.000292 and a P = 0.0001. GDP per capita (GDPPC) has a negative and significant effect, with a coefficient of −12.4553 and a P = 0.0009, implying that higher GDPPC is associated with a lower value of CO_2 emissions. Foreign direct investment (FDI) does not have a significant effect on CO_2 emissions, with a P = 0.4297.

Figure 13: Dot plot of ARDL(1,1,2,2,0,0) model residuals with boxplot

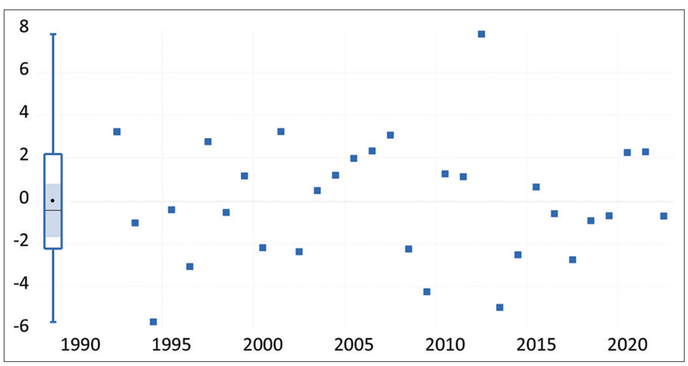


Table 9: Serial Correlation and Heteroskedasticity Tests of the residuals of the ARDL (1,1,2,2,0,0) model

Test	χ^2 value	P-value
Lagrange multiplier (LM) test	1.032076	0.5969
Breusch-Pagan-Godfrey test	14.11498	0.2267

Table 10: F-Bounds cointegration test of the estimated ARDL (1,1,2,2,0,0) model

Statistic	Value	Significant Level (α)	I (0)	I (1)
			Asymptotic sample (n=1000)	
F-statistic	15.155	α = 1%	3.060	4.150
k	5	α = 5%	2.390	3.380
Actual sample size	31		Finite Sample (n=35)	
		α = 1%	3.900	5.419
		α = 5%	2.804	4.013
			Finite Sample (n=30)	
		α = 1%	4.134	5.761
		α = 5%	2.910	4.193

4.8. Error Correction Model

The ECM is a dynamic econometric framework used to analyze the relationship between variables by distinguishing between short-term adjustments and long-term equilibrium. It is particularly useful when variables are cointegrated, meaning they share a stable long-run relationship despite being non-stationary in their levels. ECM includes an ECT, which represents the deviation from the long-run equilibrium in the previous period. This term captures the speed at which the dependent variable adjusts back to its equilibrium after a short-term shock. A significant and negative coefficient for the ECT indicates that the system corrects deviations over time, ensuring a return to long-run equilibrium.

The ECM results, as shown in Table 12, show significant short-term dynamics influencing CO_2 emissions (CO2EM). The coefficient for $\Delta MANUF_t$ is −1.649900 with a P = 0.0006, indicating that an increase in the change of manufacturing activity significantly decreases CO_2 emissions in the short run. Conversely, $\Delta TRADE_t$ has a positive and highly significant coefficient of 0.731320 (P = 0.0001), suggesting that trade positively influences CO_2

Table 11: The results of the ARDL (1,1,2,2,0, 0) model in the long-run

Variable	Estimate	Standard Error	t-value	P-value
$MANUF_t$	−9.83057	2.297639	−4.27855	0.0004***
$TRADE_t$	1.673377	5.38E-01	3.11E+00	0.0057**
$LAND_t$	0.000292	3.21E-05	9.10E+00	0.0001***
$GDPPC_t$	−12.4553	3.17E+00	−3.93E+00	0.0009***
FDI_t	3.430934	4.251792	0.806938	0.4297
Constant	−405.726	66.57969	−6.093845	0.0001***

***Indicates that the variable is significant at 0.001, **significant at 0.01

Table 12: The results of the error correction model for the ARDL (1,1,2,2,0, 0) model

Variable	Estimate	Standard Error	t-value	P-value
$\Delta MANUF_t$	−1.649900	0.404733	−4.076515	0.0006***
$\Delta TRADE_t$	0.731320	0.117908	6.202448	0.0001***
$\Delta TRADE_{t-1}$	0.251876	0.107059	2.352684	0.0296*
$\Delta LAND_t$	1.38E-05	3.12E-06	4.431313	0.0003***
$\Delta LAND_{t-1}$	−1.70E-05	3.48E-06	−4.882184	0.0001***
ECT	−0.219717	0.018597	−11.81467	0.0001***

***Indicates that the variable is significant at 0.001 and *significant at 0.05

emissions. The lagged term $\Delta TRADE_{t-1}$ also shows a positive impact with a coefficient of 0.251876 (P = 0.0296), implying that past trade levels continue to affect current CO_2 emissions. Land use changes are represented by $\Delta LAND_t$ and $\Delta LAND_{t-1}$, with coefficients of 1.38E-05 and −1.70E-05 respectively, both statistically significant at the 0.001 level, indicating complex short-term effects on CO_2 emissions. Lastly, the ECT has a negative and highly significant coefficient of −0.219717 (P = 0.0001), which ensures that any deviation from long-term equilibrium in CO_2 emissions is corrected over time. These findings underscore the importance of both contemporaneous and lagged effects of manufacturing, trade, and land use in understanding short-term fluctuations in CO_2 emissions. Moreover, the speed of return to long-run equilibrium after a short-run deviation occurs within about 4.5 years based on the value of the error correction term.

5. CONCLUSIONS

By means of a dynamic econometric approach throughout the ARDL model, the research offers a thorough investigation of the economic and environmental elements affecting CO_2 emissions in Egypt. The results expose important new directions on the short-term and long-term interactions between CO_2 emissions and important economic variables like land under cereal production, manufacturing, trade openness, GDP per capita, and foreign direct investment. Identified by the lowest AIC value, the ideal ARDL(1,1,2,2,0,0) model emphasizes the need of addressing both instantaneous and long-term effects of these factors on environmental outcomes. Especially, the findings show that manufacturing and GDP per capita have a little impact on CO_2 emissions, implying that developments in industrial efficiency and economic growth might help to ensure environmental sustainability. On the other hand, trade openness and acreage under cereal production have favorable long-term impacts on emissions, therefore stressing the environmental trade-offs related to economic activity and agricultural development. The considerable effect of delayed trade and land variables underlines even more the continuous influence of these elements on CO_2 levels. Policymakers would benefit much from the findings of the error correction model, which show a 4.5-year adjustment time to bring long-run equilibrium back after short-run aberrations. This implies that while temporary shocks could throw off the equilibrium, the system has a self-correcting process running over a medium-term horizon.

Finally, this research highlights the intricate interaction in Egypt between environmental sustainability and economic development. It advocates focused policy interventions aimed at encouraging sustainable industrial methods, smart land use, and balanced trade policies to lower CO_2 emissions and thereby support economic growth. To better grasp these patterns and guide more solid environmental policies, future studies may look at other factors and longer time periods.

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