Determinants of CO2 Emissions in Azerbaijan's Manufacturing and Construction Sectors: The Roles of Energy Intensity, Output, and Investment (ARDL–ECM with Structural Breaks)

MAYIS GULALIYEV[1,2,3,*], GULSURA MEHDIYEVA[4,5], IRSHAD ABBASOV[4], MEHRIBAN ZEYNALOVA[6], ZIYA GULIYEV[7]

[1]Department of Management and Tourism, Ganja State University, 429 Heydar Aliyev Avenue, Ganja, AZ2000, AZERBAIJAN

[2]Department of Management, Azerbaijan Technological University, 103 Shah Ismayil Khatai Avenue, AZ2011 Ganja, AZERBAIJAN

[3]Economic Research Center, Baku Eurasian University, Ak. H.Aliyev street, 135 A, AZ1110 Baku, AZERBAIJAN

[4]Department of Environmental Protection, Azerbaijan Technological University, 103 Shah Ismayil Khatai Avenue, AZ2011 Ganja, AZERBAIJAN

[5]Department of Economics and Management, Azerbaijan Technical University, 25 Huseyn Javid Avenue, AZ1073, Baku, AZERBAIJAN

[6]Department of Commodity Science and Expertise of Non-Food Products, Azerbaijan State University of Economics, 22 Istiglaliyyat Street, Sabail District, Baku, AZ1001, AZERBAIJAN

[7]Department of Accounting and Finance, Nakhchivan State University, 85 Istiglal Street, Nakhchivan city, AZ7000, AZERBAIJAN

**Correspondent Author*

Abstract: - This study investigates the determinants of CO2 emissions in Azerbaijan's manufacturing and construction sector (MC), focusing on the roles of energy intensity, output scale, and investment. Using annual time-series data for the period 2007–2023, we apply the ARDL-ECM model, which is suitable for mixed integration orders and small samples. Structural breaks related to the national currency devaluation in 2015 and the COVID-19 pandemic during 2020–2022 are controlled for through dummy variables. The ARDL results confirm the existence of a stable long-run relationship between MC emissions, energy intensity, output volume, and investment. In the baseline specification, both energy intensity and output volume have a positive and statistically significant effect on CO2 emissions. The findings also confirm the dominance of scale and technique channels. Specifically, increased economic activity and higher energy use per unit of output lead to higher CO_2 emissions in the MC sector in both the short and long run. In contrast, investment is negatively associated with emissions. This suggests that capital deepening in this sectoral aggregate is more aligned with modernization and efficiency-enhancing upgrades rather than purely capacity-expanding effects. The error correction term (ECM) is negative and highly significant, indicating a rapid adjustment toward long-run equilibrium following shocks.

Key-Words: - Azerbaijan; manufacturing and construction; CO_2 emissions; energy intensity; investment; ARDL–ECM; structural breaks

Received: January 15, 2026. Revised: March 21, 2026. Accepted: July 15, 2026. Published: September 14, 2026.

1 Introduction

Improving energy efficiency and advancing the decarbonization agenda have become strategic factors that simultaneously reshape competitiveness, cost structures, and market access conditions in energy-intensive sectors such as manufacturing and construction. As energy price shocks, supply chain disruptions, and tightening emission constraints intensify, the ability to carry out the same level of economic activity with lower energy consumption becomes crucial for both firm-level productivity and sector-level green transition outcomes.

In the context of Azerbaijan, the issue is even more sensitive. While the non-oil diversification strategy has stimulated the expansion of manufacturing and construction activities, these sectors may exhibit unstable trajectories in terms of investment cycles and energy use under the influence of recurrent macroeconomic shocks. In particular, two episodes may have altered the regime of relationships. The first is the 2015 devaluation of the Azerbaijani manat, and the second is the COVID-19 pandemic shock during 2020-2022. Therefore, assessing short- and long-run effects requires a flexible time-series methodology that accounts for structural breaks.

The empirical "measurement unit" (dependent variable) of this study is the emissions indicator for the "Manufacturing and construction" sectors. Specifically, the emissions series used is presented as the "Manufacturing and construction" category based on disaggregated annual sectoral emissions [1], and is transformed into its natural logarithmic form ($lnCO_2$) for the analysis. This choice offers two main advantages. First, by jointly covering the energy-intensive segments of the manufacturing and construction real sectors, it allows the "scale" and "technique" effects to be tracked within a broader sectoral framework. Second, it enables capturing the additional channel through which the energy use and price dynamics of the construction sector influence the emissions trajectory. At the same time, the interpretation limits of this aggregation are explicitly acknowledged in the "limitations of the research" section.

The main objective of this article is to evaluate the roles of energy intensity, economic scale (output), and investment in CO_2 emissions ($lnCO_2$) of the manufacturing–construction sector in both the short and long run, and to demonstrate how these elasticities can be translated into policy instruments when structural breaks are taken into account. For this purpose, the ARDL–ECM framework is employed because: a) it has practical advantages in small samples where variables may be a mixture of I(0) and I(1); b) it separates short-run shock effects from the long-run equilibrium relationship; and c) it directly measures the speed of adjustment toward equilibrium (ECT).

1.1 Research Questions and Hypotheses

This study formulates the following research questions (RQ) and testable hypotheses (H):

RQ1: How do changes in energy intensity affect CO_2 emissions in the manufacturing–construction sector in the short and long run?

RQ2: With what elasticity is sectoral activity (output) transmitted to emissions, and does this effect change after structural breaks?

RQ3: Through which channels does an increase in investment affect CO2 emissions: a) via the capacity expansion channel (positive effect), or b) via the modernization/efficiency channel (negative effect)?

RQ4: How do the 2015 devaluation and the COVID-19 pandemic shock affect the level of relationships and the dynamics of adjustment toward equilibrium?

Hypotheses:

H1: An increase in energy intensity leads to higher CO_2 emissions in the manufacturing–construction sector ($\beta(\log EI) > 0$).

H2: As output (scale) increases, CO2 emissions also increase ($\beta(\log Y) > 0$).

H3: The long-run effect of investment reduces emissions through the modernization/efficiency channel ($\beta(\log INV) < 0$), while its short-run effect may be ambiguous.

H4: If structural breaks (the 2015 devaluation and the COVID-19 pandemic during 2020–2022) are not accounted for, long-run elasticities may be biased; when dummies are included, the error correction term (ECT) should be negative and statistically significant.

1.2 Contribution and Novelty

The contribution of this study can be summarized in four main aspects.

First, focusing on Azerbaijan, it evaluates the determinants of CO2 emissions within a unified mechanism linking energy intensity, output, and investment, based on the "manufacturing and construction" emissions series that captures energy-intensive segments of the real sector, using the ARDL–ECM framework.

Second, by modeling the 2015 devaluation and the COVID-19 shock as structural breaks, the study seeks to prevent the "leakage" of short-run shock effects into long-run equilibrium elasticities and tests the robustness of results through diagnostic checks (stability, specification, and residual diagnostics).

Third, without imposing an a priori assumption on the sign of investment, the study empirically distinguishes whether the investment–emissions relationship is more consistent with the modernization (decarbonization) channel or the capacity expansion (scale) channel in both the short and long run.

Fourth, it translates the estimated long-run elasticities into a measurable policy framework: the impact of a 1% improvement in energy intensity on emissions, the potential "decarbonization dividend" of investment waves, and the magnitude of the output–emissions trade-off, thereby informing the prioritization of policy actions.

2 Literature Review

The literature explaining the relationship between CO2 emissions and economic activity is mainly built around three mechanisms: a) scale effects; b) technique effects; and c) composition effects. The scale effect suggests that as economic activity and output increase, energy demand – and consequently emissions – also rise. In contrast, the technique effect emphasizes that improvements in technology, energy efficiency, and management quality enable production with lower energy use and fewer emissions for the same level of output. The composition effect refers to structural shifts in the economy from energy- and carbon-intensive sectors toward less emission-intensive activities. Recent empirical literature tests these mechanisms using STIRPAT, LMDI, and dynamic time-series models, showing that energy intensity and the level of economic activity are among the most consistent determinants of carbon emissions [2], [3], [4], [5], [6].

This framework is particularly important for the present study because the dependent variable is constructed based on the "manufacturing and construction" aggregate. This implies that the dynamics of emissions are shaped not only by energy use in manufacturing but also by the direct and indirect carbon impacts of construction activities. The construction sector generates substantial emissions both directly – through fuel and electricity consumption – and indirectly via material supply chains such as cement, metals, glass, and other inputs. Therefore, emissions behavior within the "manufacturing + construction" aggregate reflects a more complex real-sector mechanism where scale, technique, and composition channels intersect [7], [8], [9], [10].

Energy intensity is widely regarded in the literature as a compact indicator of technological backwardness, process inefficiency, and the quality of resource use. Numerous studies conducted at both macro and sectoral levels show that higher energy intensity is typically associated with increased CO_2 emissions, while improvements in energy efficiency represent one of the most direct channels for decarbonization. For OECD countries, [11], demonstrates that energy efficiency plays a significant role in reducing emissions. [12], argue that there is a positive long-run relationship between energy intensity and CO2 emissions. More recent evidence confirms similar findings, indicating that labor–capital clustering can mitigate emissions by reducing energy intensity [6].

Energy intensity plays a particularly critical role in energy-intensive sectors such as manufacturing and construction. [13], shows that energy intensity in production sectors is closely related to capital formation, prices, and sectoral development. Studies on embodied energy intensity in the construction sector further demonstrate that energy intensity determines the emissions trajectory not only at the operational stage but also throughout material production and supply chains [8]. Therefore, for the "manufacturing and construction" aggregate, a positive emissions elasticity of energy intensity is theoretically and empirically expected.

The role of economic scale in increasing carbon emissions is one of the most robust findings in the literature. Energy use, industrial expansion, and growth in real output are typically associated with higher emissions. [2], finds a strong relationship between energy use, economic growth, and CO2 emissions across global and regional samples. [3], Emphasize the dynamic and interdependent nature of the energy-emissions-growth nexus across country groups. [4], show that urbanization and economic development contribute to rising emissions in lower-income countries. These findings suggest that as the real sector expands, the scale effect may dominate the technique effect unless technological and structural changes are sufficiently strong.

Construction activity plays a specific role within this scale effect. The expansion of infrastructure and residential construction not only increases energy demand within the sector itself but also generates indirect emission channels by raising demand for cement, steel, and other materials. [7] and [9], demonstrate that construction – and particularly the cement supply chain – is a strategic area for carbon mitigation.

The impact of investment on emissions is not unambiguous in the literature. On the one hand, capital formation can increase emissions by creating new capacity, expansion, and higher levels of production. On the other hand, investment may reduce emissions through the replacement of outdated equipment, energy efficiency projects, technological modernization, and the formation of green capital. Therefore, the sign of investment depends on the country's technological level, the sectoral allocation of investment, and institutional quality.

[13], emphasizes the role of capital formation in sectoral energy intensity. [14], use gross fixed capital formation as an important control variable in the energy-growth-emissions nexus. More recent studies also identify both emission-increasing and emission-reducing channels of capital formation [15], [16], [17]. If investment is directed toward energy-efficient technologies, cleaner production, and improved construction standards, its long-run effect may be negative. This highlights the "capacity versus efficiency" dilemma, particularly in transition economies.

One of the key distinguishing features of the present study is the use of the "manufacturing and construction" aggregate as the emissions indicator. This choice addresses a frequently noted issue in the literature: the construction sector and its supply chain account for a significant share of industrial emissions. Due to its material- and project-intensive nature, construction should not be viewed merely as a service or assembly activity, but also as a strong derived demand component of industrial and energy systems. Therefore, analyses of industrial emissions that exclude the construction component may provide incomplete assessments of scale and investment effects.

In recent years, a rapidly growing body of literature has emerged in this field. [7], analyze life-cycle emissions and their drivers in China's construction sector. [8], examine embodied energy intensity in the global construction industry. [9], forecast future carbon emissions from cement production in developing countries. [10], provide a comprehensive review of building lifecycle carbon emissions. These studies demonstrate that the construction component is not merely additional "noise" but rather a core mechanism in emission models.

The ARDL/ECM approach is widely used in analyzing the relationships between energy, economic growth, and emissions, as it allows for handling variables with mixed orders of integration and distinguishes between short- and long-run effects. [18], establish the theoretical foundations of the ARDL model through the bounds testing approach, while, [19], highlight its flexibility for cointegration analysis. In the emissions literature, this approach is particularly practical for small-sample annual time-series data.

Applied studies further support this. [20], finds a relationship between CO2 emissions, energy consumption, and economic growth using ARDL. [21], test the pollution haven hypothesis for China using a structural break ARDL approach. [15], investigate both symmetric and asymmetric relationships between capital formation and carbon emissions within the ARDL framework.

Although the existing literature extensively examines the relationship between energy intensity, economic activity, and emissions, there is limited analysis for Azerbaijan focusing on the "manufacturing and construction" aggregate within an ARDL/ECM framework that accounts for structural breaks. Most studies either focus on aggregate CO2 emissions at the macro level or treat manufacturing and construction jointly within a broader industrial category rather than as a distinct analytical unit. Moreover, the "modernization versus capacity expansion" duality of investment effects on emissions has not been sufficiently tested empirically in the Azerbaijani context.

3 Data & Variables

This study is based on annual time-series data and evaluates the determinants of CO_2 (more precisely, GHG/CO_2 -equivalent) emissions for the energy-intensive segment of Azerbaijan's real sector. The dependent variable is the emissions series for the "manufacturing and construction" category. This series is obtained from the Our World in Data (OWID) database, specifically from the "GHG emissions by sector" dataset, where emissions are reported in CO_2 -equivalent tons based on the 100-

year global warming potential (GWP100). In the analysis, the variable is log-transformed and used as $lnCO_2$. Additional data – including energy consumption, investment, output, and price indices – are obtained from the official website of the State Statistical Committee of Azerbaijan, [22], [23], [24].

All quantitative variables used in the model are transformed into their natural logarithmic form so that the estimated coefficients can be interpreted as elasticities. Energy intensity is constructed based on the principle of sectoral consistency: since the dependent variable is "manufacturing and construction," the energy use series should, as far as possible, capture energy consumption in both manufacturing and construction.

The baseline is taken from the AzStat energy balance table "Energy consumption of energy products in industrial sectors" (in physical units). If a separate series for "Energy consumption in construction" is available in the same units, total sectoral energy use is calculated as $E(MC) = E(M) + E(C)$ to improve consistency. Otherwise, $E(M)$ is used as a proxy for the real-sector emissions aggregate, and this limitation is explicitly acknowledged.

The scale variable Y is constructed as a composite measure of real output in the manufacturing and construction sectors. Specifically, real output in manufacturing $Y(M)$ is calculated using the Producer Price Index (PPI) for manufacturing with the base year 2000, while real output in construction $Y(C)$ is derived using the construction cost index with the base year 2007. The total real output is then obtained as the sum of the two components: $Y = Y(M) + Y(C)$

The energy intensity (EI) indicator is calculated as $EI = E(MC)/Y(MC)$ and is incorporated into the model in logarithmic form.

The investment (INV) variable represents real investment in the "manufacturing and construction" sector. The transition from nominal to real investment series is carried out using a deflator constructed with the base year 2000.

Structural breaks. Dummy variables are included to capture structural shocks: D_{2015} for the 2015 devaluation (step dummy: 2015–2023 = 1; otherwise 0) and D_{cov} for the COVID episode (2020–2022 = 1; otherwise 0). This helps prevent bias in the estimated coefficients arising from regime shifts.

4 Methodology

This study evaluates the determinants of CO_2 emissions in Azerbaijan's "manufacturing and construction" (MC) sector using the ARDL/ECM approach. The ARDL framework is chosen for three main reasons. First, in annual time-series data, variables often exhibit mixed orders of integration (I(0) and I(1)), and ARDL can accommodate such a structure as long as none of the variables is I(2). Second, the ECM representation of ARDL allows for separating short-run effects from the long-run equilibrium relationship. Third, in small samples (annual data), ARDL provides a practical way to construct parsimonious specifications and to apply the cointegration (bounds) testing procedure.

In the baseline model, the dependent variable is specified as $lnCO2_t$. The independent variables include output (lnY_t), energy intensity $(lnEI_t)$, investment $(lnINV_t)$, and structural break dummy variables (D_{2015}, D_{COV}).

The baseline ARDL is as (1)

$$lnCO2_t = \alpha_0 + \sum_{i=1}^{p} \beta_i * lnCO2_{t-i} + \sum_{j=1}^{q_1} \gamma_j * lnY_{t-j} + \sum_{k=0}^{q_2} \delta_k * lnE\dot{I}_{t-k} + \sum_{l=0}^{q_3} \rho_l * lnINV_{t-l} + \varphi_1 * D2015_t + \varphi_2 * DCOV_t + \varepsilon_t \quad (1)$$

Here, ε_t is a white-noise error term. Short-run dynamics are captured through lagged differences, while the long-run relationship is identified through level terms.

The ECM representation of the ARDL model combines short-run adjustments and the speed of return to equilibrium within a single equation. The general ECM form of the ARDL model is as (2) and (3).

$$\Delta lnCO2_t = \alpha_0 + \sum_{i=1}^{p-1} \beta_i * \Delta lnCO2_{t-i} + \sum_{j=0}^{q_1-1} \gamma_j * \Delta lnY_{t-j} + \sum_{k=0}^{q_2-1} \delta_k * \Delta lnE\dot{I}_{t-k} + \sum_{l=0}^{q_3-1} \rho_l * \Delta lnINV_{t-l} + \varphi_1 * lnCO2_{t-1} + \varphi_2 * lnY_{t-1} + \varphi_3 * lnE\dot{I}_{t-1} + \varphi_4 * ln\dot{I}NV_{t-1} + \omega_1 * D2015_t + \omega_2 * DCOV_t + \varepsilon_t \quad (2)$$

Here, $H_0: \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4$

$$\Delta lnCO2_t = \alpha_0 + \sum_{i=1}^{p-1} \beta_i * \Delta lnCO2_{t-i} + \sum_{j=0}^{q_1-1} \gamma_j * \Delta lnY_{t-j} + \sum_{k=0}^{q_2-1} \delta_k * \Delta lnE\dot{I}_{t-k} + \sum_{l=0}^{q_3-1} \rho_l * \Delta lnINV_{t-l} + \omega_1 * D2015_t + \omega_2 * DCOV_t + \tau_t * ECT_{t-1} + \varepsilon_t \quad (3)$$

Here, ECT_{t-1} is the error correction term that represents the deviation from the long-run equilibrium and is defined as (4)

$$ECT_{t-1}=lnCO2_{t-1} - (\theta_0 + \theta_1 * lnY_{t-1} - \theta_2 * lnEI_{t-1} - \theta_3 * lnINV_{t-1} \quad (4)$$

Here, $\theta_1 = -\frac{\varphi_2}{\varphi_1}; \theta_2 = -\frac{\varphi_3}{\varphi_1}; \theta_3 = -\frac{\varphi_4}{\varphi_1}$

The parameter τ represents the speed of adjustment toward equilibrium and is theoretically expected to be negative ($\tau < 0$). As τ increases, the system returns more rapidly to its equilibrium path after shocks.

5 Results

5.1 Descriptive Statistics

This subsection presents the descriptive statistics and the pairwise correlation structure of the main variables used in the model ($LOGCO_2$, EI, LOGY, LOGINV). The sample covers the period 2007–2023 (17 observations). The descriptive statistics (mean, standard deviation, minimum, and maximum) are reported in Table 1, while the correlation matrix is presented in Table 2.

Table 1. Descriptive statistics (2007–2023)

Variable	Mean	Std. Dev.	Min	Max	Obs
LOGCO2	14.562316	0.212660	14.122995	14.845130	17
EI	-6.940135	0.354748	-7.480982	-6.169960	17
LOGY	22.856440	0.237129	22.346135	23.100736	17
LOGINV	21.922801	0.228722	21.494193	22.298278	17

Source: Calculated by the authors using EViews-12

Table 2. Correlation matrix

	LOGCO2	EI	LOGY	LOGINV
LOGCO2	1.0000	-0.1542	0.2789	-0.0229
EI	-0.1542	1.0000	-0.8745	-0.3155
LOGY	0.2789	-0.8745	1.0000	0.6826
LOGINV	-0.0229	-0.3155	0.6826	1.0000

Source: Calculated by the authors using EViews-12

5.2 Stationarity and Order of Integration

For the application of the ARDL/ECM approach, the variables must be integrated of order I(0) or I(1), but not I(2). To this end, three sets of tests are employed: the ADF test (H_0: unit root), the KPSS test (H_0 : stationarity), and the Zivot-Andrews (ZA) test, which accounts for structural breaks (H_0 : unit root with break; H_0: trend/stationarity with break). The unit-root test results at levels and first differences are summarized in Table 3 and Table 4, respectively.

Table 3. Unit-root tests (levels)

Variable	ADF (stat)	ADF(p)	KPSS (stat)	KPSS(p)	ZA (stat)	ZA (p)	ZA(break year)
LOGCO2	-2.9403	0.0409	0.1214	0.1000	-9.7743	0.0000	2015
LOGY	-3.3674	0.0121	0.4857	0.0449			2012
logEI	1.3663	0.9970	0.6450	0.0186	-4.0871	0.2993	2014
LOGINV	-1.8281	0.3666	0.1892	0.1000	-3.3374	0.7754	2011

Source: Calculated by the authors using EViews-12

Table 4. Unit-root tests (first differences)

Variable	ADF (stat)	ADF(p)	KPSS (stat)	KPSS (p)	ZA (stat)	ZA (p)	ZA(break year)
LOGCO2	-5.3065	0.0000	0.0788	0.1000	-	-	-
LOGY	-0.7280	0.8394	0.2382	0.1000	-	0.0000	2013
logEI	-1.9972	0.2878	0.2860	0.1000	-26.8492	0.0000	2020
LOGINV	-2.8430	0.0524	0.3447	0.1000	-5.0792	0.0222	2015

Source: Calculated by the authors using EViews-12

The interpretation is based on the different null hypotheses of the two tests: ADF tests for the presence of a unit root, while KPSS tests for stationarity. Therefore, in small samples (T = 17), ADF and KPSS may sometimes provide conflicting signals. In particular, for LOGY, the ADF test rejects the unit root at levels (p = 0.0121), whereas the KPSS test rejects the null of stationarity at a borderline level (p = 0.0449). This contradiction suggests two possibilities: a) LOGY may follow a near-unit-root process at levels, with KPSS being more sensitive; or b) the series may contain a trend or structural break that is not fully captured by the standard ADF/KPSS specifications. For this reason, the decision regarding LOGY is not based on a single test but on a combined interpretation of the test package. The key requirement for the ARDL approach is that no variable is integrated of order I(2). Considering the sensitivity of LOGY's stationarity, appropriate lag selection and the inclusion of D2015 and DCOV are implemented. In the robustness section, the stability of results is further tested using alternative trend specifications and lag limits.

5.3 Model Selection

The Model Selection Criteria table indicates that the specification with the lowest Akaike Information Criterion (AIC*) corresponds to the ARDL(1,1,0,0,1,1) model (AIC* = −0.994479; BIC = −0.511611; Included observations = 16). However, as the baseline model, we adopt the ARDL(1,0,0,0,0,0) specification (AIC* = −0.644; BIC = −0.306; Included observations = 16) (Table 5). The ARDL(1,0,0,0,0,0) model implies that one lag of the dependent variable ($LOGCO_2$ (-1)) captures inertia in emissions dynamics, while the effects of the explanatory variables are primarily contemporaneous (0 lag). In small samples, unnecessary lags increase the number of parameters and are penalized by information criteria such as AIC and BIC, which tend to favor more parsimonious specifications. This choice allows for a clearer interpretation of short- and long-run effects in the subsequent ARDL/ECM representation. The ARDL(1,1,0,0,1,1) model is retained for robustness analysis.

Table 5. Model selection summary (information criteria)

Max lag (annual)	Selected ARDL	Included obs.	AIC*	BIC
Baseline:	ARDL(1,0,0,0,0,0)	16	-0.644172	-0.306164
Robustness:	ARDL(1,1,0,0,1,1)	16	-0.994479	-0.511611

Source: Calculated by the authors using EViews-12

5.4 Bounds test for Cointegration

In the ARDL(1,0,0,0,0,0) model, the existence of a long-run (level) relationship is tested using the [18], [19] ARDL bounds test. The null hypothesis H_0 "no levels relationship" is formulated and evaluated based on the F-statistic, which tests the joint significance of the level terms in the conditional ECM equation.

Table 6. ARDL bounds test: critical values and decision

Source	Signif.	I(0)	I(1)	Compare with F	Decision	Implication
Asymptotic (n=1000)	10%	2.080	3.000	F > I(1)	Cointegration	Long-run relationship supported
Asymptotic (n=1000)	5%	2.390	3.380	F > I(1)	Cointegration	Long-run relationship supported
Asymptotic (n=1000)	2.5%	2.700	3.730	F > I(1)	Cointegration	Long-run relationship supported
Asymptotic (n=1000)	1%	3.060	4.150	F > I(1)	Cointegration	Long-run relationship supported
Finite sample (n=35)	10%	2.331	3.417	F > I(1)	Cointegration	Long-run relationship supported
Finite sample (n=35)	5%	2.804	4.013	F > I(1)	Cointegration	Long-run relationship supported
Finite sample (n=35)	1%	3.900	5.419	I(0) < F < I(1)	Inconclusive	Use additional evidence (ECT, stability)
Finite sample (n=30)	10%	2.407	3.517	F > I(1)	Cointegration	Long-run relationship supported
Finite sample	5%	2.910	4.193	F > I(1)	Cointegration	Long-run

(n=30)						relationship supported
Finite sample (n=30)	1%	4.134	5.761	I(0) < F < I(1)	Inconclusive	Use additional evidence (ECT, stability)

Source: Calculated by the authors using EViews-12

The results of the bounds test are presented in Table 6. Based on the obtained results, the F-statistic is 4.416890 (k = 5), with a sample size of n = 16. The F-statistic supports cointegration even at the 1% significance level under asymptotic critical values (4.4169 > 4.15). Under small-sample critical values, the result supports cointegration at least at the 5% level (for n = 35: 4.4169 > 4.013; for n = 30: 4.4169 > 4.193). Therefore, the existence of a long-run equilibrium relationship between $\ln CO_2$, lnEI, lnY, lnINV, and the control variables is confirmed for the baseline model.

5.5 Baseline ARDL results (short-run) and long-run coefficients

Table 7. Baseline ARDL(1,0,0,0,0,0) short-run coefficients (Dependent variable: LOGCO2)

Regressor	Coefficient	Std. Error	t-Stat.	p-value
LOGCO2(-1)	0.229476	0.163839	1.400618	0.1948
LOGEI	1.598536	0.389038	4.108942	0.0026
LOGINV	-1.651096	0.337958	-4.885502	0.0009
LOGY	3.245991	0.640173	5.070486	0.0007
D2015	0.055168	0.068049	0.810711	0.4384
DCOV	0.001288	0.068002	0.018948	0.9853
C	-15.695340	6.499874	-2.414714	0.0389

Source: Calculated by the authors using EViews-12

The specification of this model yields R^2=0.714, Adj.R^2=0.523, SER=0.151, AIC=-0.644, BIC=-0.306, DW=2.922, and n=16 (2008–2023, adjusted). The short-run results clearly reveal the main mechanisms (Table 7). The coefficient of energy intensity (LOGEI) is positive and statistically significant (β=1.599; p=0.0026), indicating that a 1% increase in energy intensity leads to approximately a 1.6% increase in emissions. The effect of output (LOGY) is also positive and strong (β=3.246; p=0.0007), confirming the scale effect. The coefficient of investment (LOGINV) is negative and significant (β=−1.651; p=0.0009), suggesting that investment in this sample is more aligned with the modernization/efficiency channel. The 2015 devaluation and COVID dummy variables do not show a statistically significant effect in the baseline specification. Instead, they primarily serve to control for potential level effects associated with regime shifts.

Table 8. Long-run coefficients (Levels Equation) for ARDL(1,0,0,0,0,0)

Regressor	Long-run coef.	Std. Error	t-Stat.	p-value
LOGEI	2.074610	0.651461	3.184548	0.0111
LOGINVEST	-2.142824	0.555591	-3.856837	0.0039
LOGY	4.212707	1.162501	3.623831	0.0055
D2015	0.071598	0.085165	0.840703	0.4223
DCOV	0.001672	0.088481	0.018899	0.9853
C	-20.369710	11.040390	-1.845017	0.0981

Source: Calculated by the authors using EViews-12

The long-run elasticities maintain the same direction: LOGEI (2.075; p = 0.011) and LOGY (4.213; p = 0.0055) increase emissions in the long run, while LOGINV reduces emissions (−2.143; p = 0.0039). This indicates that energy efficiency improvements (i.e., reductions in EI) and "green" modernization investments are key instruments for long-term decarbonization. The dummy coefficients are also not statistically significant in the long run. This suggests that, within the selected period and model specification, the effects of structural shocks are either absorbed by the main determinants (EI, Y, INV) or the dummies primarily serve a stability control function.

In Table 7 and Table 8, the coefficients are interpreted as elasticities due to the log–log specification: a 1% increase in an explanatory variable leads to an approximate β% change in CO_2 emissions. Since the model is estimated using HAC/Newey–West standard errors, the inference is more robust to heteroskedasticity and autocorrelation.

5.6 Error-Correction Model (ECM) and Speed of Adjustment

Table 9 presents the conditional ECM representation of the baseline ARDL specification and interprets the results of the error-correction term (ECT), which measures how quickly deviations from the long-run equilibrium are corrected. Within the ECM framework, $\Delta \ln CO_2$ captures the short-run changes in emissions, while ECT(−1) indicates the extent to which the previous period's deviation from equilibrium is corrected in the current period

Table 9. Error-correction model estimates (Dependent variable: ΔLOGCO2)

Term	Coefficient	Std. Error	t-Stat.	p-value
D(LOGEI)	1.598536	0.250229	6.387562	0.0001
D(LOGINVEST)	-1.651096	0.260317	-6.342227	0.0001
D(LOGY)	3.245991	0.425258	7.631361	0.0000
D(D2015)	0.055168	0.061416	0.898391	0.3901
D(DCOV)	0.001288	0.057779	0.022295	0.9826
CointEq(-1)	-0.770524	0.119968	-6.423159	0.0001
C	-15.695340	2.803748	-5.598737	0.0002

Source: Calculated by the authors using EViews-12

Based on the model specification, R^2=0.806, Adj.R^2=0.710, SER=0.081, AIC=-1.949, BIC=-1.616, DW=2.703,and n=16. In the ECM results, the most important parameter is the coefficient of ECT(−1) (CointEq(−1)). The negative and statistically significant coefficient of ECT(−1) (τ = −0.7705; p=0.0001) confirms the existence of a long-run equilibrium relationship and the system's adjustment mechanism toward equilibrium after shocks. In terms of magnitude, approximately 77% of the deviation from equilibrium in the previous year is corrected in the current year. In other words, the emissions system returns to equilibrium relatively quickly. This high speed of adjustment indicates that shocks in key determinants such as energy intensity, output, and investment do not persist for long in influencing the emissions trajectory.

From the perspective of short-run dynamics, ΔLOGEI and ΔLOGY are positive and highly significant. This indicates that increases in energy intensity and economic scale lead to higher emissions in the short run. The negative and significant coefficient of ΔLOGINV suggests that investment also reduces emissions in the short run, consistent with the modernization/efficiency channel. The differences of the structural break dummies are not statistically significant in this specification. Their role is primarily to control for regime shifts and to prevent bias in the estimated coefficients.

It can be argued that the ECT(−1) result complements the cointegration evidence obtained from the bounds test. While the bounds test confirms the existence of a long-run relationship, the ECM measures the speed of adjustment toward equilibrium. Thus, the ARDL/ECM framework provides both long-run elasticities and short-run shock dynamics within a unified analytical structure.

5.7 Diagnostic Tests and Stability

The reliability of the ARDL specification is assessed through residual diagnostics and parameter stability tests. In a small sample setting (n = 16), the risks of autocorrelation and heteroskedasticity are particularly important; therefore, all inference results are supported by HAC (Newey–West) standard errors. The results of the diagnostic tests are summarized in Table 10, while the CUSUM and CUSUMSQ stability plots are presented in Figure 1 and Figure 2, respectively.

Table 10 shows that there are no serious issues regarding heteroskedasticity (Breusch–Pagan–Godfrey) or functional form (RESET), and the null hypothesis of normality of residuals cannot be rejected. However, for serial correlation, the χ^2 version of the Breusch–Godfrey LM test indicates a risk of autocorrelation at the 5% level ($p < 0.05$), while the F-version remains in the borderline (≈10%) region. This result should be interpreted cautiously, considering the size properties of the LM test in small samples. In practice, since the main results are reported using HAC (Newey–West) standard errors, the sensitivity of coefficient significance to serial correlation is substantially reduced.

Table 10. Diagnostic tests (baseline model)

Test	**Null**	**Statistic**	**p-**	**Conclusion**

	hypothesis (H0)		value	(5%)
BG LM (1 lag)	No serial correlation up to 1 lag	F=4.8602; Obs*R²=6.0468	0.0586; 0.0139	Borderline by F; reject by χ^2
BG LM (2 lags)	No serial correlation up to 2 lags	F=3.6755; Obs*R²=8.1957	0.0811; 0.0166	Borderline by F; reject by χ^2
Breusch–Pagan–Godfrey	Homoskedasticity	F=1.4451; Obs*R²=7.8508	0.2972; 0.2492	Fail to reject (no heteroskedasticity)
Ramsey RESET	Correct functional form (no omitted nonlinearities)	F=0.0797; t=0.2822	0.7849; 0.7849	Fail to reject (specification adequate)
Jarque–Bera	Normality of residuals	JB=0.3312	0.8474	Fail to reject (residuals approx. normal)

Source: Calculated by the authors using EViews-12

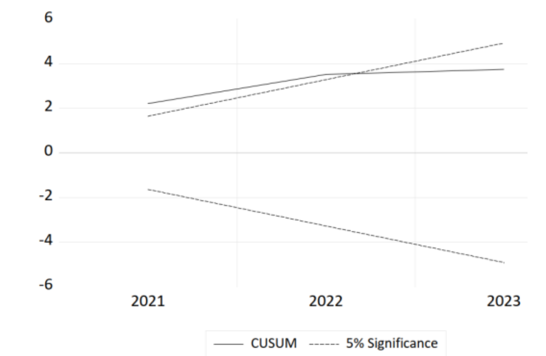

Fig. 1:CUSUM stability test (baseline model)
Source: Calculated by the authors using EViews-12

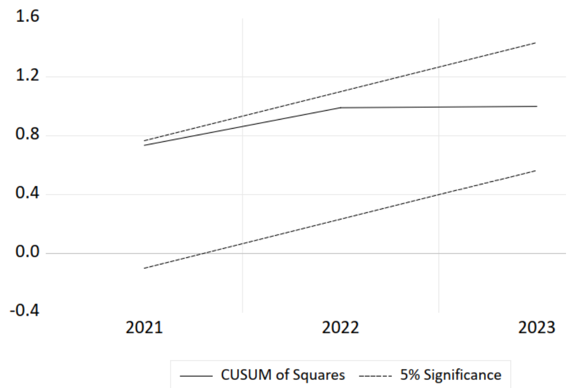

Fig. 2:CUSUMSQ stability test (baseline model)
Source: Calculated by the authors using EViews-12

5.8 Robustness: Alternative Lag Dynamics (Model 2) and Comparison

To address the potential presence of serial correlation (particularly indicated by the χ^2 version of the BG LM test) and to assess the sensitivity of the dynamic specification, an alternative lag structure – ARDL(1,1,0,0,1,1) – is estimated as a robustness model in addition to the baseline specification. This model is selected in EViews based on the AIC criterion, incorporating an additional lag for LOGEI and the dummy variables among the dynamic regressors. Standard errors are reported using HAC (Newey-West) corrections.

Model 2 (ARDL(1,1,0,0,1,1)) provides a better fit in terms of information criteria (AIC = −0.994, BIC = −0.512; Adj. R² = 0.654; n=16). The evidence of cointegration is also stronger: the bounds test yields F = 6.953, exceeding the 1% upper bound of the asymptotic critical values, thus providing stronger support for the existence of a long-run relationship compared to the baseline model (Table 11). In the ECM representation, the coefficient of ECT(−1) is negative and highly significant (−1.023; p<0.001), indicating a very rapid adjustment toward equilibrium.

In terms of the main mechanisms, both models maintain the same direction of effects. Specifically, the coefficient of output (LOGY) remains positive and strong; energy intensity (LOGEI) is positive, while investment (LOGINV) retains a negative sign. However, in Model 2, the inclusion of additional lags increases the number of parameters, causing the significance levels of EI and investment to shift from the 5% level toward the 10% level (p ≈ 0.067 and p ≈ 0.073). This reflects the sensitivity of inference in a small sample.

Table 11. Model 1 vs Model 2: selection metrics, cointegration, and key coefficients

Model	ARDL order	Adj.R²	DW	Bounds F	LOGEI (p)	LOGINV (p)	LOGY (p)
Model 1 (baseline)	ARDL(1,0,0,0,0,0)	0.523493	2.922	4.416890	1.599 (0.0026)	-1.651 (0.0009)	3.246 (0.0007)
Model 2 (robustness)	ARDL(1,1,0,0,1,1)	0.653930	2.938	6.953417	1.562 (0.0671)	-0.975 (0.0733)	3.672 (0.0001)

Source: Calculated by the authors using EViews-12

Therefore, the main results of the study are presented based on the parsimonious Model 1, while Model 2 is used as a robustness check, demonstrating that the signs and magnitudes of the results remain stable under an alternative dynamic specification.

The diagnostic test results for Model 2 are reported in Table 12. Based on these results, the normality of residuals is confirmed, the risk of serial correlation persists to some extent, no heteroskedasticity is detected, and no functional-form misspecification is observed at the 5% significance level.

Table 12. Diagnostic checks for Model 2 (ARDL(1,1,0,0,1,1))

Test	Statistic	p-value
Normality (JB)	JB=0.4635	p=0.7932
BG LM (1 lag)	F=2.7748 / χ^2=5.7104	p(F)=0.1566; p(χ^2)=0.0169
BG LM (2 lags)	F=3.0038 / χ^2=9.6049	p(F)=0.1598; p(χ^2)=0.0082
Heteroskedasticity (BPG)	F=1.5771 / χ^2=11.2460	p(F)=0.2982; p(χ^2)=0.2592
RESET	F=1.0531; t=1.0262	p=0.3518

Source: Calculated by the authors using EViews-12

Thus, based on the results of both Model 1 and Model 2, it can be concluded that the increase in emissions in the manufacturing and construction sector is mainly explained by energy intensity and scale expansion, while investment contributes to decarbonization through the modernization/efficiency channel. These findings support prioritizing energy efficiency measures and “green” capital investments within the decarbonization strategy of the real sector.

6 Discussion

6.1 Interpreting the Core Mechanisms: Scale, Technique, and Investment Channels

The empirical results of this study show that emissions dynamics in the manufacturing and construction (MC) sector are mainly driven by three mechanisms: scale (output), technique (energy intensity), and capital/modernization (investment). First, the positive and strong coefficient of output (LOGY) in both the short and long run confirms the dominance of the scale effect in the MC sector. In other words, as real sector activity expands, energy demand increases, and under existing technological conditions, this expansion leads to higher emissions. This finding is consistent with the widely documented “growth–emissions” relationship in the energy–environment literature and suggests that, within the framework of non-oil diversification strategies, there exists a measurable trade-off between growth objectives and decarbonization goals.

Second, the positive coefficient of energy intensity (LOGEI) highlights the critical role of the technique effect: higher energy use for the same level of output (i.e., lower efficiency) leads to increased emissions. This result is particularly important for the MC sector, as the energy-intensive nature of construction activities – especially through infrastructure development and material supply chains – amplifies the EI channel. The findings suggest that energy efficiency measures have a direct impact on emission reduction and can help mitigate the carbon burden associated with scale expansion.

Third, the negative coefficient of investment (LOGINV) indicates that, within the “capacity vs. efficiency” trade-off, the efficiency/modernization channel is more dominant in this sample. This supports the idea of a potential “decarbonization dividend,” whereby investment not only creates new capacity (and potentially higher emissions) but also reduces emission intensity through the replacement of outdated technologies, improvements in energy-intensive processes, and the adoption of more efficient capital. Given that the effect of investment may be sensitive to measurement proxies and deflator choices, this claim has been tested and confirmed within the robustness framework.

7 Study Limitations and Avenues for Future Research

Several limitations should be considered when interpreting the results of this study. First, since the dependent variable is constructed as the MC aggregate, it is not possible to fully disentangle the separate effects of the manufacturing and construction sectors. Second, due to data limitations, the sectoral alignment of energy consumption and investment variables may introduce proxy measurement errors. The choice of deflator may also affect the estimated impact of investment. Third, there is a potential simultaneity (feedback) issue between energy intensity and output. Although ARDL partially mitigates this concern, the results should be interpreted as reflecting dynamic associative relationships rather than strict structural causality.

For future research, several priority directions can be identified: a) constructing disaggregated models by developing separate emissions and energy series for manufacturing and construction; b) incorporating alternative proxies for energy prices and technology, such as energy tariffs, capital quality, and technology imports; c) addressing endogeneity more rigorously through the use of instrumental variables or structural modeling approaches where feasible; d) conducting scenario analysis and policy simulations to quantify the emission-reducing effects of energy intensity improvements and investment measures.

8 Conclusion

A long-run equilibrium relationship exists: the bounds test supports cointegration in the baseline specification, and the negative and statistically significant error correction term (ECT) in the ECM further reinforces this result. The scale effect is dominant: the positive elasticity of output indicates that the expansion of real sector activity increases emissions in both the short and long run. The technique effect is decisive: energy intensity has a positive elasticity with respect to emissions, highlighting that improvements in energy efficiency represent one of the most direct policy channels for decarbonization. The investment channel appears consistent with decarbonization: the negative coefficient of investment suggests that modernization and efficiency gains can reduce emission intensity. The speed of adjustment is high: based on the magnitude of the ECT coefficient, a large portion of deviations from equilibrium is corrected within one year, indicating that the persistence of shock effects is relatively limited.

References:

[1] Climate Watch, (2026). Greenhouse gas emission by sector (Azerbaijan) [Data set]. Our World in Data. https://ourworldindata.org/grapher/ghg-emissions-by-sector?tab=table&country=~AZE&overlay=download-data (Accessed Date: January 23, 2026

[2] Acheampong, A. O. (2018). Economic growth, CO2 emissions and energy consumption: What causes what and where? Energy Economics, 74, 677–692. https://doi.org/10.1016/j.eneco.2018.07.022

[3] Antonakakis, N., Chatziantoniou, I., & Filis, G. (2017). Energy consumption, CO_2 emissions, and economic growth: An ethical dilemma. Renewable and Sustainable Energy Reviews, 68 (Part 1), 808–824. https://doi.org/10.1016/j.rser.2016.09.105

[4] Lin, S., Wang, S., Marinova, D., Zhao, D., & Hong, J. (2017). Impacts of urbanization and real economic development on CO_2 emissions in non-high income countries: Empirical research based on the extended STIRPAT model. Journal of Cleaner Production, 166, 952–966. https://doi.org/10.1016/j.jclepro.2017.08.107

[5] Shahbaz, M., Sharma, R., Sinha, A., & Jiao, Z. (2021). Analyzing nonlinear impact of economic growth drivers on CO_2 emissions: Designing an SDG framework for India. Energy Policy, 148(Part B), 111965. https://doi.org/10.1016/j.enpol.2020.111965

[6] Tao, M., Wen, L., Sheng, M. S., Yan, Z. J., & Poletti, S. (2024). Dynamics between energy intensity and carbon emissions: What does the clustering effect of labor and capital play? Journal of Cleaner Production, 452, 142223. https://doi.org/10.1016/j.jclepro.2024.142223

[7] Cui, C., Wang, Z., & Bin, G. (2019). Life-cycle CO_2 emissions and their driving factors in the construction sector in China. Chinese Geographical Science, 29(2), 293–305. https://doi.org/10.1007/s11769-019-1029-z

[8] Chen, L., Zhao, Y., Xie, R., Su, B., Liu, Y., & Renfei, X. (2023). Embodied energy intensity of global high energy consumption industries: A case study of the construction industry. Energy, 277, 127628. https://doi.org/10.1016/j.energy.2023.127628

[9] Cheng, D., Reiner, D. M., Yang, F., Cui, C., Meng, J., Shan, Y., Liu, Y., Tao, S., & Guan, D. (2023). Projecting future carbon emissions from cement production in developing countries. Nature Communications, 14, 8213. https://doi.org/10.1038/s41467-023-43660-x

[10] Wang, G., Luo, T., Luo, H., Liu, R., Liu, Y., & Liu, Z. (2024). A comprehensive review of building lifecycle carbon emissions and reduction approaches. City and Built Environment, 2, Article 12. https://doi.org/10.1007/s44213-024-00036-1

[11] Tajudeen, I. A., Wossink, A., & Banerjee, P. (2018). How significant is energy efficiency to mitigate CO_2 emissions? Evidence from OECD countries. Energy Economics, 72,

200–221. https://doi.org/10.1016/j.eneco.2018.04.010

[12] Danish, Ulucak, R., & Khan, S.-U.-D. (2020). Relationship between energy intensity and CO_2 emissions: Does economic policy matter? Sustainable Development, 28(5), 1457–1464. https://doi.org/10.1002/sd.2098

[13] Miketa, A. (2001). Analysis of energy intensity developments in manufacturing sectors in industrialized and developing countries. Energy Policy, 29(10), 769–775. https://doi.org/10.1016/S0301-4215(01)00010-6

[14] Soytas, U., & Sari, R. (2009). Energy consumption, economic growth, and carbon emissions: Challenges faced by an EU candidate member. Ecological Economics, 68(6), 1667–1675. https://doi.org/10.1016/j.ecolecon.2007.06.014

[15] Prakash, N., & Sethi, M. (2023). Relationship between fixed capital formation and carbon emissions: Impact of trade liberalization in India. Cogent Economics & Finance, 11(2), Article 2245274. https://doi.org/10.1080/23322039.2023.2245274

[16] Kobayakawa, T. (2022). The carbon footprint of capital formation: An empirical analysis on its relationship with a country's income growth. Journal of Industrial Ecology, 26(2), 522–535. https://doi.org/10.1111/jiec.13199

[17] Hordofa, T. T., Vu, H. M., Maneengam, A., Purnomo, E. P., Cong, P. T., & Liying, S. (2023). Does eco-innovation and green investment limit the CO_2 emissions in China? Economic Research-Ekonomska Istraživanja, 36(1), 634–649. https://doi.org/10.1080/1331677X.2022.2116067

[18] Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326. https://doi.org/10.1002/jae.616

[19] Pesaran, M. H., & Shin, Y. (1999). An autoregressive distributed-lag modelling approach to cointegration analysis. In S. Strøm (Ed.), Econometrics and economic theory in the 20th century: The Ragnar Frisch Centennial Symposium (pp. 371–413). Cambridge University Press. https://doi.org/10.1017/CCOL521633230.011

[20] Gessesse, A. T., & He, G. (2020). Analysis of carbon dioxide emissions, energy consumption, and economic growth in China. Agricultural Economics (Czech), 66(4), 183–192. https://doi.org/10.17221/258/2019-AGRICECON

[21] Sun, C., Zhang, F., & Xu, M. (2017). Investigation of pollution haven hypothesis for China: An ARDL approach with breakpoint unit root tests. Journal of Cleaner Production, 161, 153–164. https://doi.org/10.1016/j.jclepro.2017.05.119

[22] State Statistical Committee of the Republic of Azerbaijan (SSCRA). (2026a). Industry production. https://stat.gov.az/source/industry/?lang=en (Accessed Date: January 5, 2026)

[23] State Statistical Committee of the Republic of Azerbaijan (SSCRA). (2026b). Main indicators of construction in the Republic of Azerbaijan. https://stat.gov.az/source/construction/?lang=en (Accessed Date: January 15, 2026)

[24] State Statistical Committee of the Republic of Azerbaijan (SSCRA). (2026c). Consumption of energy products by types of economic activity. https://stat.gov.az/source/balance_fuel/?lang=en (Accessed Date: January 5, 2026)

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Mayis Gulaliyev: conceptualization, methodology, data analysis, statistical analysis, writing and revising the manuscript.

Gulsura Mehdiyeva: data collection and literature review.

Irshad Abbasov: interpretation of results, revision of the manuscript.

Mehriban Zeynalova: data processing, visualization, and validation of the findings.

Ziya Guliyev: results verification, editing of the manuscript.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no.