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What Drives Emissions Intensity in Azerbaijan's Light Industry? Evidence from ARDL with Structural Breaks

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ABSTRACT

The article examines emission intensity drivers in Azerbaijan's light industry (NACE C13–C15: textiles, apparel, leather) over 2007-2023. Air pollutant intensity is defined as the weight of pollutants per 1 AZN of output (kg/AZN), calibrated where relevant to CO_2 intensity. Unit root tests (ADF, Zivot–Andrews) reveal a mix of I(0) and I(1) series, allowing ARDL estimation. Considering shocks from the 2015 exchange rate shift, an ARDL (1,2,1,2,2) with a post-break dummy is estimated. Bounds testing confirms cointegration (F = 12.83). The error correction coefficient (−1.90) indicates rapid adjustment to long-run equilibrium. Long-run results show that currency depreciation raises emission intensity, while sectoral productivity lowers it, consistent with scale effects. Exports have a weak negative impact. In the short run, depreciation raises intensity immediately but partially corrects after one year; output growth mitigates the effect. Model checks (LM, RESET, CUSUM, CUSUMSQ) confirm robustness in a small sample. Policy implications suggest that exchange rate shocks temporarily worsen environmental outcomes, whereas expansion and modernization reduce intensity. Priorities include boosting energy efficiency, strengthening cleaner production, and expanding exports to improve environmental performance.

Keywords: Light Industry, Emissions Intensity, ARDL, Bounds Testing, ECM), Structural Breaks, Textiles and Apparel, Azerbaijan
JEL Classifications: Q56, Q53, C32, F31, L67, O14

1. INTRODUCTION

The agile modernization of production sectors and the improvement of resource efficiency lie at the intersection of strategic areas such as climate change mitigation, energy security, and competitive industrial policy. In this context, the light industry—particularly textiles, apparel, and leather products (ISIC Rev.4: C13–C15)—is in focus due to its employment and export potential, as well as its intensive use of water, energy, and chemicals. The high consumption of water and chemicals during the dyeing–finishing–treatment stages, along with intensive demand for thermal and electrical energy and the composition of wastewater, exacerbate the ecological footprint of these subsectors. Under such conditions, the adoption and widespread implementation of "resource-efficient technologies" (RETs), as well as the integration of circular economy principles into the production chain, are crucial not only from an environmental standpoint but also for reducing costs and improving product quality.

Systematic, comparative, and methodologically rigorous assessment of the environmental performance of light industry enterprises in Azerbaijan is still represented by limited research. Most existing studies either focus on single indicators (e.g., total emissions or energy consumption) or are constrained by a lack of disaggregated data at the enterprise level, limiting methodological integration. As a result, the evidence base for policy tools, including energy tariffs, inspection intensity, the implementation of eco-standards, and incentives for clusters and eco-industrial parks, remains weak in terms of clearly quantifying real impact channels. This gap makes it difficult to design effective decision-support mechanisms for both regulatory authorities and enterprise managers.

In conclusion, this study not only provides a systematic, evidence-based perspective on the ecological performance of Azerbaijan's light industry, but also quantitatively demonstrates the real impact of "resource-saving technology," thereby laying the groundwork for practice-oriented recommendations in the design of policy instruments. The remainder of the study is structured as follows: Section II summarizes the relevant literature and theoretical framework. Section III presents the methodology and data sources. Section IV covers the empirical findings. Section V discusses the study's limitations and the future research agenda. Section VI analyzes the comparison of the empirical results obtained with findings from other studies. Finally, Section VIII presents the overall conclusions.

The aim of the study is to measure the atmospheric emissions of light industry enterprises (specifically: C13–Textiles; C14–Apparel; C15–Leather and related products), to evaluate their eco-efficiency, and to econometrically analyze the determinants. It should be noted that according to ISIC Rev.4, i.e., the United Nations International Standard Industrial Classification of All Economic Activities (4th revision), Textiles are classified as C13, Apparel as C14, and Leather and related products as C15. The research questions are as follows:

a) What are the levels and intensity dynamics of CO_2, SO_2, NOx, PM, and waste indicators during the period 2000-2023?
b) To what extent does the intensity dynamic depend on different determinants: production volume, structural or subsectoral share, or other factors?
c) Do export orientation, subsector size, and financial stability have an impact on eco-efficiency?

2. LITERATURE REVIEW

Light industry, particularly textiles, apparel, leather–footwear, and household textiles, is characterized by two main channels of impact on atmospheric air: First, process-related emissions. For example, during production processes such as dyeing, printing, drying, and tentering, as well as in solvent-based operations, volatile organic compounds (VOCs), formaldehyde, and other pollutants are generated. Second, stationary combustion sources. These include small- and medium-capacity boilers used for steam or heating within workshops, which lead to the release of pollutants into the atmosphere. Early studies dedicated to this issue—for instance, Müezzinoğlu (1998)—systematized the potential of air pollutants according to different stages of textile production, showing that VOC emissions can dominate particularly in dyeing–finishing and drying lines. Subsequent research has quantitatively assessed the ozone formation potential (OFP) and carcinogenic risk indicators of VOC mixtures in industrial sectors, including textiles, thereby revealing distinct profile differences (Yang et al., 2020).

In light industry subsectors closely related to textiles—for example, footwear or rubber enameling—assessments have shown that ethylbenzene, xylenes, toluene, and other aromatics predominate, significantly influencing both ozone formation potential (OFP) and health risks (Li et al., 2019; Wang et al., 2022; Huang et al., 2022; Shang et al., 2022). Within textile production itself, it has been demonstrated that solvent use in polyester fabric lines and thermal processes can lead to a high VOC "chemical footprint." Moreover, it is possible to identify priority compounds and control points along the process line (Qian et al., 2022; Guo et al., 2022). These findings highlight that the proper specification of the source–process profile is critical for model development (OFP, risk) and for the effective targeting of policy instruments.

The energy demand of light industry enterprises is often met by in-house boilers operating on natural gas, fuel oil, or, in some cases, coal. Unit-based inventories conducted across Chinese cities and regions quantitatively confirm the systematic impact of such boilers on PM, SO_2, and NO_x emissions. Although recent regulatory tightening has led to reductions in emission volumes, the large number of distributed small-scale units continues to represent a "difficult-to-control" source (Xue et al., 2016; Tong et al., 2021; An et al., 2021; Li et al., 2019; Zheng et al., 2019). These literature findings reinforce the methodological basis for proportional allocation strategies of stationary sources with similar configurations to light industry in the post-Soviet context. However, additional uncertainty arises precisely from the heterogeneity of fuel mixes and technologies.

Since light industry products are highly export-oriented, the "consumption-based" pollution burden carries significant weight. Some studies have shown that export-oriented industrial clusters increase O_3 and its precursors, particularly VOCs, in coastal areas, while this effect can sharply decline once the technology gap is closed (Ou et al., 2020). On a broader scale, the growing consumption of light industry goods by the G20 has been shown to account for a large share of the global $PM_{2.5}$-related mortality burden being "imported" (Nansai et al., 2021). Other studies, such as McDuffie et al. (2021), report that the sectoral impacts of industrial and energy fuel mixes differ significantly in terms of $PM_{2.5}$ health risks. This body of evidence justifies the targeted role of policy instruments—such as supply chain restructuring and technology transfer—in reducing emission intensity in light industry.

In recent years, it has been confirmed that textile-derived microfibers are emitted not only into water but also into the air. Studies have shown that household tumble dryers can release hundreds of thousands of fibers into the atmosphere within just 15 min (O'Brien et al., 2020; Tao et al., 2022). Quantitative measurements of fiber fluxes during washing–drying cycles (Kärkkäinen and Sillanpää, 2021) and the impact of domestic laundry on global microplastic pollution (De Falco et al., 2019; Gaylarde et al., 2021) have been widely investigated. From the perspective of light industry, this implies that in-house dust–fiber management and filtration technologies need to be considered alongside OFP-centered VOC control.

The use of process-line "chemical footprint" indicators (Qian et al., 2022; Guo et al., 2022) enables substance-specific prioritization in light industry. For the calibration of inventories, field measurements and unit-based data are essential (Zheng et al., 2019; An et al., 2021). In the economic assessment of the determinants of emission intensity, both linear and nonlinear ARDL and NARDL frameworks are widely applied. Findings on the asymmetric effects of textile–apparel activity, energy intensity, FDI and transaction variables, as well as trade structure on emissions (Haseeb et al., 2020; Adebayo et al., 2021; Zhang and Zhang, 2018), align the ARDL-SB (ARDL with structural breaks) model developed in this article with the existing literature.

The general conclusion is that the main share of atmospheric impacts in light industry originates either from process-line VOCs or from in-house boilers. The appropriate policy mix should therefore consist of:
1. The application of solvent-reducing technologies and hermetic sealing
2. Ensuring NO_x/PM control in boilers
3. The diffusion of "clean technology" throughout supply chains, and
4. The implementation of multi-component measures such as fiber–dust filtration.

3. METHODOLOGY

Since subsectors C13–C15 were selected as the objects of the study, the ecological impacts of other light industry subsectors—such as wood processing (C16), paper (C17), and printing (C18)—were not examined. The study relies on data covering the period 2007-2023. The atmospheric pollutants considered include CO_2, SO_2, NOx, and PM.

For the purposes of the study, quantitative data were obtained from the official databases of the State Statistical Committee of the Republic of Azerbaijan (ARDSK, 2025) and the Ministry of Ecology and Natural Resources (MENR, 2025).

To evaluate, at the macro level, the environmental impacts of Azerbaijan's light industry enterprises (ISIC Rev.4 subsectors C13–C15: textiles, apparel, and leather products), we identify practical dependent and independent indicators, along with their measurement units, based on available sources. As the dependent indicator, we use:
1. Air Pollution Intensity (API), defined as the ratio of air pollutants (SO_2, NO_x, CO, dust, etc.) to the value of output in the sector (tons per million AZN).

The following independent macro indicators have been adopted as potential determinants of the dependent variable:
a) Output volume in sectors C13, C14, and C15 (million AZN, constant prices) — C1315
b) Volume of textile–apparel–leather exports — EXPC1315
c) Exchange rate (EXCH) (AZN/USD, annual average), serving as a control for imported equipment and energy price pass-through.

It should be noted that deflators (control indicators) were used to convert nominal values of C1315 and EXPC1315 into real values. One of the main challenges and limitations of the study is the lack of accessible data on most of the factors that may affect "Air Pollution Intensity" (API). To address this problem to some extent, the following method will be applied. For instance, in order to calculate the indicator "Air Pollution Intensity (SO_2, NOx, CO, dust, etc.)," data on the volume of "air pollutants" are required. However, in the publicly available database of the State Statistical Committee (SSC), only the indicator "Emissions into the atmosphere from stationary sources" is provided. Considering that all economic activity sectors—except road transport—are classified as "stationary sources," it is difficult to accurately determine the volume of pollutants emitted into the atmosphere specifically from the C13–C15 subsectors of light industry, as opposed to industry, agriculture, and other sectors in general.

To estimate the volume of pollutants from the C13–C15 subsectors, several assumptions will be made:
1. It will be assumed that light industry primarily uses natural gas
2. It will be assumed that the main waste gas emitted into the atmosphere is CO_2. Since the volume of other waste gases is very small compared to CO_2, they will be disregarded
3. It will be assumed that the combustion of 1 kg of gas (in oil equivalent) results in 2.349 kg of CO_2 released into the atmosphere.

Based on these assumptions, and using the amount of energy consumption in subsectors C13–C15, the API can be calculated as follows:

$$API = \frac{QAPC1315}{C1315} = \frac{ECC1315*2.349}{C1315} = \frac{a*C1315*2.349}{C1315} = a*2.349 \quad (1)$$

Here, "a" represents the volume of energy products consumed for the production of 1 AZN worth of C13–C15 output (at current prices), calculated as "(kg of oil equivalent)/AZN." When expressed in real terms, it is defined as ar=a100×CPIa_r = \frac{a}{100} \times CPIar = 100a × CPI.
- QAPC1315 — the amount of pollutants generated and released into the atmosphere in the C13–C15 subsectors of light industry
- C1315 — the value of output in the C13–C15 subsectors of light industry
- ECC1315 — the amount of energy consumption (in oil equivalent) in the C13–C15 subsectors of light industry.

According to the data of the State Statistical Committee of the Republic of Azerbaijan (SSCRA, 2025), the dynamics of C1315, EXPC1315, and API in real terms (base year 2000) for the period 2007-2023 are presented in Table 1.

4. RESULTS

4.1. Dynamics and Descriptive Statistics of the Variables

Based on these indicators, we will attempt to quantitatively assess the dependence of air pollutant intensity (API) on:

- The volume of value added created in light industry (in national real currency — manat; base year 2000) (C1315)
- The export volume of light industry products (in national real currency — manat; base year 2000) (EXPC1315), and
- The exchange rate (EXCH).

The dynamics of these indicators for the period 2007-2023 are presented in Table 1.

In the study, the logarithms of the indicators C1315 and EXPC1315 were used. The results of the descriptive statistics for these indicators are presented in Table 2. Based on the results, moderate variability is observed in API (CV ≈ 19%), while the exchange rate exhibits high variability (CV ≈ 36%). By contrast, log-level output and exports are relatively stable (CV ≈ 2.6-4.1%). The Jarque–Bera tests do not reject normality for any of the time series (in particular, for API, P = 0.846). Such a result can be considered favorable for OLS/ARDL models in small samples.

Based on the results of the descriptive statistics, the high volatility of EXCH increases the likelihood of a strong effect in short-term dynamics (ΔEXCH). This justifies the inclusion of a break dummy variable in the model. Accordingly, we introduce into the model a dummy indicator that characterizes the sharp change in the exchange rate: it takes the value "1" only in 2015, and "0" in all other years. The stability of the log-transformed variables is favorable for the existence of a long-term cointegration relationship. The results indicate that there is no problem of normality in these time series.

Table 1: Dynamics of the variables

Years	CPI	API	C1315	expC1315	EXCH	a-nominal
2007	151.9	0.288	49703752	39824709	0.858	0.081
2008	175.1	0.392	53398058	25653627	0.822	0.095
2009	195.9	0.493	39509954	21924682	0.804	0.107
2010	199.5	0.463	42606516	21969113	0.803	0.099
2011	216.1	0.389	51272559	25406670	0.790	0.077
2012	226.4	0.463	54814488	23303033	0.786	0.087
2013	228.3	0.346	64432764	25980248	0.785	0.065
2014	233.2	0.400	58747856	19294592	0.784	0.073
2015	233.7	0.558	50962773	19824454	1.026	0.102
2016	265.6	0.624	74209337	32565854	1.596	0.100
2017	297.1	0.500	1.02E+08	53486933	1.721	0.072
2018	313.4	0.465	1.21E+08	80663373	1.700	0.063
2019	318.8	0.477	1.37E+08	1.06E+08	1.700	0.064
2020	327.5	0.420	1.16E+08	99345456	1.700	0.055
2021	338.2	0.371	1.54E+08	1.59E+08	1.700	0.047
2022	380.4	0.332	1.51E+08	1.16E+08	1.700	0.037
2023	432.2	0.445	1.21E+08	80436865	1.700	0.044

Calculated by the authors using SSCRA (2025) data

Table 2: Descriptive statistics of the variables

Statistic	API	EXCH	LOGC1315	LOGEXPC13
Mean	0.436874	1.233724	18.14967	17.58120
Median	0.445126	1.026100	17.98113	17.29877
Maximum	0.623578	1.721100	18.85433	18.88231
Minimum	0.288286	0.784400	17.49206	16.77534
Standard Deviation	0.083695	0.447192	0.474706	0.726400
Skewness	0.342235	0.087186	0.227259	0.448147
Kurtosis	2.929396	1.058188	1.484860	1.630549
Jarque-Bera	0.335384	2.692404	1.772416	1.897442
Probability	0.845614	0.260227	0.412216	0.387236
Sum	7.426853	20.97330	308.5444	298.8804
Sum Sq. Dev.	0.112076	3.199689	3.605525	8.442502
Number of observations	17	17	17	17

Calculated by the authors using Eviews-12 software

4.2. Stationarity

For model selection, the stationarity of the time series for the indicators in Table 2 should be tested using the ADF test and the Zivot–Andrews test. The results of the stationarity tests are presented in Table 3.

According to the ADF tests, API is non-stationary at the level at the 5% significance level (intercept P = 0.072; trend P = 0.247), but becomes stationary after the first difference (P = 0.026). Therefore, we treat API as I(1) in the baseline results. The Zivot–Andrews unit root tests with an endogenous structural break do not reject the null of a unit root in API at the level (ZA–C: t = −3.64, P = 0.31, break = 2013; ZA–CT: t = −4.59, P = 0.105, break = 2015). However, after the first difference, the series becomes stationary (ZA–C: t = −6.00, P = 0.033, break = 2016; ZA–CT: t = −4.81, P = 0.058, break = 2013). Therefore, we consider API to be I(1) with a structural break during 2013-2015. According to the ADF test, the EXCH exchange rate series is non-stationary at the level under both the intercept and trend specifications (P = 0.650; p = 0.290). For the first difference, the ADF test in our small sample does not reject the null of a unit root at conventional levels (t = −2.253; P = 0.198). Given the limited power of the ADF test with structural breaks and n = 15, we rely on the Zivot–Andrews test to confirm the order of integration.

The results of the Z-A test indicate that, with an endogenously selected break, the unit root hypothesis is strongly rejected. In other words, with the 2015 break, EXCH is stationary at order I(0). The break-aware Zivot–Andrews tests reject the unit root in the EXCH time series at the 1% significance level under both the "intercept only" and the "trend + intercept" specifications, with the break endogenously selected in 2015. Therefore, we treat EXCH as I(0) with a structural break, and we include a post-2015 dummy variable in the ARDL/ECM specification.

The LOGC1315 time series is not stationary at order I(0), but becomes stationary at the first difference, meaning that it is suitable for ARDL estimation as there is no I(2) integration. According to the Zivot–Andrews test results, the break-aware tests for LOGC1315 do not reject the unit root at the level under either the "intercept only" or "trend + intercept" specifications (ZA–C: t = −3.60, P = 0.331, break = 2015; ZA–CT: t = −4.36, P = 0.80, break = 2015). However, under the "trend + intercept" specification at the first difference, the null is strongly rejected (t = −13.91, P < 0.01, break = 2022). Thus, unit root tests indicate that LOGC1315 is I(1) at the level under both deterministic specifications. The structural breaks appear within the 2015-2018 interval, which is consistent with the shocks observed during 2014-2016.

The classical ADF tests do not reject the null of a unit root for LOGEXPC1315 either at the level ("intercept": P = 0.845; "intercept + trend": P = 0.640) or at the first difference ("intercept":

Table 3: Stasionarity (ADF and Z-A)

Variables	I (0)				I (1)			
	Intercept		Intercept and trend		Intercept		Intercept and trend	
	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.
API	−2.8593	0.0724	−2.7057	0.2470	−3.4522	0.0256	−3.1791	0.1254
API (Z-A)	−3.6436	0.3102	−4.5898	0.1050	−4.5980	0.0331	−4.8086	0.0579
EXCH (ADF)	−1.1878	0.6503	−2.5869	0.2895	−2.2534	0.1976	−2.1301	0.4898
EXCH (Z-A)	−446.8789	<0.01	−291.9139	<0.01	−5.8506	<0.01	−5.0604	0.0277
LOGC1315	−0.7611	0.8029	−2.3667	0.3801	−3.3406	0.0314	−3.1623	0.1286
LOGC1315 (Z-A)	−3.5997	0.3306	−4.3620	0.1826	3.5410	0.3649	−13.9108	<0.01
LOGEXPC1315	−0.6007	0.8446	−1.8298	0.6395	−2.6657	0.1027	−2.1910	0.4604
LOGEXPC1315 (Z-A)	−4.3088	0.0731	−4.9385	0.0394	−3.1930	0.5703	−4.1046	0.3109

Calculated by the authors using Eviews-12 software

P = 0.103). This is likely due to small-sample size and the effects of structural breaks. Therefore, we confirm the order of integration using break-aware tests. According to the Zivot–Andrews test results, for LOGEXPC1315 under the "intercept only" specification with a break, the unit root cannot be rejected (P = 0.073). However, under the "trend + intercept" specification, with endogenously selected breaks in 2016-2017, the null is rejected (P = 0.039). Conservatively, we treat LOGEXPC1315 as I(1) with a structural break, satisfying the preconditions for ARDL estimation. Thus, the unit root evidence with structural breaks indicates a mixture of I(0) and I(1) variables (API and LOGC1315: I(1); EXCH: I(0) with a 2015 break; LOGEXPC1315 is treated as I(1)). Since none of the series is I(2), estimation with ARDL is appropriate for our case. Naturally, a post-2015 dummy variable should also be included in the model.

4.3. Model Selection and ARDL Model Results

Thus, since none of the variables is I(2), there is no obstacle to applying the ARDL/Bounds approach. However, given the large number of possible ARDL specifications, it is necessary to select the most appropriate model among them. In Scheme 1, the 20 possible ARDL models with the highest AIC values are presented. Among them, the ARDL (1,2,1,2,2) specification is selected as the best-fitting model. This is because:

- AIC: −5.253 (ARDL (1,2,1,2,2)) < −3.695 (ARDL (1,0,0,0,1)) → better fit.
- BIC/HQ: −4.639/−5.260 < −3.357/−3.678 → again, preference is for ARDL (1,2,1,2,2)
- S.E. of regression: 0.020 < 0.033 → smaller residual error
- Adjusted R^2: 0.933 > 0.818 → higher explanatory power.

The results for the selected ARDL (1,2,1,2,2) model are presented in Table 4.

Based on the results in the table, the ARDL(1,2,1,2,2) model yields AIC = −5.253, SER = 0.020, Adj. R^2 = 0.933, and DW = 2.42 → indicating a strong fit with no signs of autocorrelation. The coefficient of API(−1) = −0.899 (statistically significant) shows that approximately 90% of the "disequilibrium" from the previous year is corrected within 1 year. The system is stable, with rapid convergence after shocks.

Devaluation increases API in the same year, but in the following year the effect is largely reversed, with a net 2-year impact of about +0.90 units (a small positive effect). An increase in logC1315 (production) reduces API in the short run (net ≈ −0.75). Exports (logEXPC1315) show an overall weak negative net effect (≈−0.12), suggesting that export shocks are subsequently "cleaned up" through structural adjustment. The break dummy is negative and large, both contemporaneously and with lags. The model results indicate that the system is stable and provides a good fit. Exchange rate shocks raise API in the short term, followed by partial reversal after one year. Production growth, on the other hand, generally reduces intensity.

Table 4: ARDL (1, 2, 1, 2, 2) results

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
API (−1)	−0.899241	0.232162	−3.873337	0.0607
DUMMY	−2.596250	0.683160	−3.800353	0.0628
DUMMY(−1)	−6.114133	1.619903	−3.774381	0.0636
DUMMY(−2)	−1.619070	0.432103	−3.746950	0.0644
EXCH	11.10809	2.838022	3.914026	0.0595
EXCH(−1)	−10.20474	2.701648	−3.777227	0.0635
LOGC1315	−0.506217	0.098284	−5.150565	0.0357
LOGC1315(−1)	0.185129	0.100030	1.850733	0.2054
LOGC1315(−2)	−0.430081	0.158274	−2.717324	0.1129
LOGEXPC1315	0.157611	0.075492	2.087777	0.1721
LOGEXPC1315(−1)	−0.370552	0.090239	−4.106315	0.0545
LOGEXPC1315(−2)	0.096006	0.075631	1.269392	0.3320
C	15.45416	2.675986	5.775126	0.0287

Calculated by the authors using Eviews-12 software

4.4. Bound Test

The results of the ARDL Bounds test are presented in Table 5. Based on these results, cointegration is confirmed. The F-statistic of the Bounds test is 12.83, which is significantly higher than both the asymptotic and finite-sample upper critical bounds (I(1)) (e.g., for n ≈ 30 at the 1% level: 5.84). Therefore, the null hypothesis of "no levels relationship" is confidently rejected.

This indicates that the ARDL (1,2,1,2,2), Case 2 (restricted constant, no trend), with k = 4 (four level regressors: DUMMY, EXCH, LOGC1315, LOGEXPC1315), exhibits a valid long-run relationship. Since F = 12.83 > upper bound critical values (10%: 3.56; 5%: 4.223; 1%: 5.84), the existence of cointegration is confirmed. The ECM (error correction term) coefficient for API(−1), equal to −1.899, is negative. This means the system corrects approximately 190% of disequilibria each year, indicating very rapid convergence, even with "overshooting." Stable but oscillatory convergence is expected.

$$API_t = -5.439*DUMMY_t + 0.476*EXCH_t - 0.396*logC1315_t - 0.062*logEXPC1315_t + 8.137 + \varepsilon_t \quad (2)$$

Scheme 1: ARDL model selection

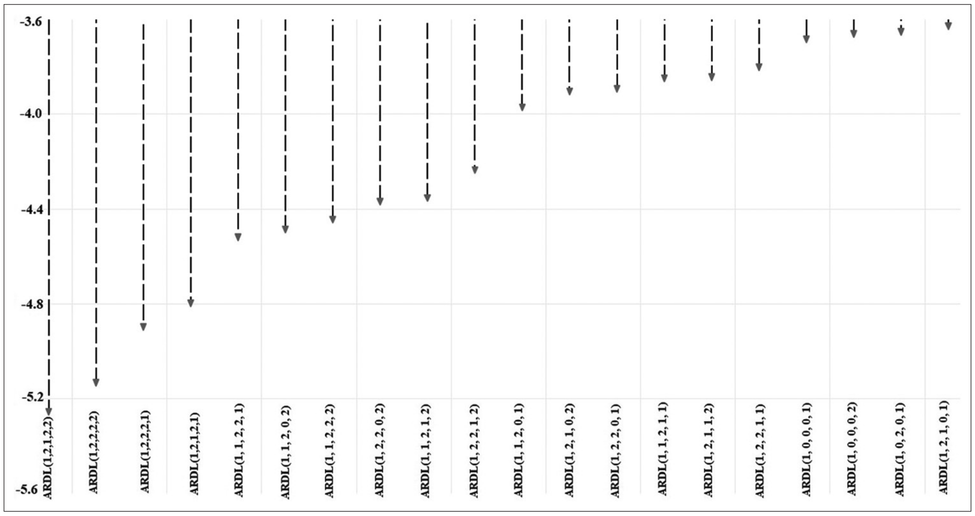


Table 5: Bound test results

Conditional error correction regression				
Variable	Coefficient	Standard Error	t-Statistic	Prob.
C	15.45416	2.675986	5.775126	0.0287
API(−1)*	−1.899241	0.232162	−8.180678	0.0146
DUMMY(−1)	−10.32945	2.732573	−3.780119	0.0634
EXCH(−1)	0.903354	0.163247	5.533650	0.0311
LOGC1315(−1)	−0.751170	0.159708	−4.703382	0.0424
LOGEXPC1315(−1)	−0.116935	0.048965	−2.388122	0.1396
D (DUMMY)	−2.596250	0.683160	−3.800353	0.0628
D (DUMMY(−1))	1.619070	0.432103	3.746950	0.0644
D (EXCH)	11.10809	2.838022	3.914026	0.0595
D (LOGC1315)	−0.506217	0.098284	−5.150565	0.0357
D (LOGC1315(−1))	0.430081	0.158274	2.717324	0.1129
D (LOGEXPC1315)	0.157611	0.075492	2.087777	0.1721
D (LOGEXPC1315(−1))	−0.096006	0.075631	−1.269392	0.3320

Calculated by the authors using Eviews-12 software

According to the equation, an increase in the exchange rate (EXCH), i.e., devaluation, leads to an increase in API. Growth in logC1315 (output/production) reduces API, reflecting an efficiency effect. LogEXPC1315 has a weak negative long-run impact on API. The effect of the DUMMY (post-break) indicator on the level of API is minor. Based on the short-run dynamics, ΔEXCH is positive and strong, meaning that devaluation raises API within the same year. ΔLOGC1315 has a negative effect, indicating that production growth reduces API even in the short term. The effects of ΔLOGEXPC are weak. Thus, the Bounds test strongly confirms the presence of cointegration. The ECM coefficient indicates rapid (and somewhat oscillatory) convergence. In the long run, the exchange rate increases API, while production reduces API. This allows us to reliably present both the long-run and short-run interpretations for the ARDL (1,2,1,2,2) model.

4.5. ECM

The ECM results are presented in Table 6. Based on these results, cointegration is confirmed and the model exhibits rapid (even somewhat oscillatory) convergence. In the short run, an increase in the exchange rate (devaluation) raises API, while an increase in production reduces API; the impact of exports is mixed in the short term. Since CointEq(−1) = −1.899 and is negative, and because |ECT| > 1, the system returns to equilibrium in less than one year "effectively," though the adjustment is wave-like with some overshooting. Put simply, if there is a deviation from equilibrium today, the next period brings an over-correction, after which the system "sticks" back to equilibrium.

Table 6: ECM results

ECM regression Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D (DUMMY)	−2.596250	0.162011	−16.02517	0.0039
D (DUMMY(−1))	1.619070	0.094505	17.13217	0.0034
D (EXCH)	11.10809	0.662759	16.76038	0.0035
D (LOGC1315)	−0.506217	0.036746	−13.77598	0.0052
D (LOGC1315(−1))	0.430081	0.032959	13.04891	0.0058
D (LOGEXPC1315)	0.157611	0.021604	7.295500	0.0183
D (LOGEXPC1315(−1))	−0.096006	0.017593	−5.456935	0.0320
CointEq(−1)*	−1.899241	0.115707	−16.41426	0.0037

Calculated by the authors using Eviews-12 software

Short-run effects (Δ-terms) are as follows:

- For ΔEXCH, the coefficient is +11.108, implying that when the exchange rate rises (devaluation), API increases in the same year
- For ΔLOGC1315, the coefficient is −0.506, while ΔLOGC1315(−1) is +0.430, meaning that production growth reduces API in the first year, with partial reversal in the following year. The net short-run effect is about −0.076
- For ΔLOGEXPC1315, the coefficient is +0.158 and ΔLOGEXPC1315(−1) is −0.096, indicating a small initial increase followed by correction, with a weak net effect
- For the break shock (ΔDUMMY), the coefficient is −2.596, while ΔDUMMY(−1) is +1.619, implying a sharp one-off negative shock in the break year, followed by partial compensation the next year. These terms are active only around the break period

- With $R^2 \approx 0.992$, SER ≈ 0.0108, and DW ≈ 2.42, the ECM model is confirmed to have a very good fit, high explanatory power, and no signs of autocorrelation.

Thus, the Bounds test (Case 2, k = 4) with F = 12.83 confirms the existence of cointegration, while the ECM test validates rapid (oscillatory) convergence (ECT = −1.899, negative and significant). In the short run, devaluation increases API, production growth reduces API, and the impact of exports is weak and mixed. During the break period, a one-off negative shock is observed.

4.6. Diagnostic Tests

The results of the diagnostic tests are summarized in Table 7. According to the LM test, no serial correlation is detected up to the first order. In the Breusch–Godfrey LM test, both the F-form (F = 0.211; P = 0.726) and the χ^2-form (Obs*R^2 = 2.616; P = 0.106) do not reject the null hypothesis of "no serial correlation." Since the Durbin–Watson statistic is ≈ 2.33, this result is consistent. This means that the model residuals are not AR(1). Therefore, the standard errors and p-values of the ARDL results are reliable with respect to AR(1) violations. In the test equation, the coefficient of RESID(−1) is not significant (P = 0.726), which supports the same conclusion. Thus, the Breusch–Godfrey LM test (lag = 1) shows that there is no serial correlation (F = 0.211, P = 0.726; Obs*R^2 = 2.616, P = 0.106). The Durbin–Watson ≈ 2.33 result is also consistent with this finding. Hence, the ARDL residuals are robust against AR(1) concerns.

According to the results of the heteroscedasticity test, no heteroscedasticity was detected. In the Breusch–Pagan–Godfrey (BPG) test, both the F-form (F = 0.165; P = 0.985) and the χ^2-form (Obs*R^2 = 7.465; P = 0.825) do not reject the null hypothesis of homoscedasticity (constant variance). The "Scaled explained SS" statistic supports the same conclusion (P = 1.000). Thus, the variance of the residuals is not systematically dependent on the explanatory variables, and the standard errors from OLS/ARDL are reliable with respect to heteroscedasticity. The auxiliary regression on RESID² shows that none of the explanatory variables has a statistically significant P-value, which also provides no signal of structural variance violations.

The negative Adjusted R^2 is simply the result of low power in a small sample ($df_2 = 2$; many regressors) and does not alter the conclusion. Thus, the Breusch–Pagan–Godfrey test does not indicate heteroscedasticity: F(12,2) = 0.165, P = 0.985; Obs·R^2 = 7.465, P = 0.825. The result is also supported by the CUSUMSQ graph. For robustness, heteroskedasticity-robust (HC3) standard errors were reported, and the results remained unchanged.

According to the results of the residual normality test, the Jarque–Bera test yields P = 0.261, so we do not reject the null hypothesis of normal distribution. In other words, Jarque–Bera = 2.69, P = 0.261. Thus, the ARDL/ECM residuals are approximately normal, with no strong evidence of normality violation. The residuals are centered around zero (mean ≈ 0), show slight left skewness (skewness = −1.01), and somewhat leptokurtic tails (kurtosis ≈ 3). Heteroskedasticity-robust standard errors remain unchanged.

According to the results of the Ramsey RESET test, there is no clear evidence of functional form misspecification. Since the p-value for both the t- and F-forms is 0.1243 ($df_2 = 1$), the null hypothesis of "correct specification/no omitted variables" is not rejected. Thus, when the squared fitted values (FITTED²) are added, the model does not improve significantly, indicating that the functional form is correct and no additional nonlinear terms are required.

The Ramsey RESET test (omitted: fitted²) shows no functional form error: F(1,1) = 25.57, P = 0.1243; t = 5.06, P = 0.1243. Although the LR statistic may yield a different result due to the small sample size, in the OLS context the decision is based on the F/t versions. Furthermore, the stability and residual diagnostics confirm that the specification is acceptable. According to the CUSUM (Brown–Durbin–Evans) diagnostic, when the cumulative recursive residuals remain within the 5% confidence bands, the null hypothesis of parameter stability over time cannot be rejected.

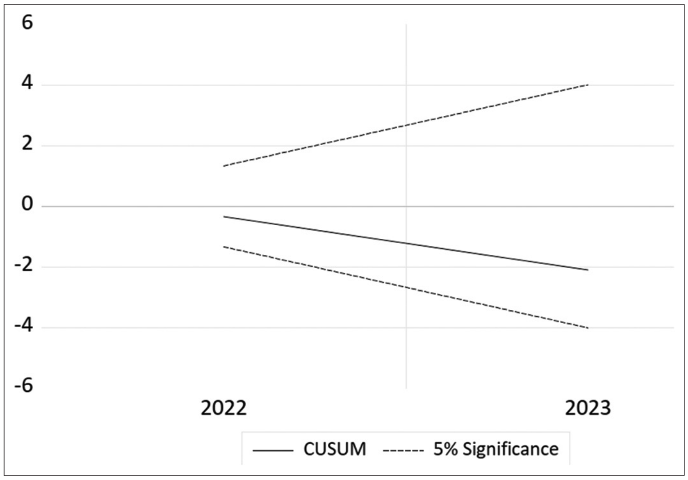
Our results (Graph 1) also do not cross the boundaries, indicating that the coefficients are stable. According to the CUSUMSQ diagnostic, if the cumulative sum of squared residuals lies within the 5% confidence bands, there is no sharp regime shift in the residual variance and no evidence of heteroskedasticity or structural breaks. In our results (Graph 2), no boundary exceedance is observed either. In both the CUSUM and CUSUMSQ graphs,

Table 7: Residual diagnostics

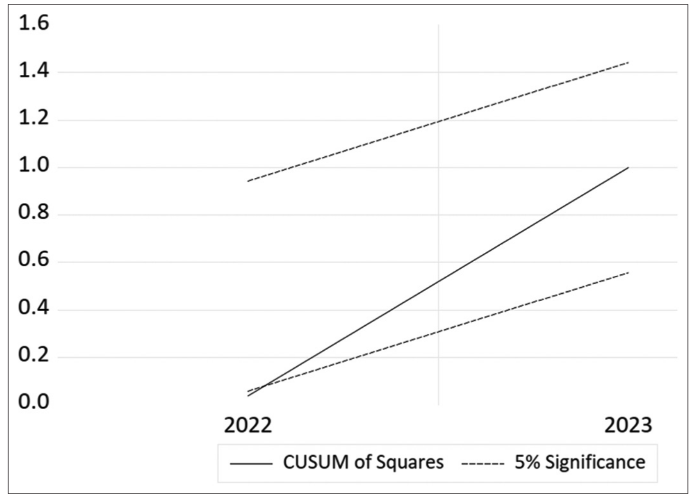
Test	Statistic	df	P-value	Decision (α=0.05)	Short note
Breusch–Godfrey LM (AR (1))	F=0.211; Obs: R^2=2.616	(1, 1); 1	0.726; 0.106	H_0 is not rejected, i.e., there is no serial correlation	Consistent with DW≈2.33
Ramsey RESET (fitted²)	F (1, 1) =25.57; t=5.06	(1, 1)	0.1243	H_0 is not rejected, i.e., there is no functional form misspecification	Small sample→F/t criterion is used as the basis
Jarque–Bera (normality)	JB=2.69	2	0.261	H_0 is not rejected, i.e., the residuals are approximately normal	Skew=−1.01; Kurtosis=3.45.
Breusch–Pagan–Godfrey (hetero.)	F=0.165; Obs·R^2=7.465	(12, 2); 12	0.985; 0.825	H_0 is not rejected, i.e., homoskedasticity holds	White/ARCH LM (optional) may be added
CUSUM	-	-	-	Parameter stability is confirmed within the 5% boundaries	There is no crossing
CUSUMSQ	-	-	-	Variance stability is confirmed within the 5% boundaries	There is no evidence of structural variance change

Calculated by the authors using Eviews-12 software

Graph 1: Results of CUSUM



Graph 2: Results of CUSUM of squares



the cumulative residual paths remain within the 5% significance bands throughout the entire observation period. Thus, there is no evidence of violations of parameter stability or variance stability, and the model is structurally stable. It should be noted that in small-sample settings ($n \approx 15$), these results, combined with the already presented LM (no serial correlation) and RESET (no functional form misspecification) diagnostics, further confirm the robustness of the findings.

5. DISCUSSION

This study investigated the key determinants of emission intensity in Azerbaijan's light industry (C13–C15) using the ARDL framework with structural breaks. Three main findings emerged.

First, higher sectoral output (as confirmed by logC1315) is associated with lower emission intensity in the long run. This reflects evidence that, once firms invest in efficiency and best available technologies, economies of scale, learning effects, and technology diffusion can reduce energy use and emissions per unit of value added (Pan et al., 2019; Chen et al., 2022). For example, in Bangladesh and China, larger-scale industrialization accompanied by openness and technological upgrading has been linked to declining energy intensity, once compositional effects are controlled for (Pan et al., 2019; Chen et al., 2022). Our findings indicate the existence of a similar "efficiency-dominant" channel in Azerbaijan's light industry.

Second, we find that currency depreciation (a higher exchange rate) increases emission intensity. In a small open economy that relies on imported energy, machinery, dyes, and chemicals, this outcome is economically intuitive. Depreciation raises the local currency cost of energy and capital upgrading, delays reductions in intensity, and locks firms into older, more energy- and emission-intensive technologies. Related time-series and quantile-ARDL studies show that exchange rate movements significantly affect energy demand and emissions; depreciation often worsens environmental footprints through cost and operational channels (Peng et al., 2022; Smaili AND Gam, 2023). In G7 economies, the effects of exchange rate movements on emissions are heterogeneous across demand states, underscoring the usefulness of flexible models such as ARDL. In the Mediterranean, exchange rate–emission linkages are also observed despite asymmetries in the level of development. This reinforces the importance of country-specific structures, such as those in Azerbaijan's energy- and import-intensive light industry.

Third, the weak and negative long-run association between C13–C15 exports and emission intensity is consistent with technology transfer facilitated by trade, as well as process upgrading. Research shows that export orientation can reduce energy/emission intensity when meeting standards in foreign markets drives the adoption of cleaner technologies and stricter quality control (Pan et al., 2019). Moreover, studies on textile production in Asian countries indicate that although the sector is energy-intensive, targeted upgrading and green technologies can bend the intensity curve downward (Haseeb et al., 2020). Our findings suggest that for Azerbaijan's light industry, the export channel may operate more through "standards/efficiency" mechanisms rather than through a "pollution haven" effect.

The identified structural breaks coincide with the macro shocks to Azerbaijan's trade sector and exchange rate regime in 2015. This aligns with the literature linking such breaks to strong spillovers into the real economy (Mukhtarov et al., 2021). In such contexts, ARDL with structural breaks is particularly informative, as it allows for parameter shifts without discarding long-run information.

Our findings are also consistent with the environmental profile specific to the textile and apparel sectors. International evidence highlights the contributions of combustion-related CO_2, as well as process emissions and volatile organic compounds (VOCs) released during dyeing and finishing. Targeted process control and substitution measures can significantly reduce these burdens (Qian et al., 2022). Therefore, policy levers that stabilize firms' access to efficient capital—such as currency risk management and concessional green credit—and those that promote export–market alignment—such as eco-labels and supplier development—should reinforce the efficiency gains observed in Azerbaijan's light industry.

6. CONCLUSION

This study examined the determinants of emissions/energy intensity in Azerbaijan's light industry (NACE C13–C15) over the period 2007-2023 using an ARDL framework explicitly adjusted for structural breaks. After establishing that all series are at most I(1) (with no I(2)) based on ADF and break tests, the Bounds test ($F = 12.83$) confirmed the existence of a long-run relationship. The associated ECM indicates rapid error correction ($ECT \approx -1.90$). Thus, deviations from equilibrium are corrected quickly.

Three main findings emerge. First, a weaker currency (higher EXCH) is associated with higher intensity in the long run, and depreciation shocks amplify the effect, although partially reversed after one year. Second, sectoral output growth (logC1315) is linked to lower intensity in both the short and long run, consistent with scale effects as firms expand and adopt better technologies. Third, exports (logEXPC1315) show a small negative long-run association with intensity, alongside mixed short-run effects, suggesting improvements driven more by standards compliance than by pollution-related behavior. Model diagnostics (LM, RESET, CUSUM/CUSUMSQ) support the adequacy of the specification despite the small sample size.

The policy implications follow directly. Exchange rate volatility can temporarily link emissions with economic activity. Targeted green financial instruments—including concessional loans, credit guarantees, and currency risk management tools for upgrading energy-saving equipment and processes—can buffer firms during depreciation episodes. The analysis also has limitations. The intensity metric was constructed in kgoe/AZN and is constrained by the absence of pollutant-specific, firm-level data for C13–C15. Hence, the results should be interpreted as sectoral intensity, not absolute damage. The sample size is short ($n \approx 17$), and the P-values do not fully account for model selection uncertainty. Future work should test nonlinear/asymmetric responses (NARDL/QARDL), apply open-band or Narayan small-sample critical values as the main inference device, and incorporate input price indices to disentangle price from activity channels. Where data permit, results should be extended to particulate/VOC proxies. Finally, micro-level energy audits or plant-level panels could significantly strengthen identification.

The findings of this study further confirm that since depreciation pressures worsen intensity, hedging programs for energy-efficient machinery and green credit lines can mitigate macro-driven downside risks (Peng et al., 2022). Support for compliance with EU/EEA product and process standards (e.g., ZDHC, ISO 14001) through technology and quality investments can also help reinforce the negative export–intensity relationship (Pan et al., 2019). Given the process-specific emission profile of the C13–C15 sector (thermal energy, dyes/solvents), policies focusing on heat recovery, electrification, and low-VOC chemistry could reduce intensity without sacrificing output (Haseeb et al., 2020; Qian et al., 2022).

The ARDL–Bounds results demonstrate the existence of a stable long-run relationship between the exchange rate, production, exports, and the ecological intensity indicator. In the long run, higher production volumes are associated with reduced intensity (efficiency/technological upgrading channel), a weaker exchange rate increases intensity (cost channel of external shocks), while exports show a weak negative effect. These findings suggest that when production growth is combined with technological upgrading and macro-financial conditions (particularly exchange rate risk) are effectively managed, it is possible to reduce the intensity of atmospheric emissions while sustaining output growth.

Extending the dataset for the indicators used in this study by at least 10-15 years would allow for more robust results: a) While the stationarity properties and bounds tests justify the use of ARDL, future research could apply NARDL or QARDL in order to capture the asymmetric effects of depreciation against price increases, as suggested in multi-country evidence; b) The study could also be expanded by incorporating input-price indices (e.g., imported energy and machinery) to disentangle price and activity channels. Furthermore, in order to reflect a more comprehensive external impact package in the light industry, environmental outcomes could be broadened beyond intensity measures—for example, by including particulates and VOC permits (Peng et al., 2022; Qian et al., 2022).

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