Journal of Sustainable Development of Energy, Water and Environment Systems

http://www.sdewes.org/jsdewes

Year 2027, Volume 15, Issue 1, 1140791

Original Research Article

Renewable Energy, Structural Transformation and Carbon Mitigation in Azerbaijan: Time-Series Evidence from an Oil-Rich Economy

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Cite as: Gulaliyev, M., Mehdiyeva, G., Aliyeva, I., Huseynova, R., Alakbarov, R., Renewable Energy, Structural Transformation and Carbon Mitigation in Azerbaijan: Time-Series Evidence from an Oil-Rich Economy, J.sustain. dev. energy water environ. syst., 15(1), 1140791, 2027, DOI: https://doi.org/10.13044/j.sdewes.d14.0791

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ABSTRACT

This study examines whether renewable electricity is associated with industrial combustion-related carbon dioxide emissions in Azerbaijan over 1995–2024. Five aggregate-share autoregressive distributed lag specifications and three pre-specified component models are estimated with 29 effective annual observations. In the baseline model, the renewable coefficient is negative, but significance depends on covariance choice (conventional p = 0.098; White robust p = 0.033; Newey–West p = 0.038). The hydropower replacement is negative and robust, whereas the non-hydropower replacement is imprecise. In the joint component equation, the hydropower coefficient remains negative (-0.0283; White robust p = 0.004; Newey–West p = 0.0025) and the non-hydropower coefficient remains statistically unsupported (White robust p = 0.423; Newey–West p = 0.3862); the finite-sample bounds statistic rejects no levels relationship at 5%, and the error-correction coefficient is -0.6386. Error-correction terms are negative across all eight equations, although collinearity, specification, serial-correlation, and endpoint cautions remain. The evidence indicates conditional dynamic associations, not causal effects or verified fossil-generation displacement. Policy evaluation should link renewable expansion to measured fossil displacement, industrial electrification, hydrological conditions, and sector-specific emissions.

KEYWORDS

renewable electricity, industrial combustion emissions, fossil-fuel displacement, oil-rich economy, Azerbaijan, time-series modelling

INTRODUCTION

Expanding renewable capacity is not the same as achieving decarbonisation. The policy-relevant outcome is the amount of fossil generation and fuel combustion that renewable electricity actually avoids, together with the sector in which that reduction is recorded. This distinction is particularly important for industry. Global industrial greenhouse-gas emissions arise from direct fuel combustion, process reactions, product use, waste, and electricity and heat purchased from the power system; each component responds to different technologies and policies [1]. A renewable megawatt-hour can lower power-sector emissions while leaving direct industrial combustion unchanged, or it can support industrial decarbonisation if it enables electrification and substitution away from on-site fossil fuels. Consequently, a credible empirical analysis must connect the renewable variable, the displacement mechanism, and the accounting boundary of the emissions outcome rather than infer mitigation from renewable growth alone.

Azerbaijan offers a demanding test of this question. Hydrocarbon output greatly exceeds domestic energy needs, and energy production was almost four times total energy supply in 2022. In the same year, natural gas generated more than 90% of electricity, whereas renewables, including hydropower, supplied about 6% [2]. The mix began to change more visibly near the end of the study period. Official operational statistics for 2024 report 28.394 TWh of total generation, comprising 24.543 TWh from thermal plants, 3.011 TWh from hydropower, 0.556 TWh from solar, and 0.051 TWh from wind; electricity exports reached 1.398 TWh and imports 0.171 TWh [3]. These figures reveal both progress and persistence: solar generation increased materially, but thermal plants continued to supply the large majority of electricity and hydropower remained the largest renewable component.

The resulting research gap is precise. There is limited evidence for Azerbaijan on whether a generation-based renewable indicator is dynamically associated with a transparently bounded measure of industrial combustion emissions after accounting for electricity demand and structural change. Existing work does not jointly confront four features of the case: the dominance of gas-fired electricity, the hydro-sensitivity of historical renewable output, the distinction between sectoral combustion and broader CO_2 measures, and the severe inferential limits of a 30-observation annual sample. Closing this gap does not require a broader list of controls. It requires a narrower estimand and an interpretation tied explicitly to the mechanism that the available data can support.

Against this background, the study asks whether increases in the renewable share of gross electricity generation are associated with lower industrial combustion-related CO_2 emissions in Azerbaijan over 1995–2024, conditional on electricity consumption, real income per capita, industrial structure, urbanisation, and weather. Three subsidiary questions organise the analysis. First, is the relationship visible in contemporaneous changes, distributed short-run responses, or a conditional long-run equilibrium? Second, is the estimated association robust to a parsimonious dynamic specification appropriate for the available sample? Third, does the interpretation remain valid once the renewable composition, hydrological exposure, and sector boundary of the emissions series are made explicit? These questions deliberately concern conditional association rather than an exogenous treatment effect.

The paper makes four bounded contributions. First, it shifts attention from national or consumption-based CO2 to a sectoral combustion outcome while making the limits of that boundary explicit. Second, it uses renewable electricity generation rather than aggregate renewable consumption or installed capacity, aligning the exposure more closely with the proposed displacement channel. Third, it combines small-sample econometric discipline with three pre-specified component models: M6a replaces RENERGY with HYDRO, M6b replaces it with NONHYDRO, and M6c enters HYDRO and NONHYDRO jointly.M6c provides the most informative within-equation composition check, and the HAC (Heteroskedasticity and Autocorrelation Consistent)-robust Wald test does not reject coefficient equality; therefore, the

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model does not establish statistically different component effects, even though Newey-West HAC inference is verified.Fourth, the study places the Azerbaijan evidence within the political economy of a gas-dominated exporter, where renewables can reduce territorial electricity emissions, free gas for other uses, or do both. The contribution is therefore a mechanism-aware country study, not a claim that one coefficient identifies the causal effect of the green transition.

LITERATURE REVIEW

The relevant question for Azerbaijan is not whether renewable energy is generally associated with lower carbon dioxide (CO_2) emissions. It is whether renewable electricity actually displaces fossil-fuel generation in a gas-dominated power system and whether that displacement is visible in a narrowly defined measure of industrial combustion emissions. These are different empirical links. A renewable generation share can rise without a one-for-one decline in fossil generation; hydropower can vary because of rainfall and reservoir conditions; and industrial combustion emissions do not have the same accounting boundary as national, power-sector, or consumption-based CO_2. The literature therefore supports a mechanism-centred review rather than a sequence of study-by-study summaries.

Renewable electricity and realised fossil-fuel displacement

The decarbonisation value of renewable electricity is mediated by dispatch. In accounting terms, gross electricity supply is allocated among fossil generation, renewable generation, other non-fossil generation, net imports, storage, and losses. Increasing the renewable share changes emissions only to the extent that it lowers output from emitting units or enables fuel switching elsewhere. The same renewable-share increase can therefore reflect at least four different processes: renewable output replacing gas-fired generation; renewable output meeting additional demand; a fall in total generation that mechanically raises the share; or hydrological conditions that temporarily increase hydroelectric output. Capacity, generation, displacement, and avoided emissions are related but non-equivalent constructs.

Hydropower variability and the hydrology problem

Hydropower is both a low-carbon electricity source and a hydrologically constrained technology. Its annual output depends on precipitation, snowmelt, river inflows, reservoir storage, release rules, irrigation priorities, and drought. As a result, year-to-year movements in a hydro-dominated renewable share can reflect weather rather than investment, policy effort, or structural transformation. The distinction matters empirically: a wet year can raise renewable generation and lower thermal dispatch even if installed renewable capacity and market institutions are unchanged. Such displacement is physically real, but it is not evidence that a durable energy transition caused the change.

The electricity-system literature documents both the emissions and reliability consequences of this variability. [4] show that climate-driven changes in hydropower can shift generation toward or away from carbon-intensive technologies and materially alter regional power-sector emissions. [5] find that greater hydropower variability can increase gas-plant starts, dispatchable-capacity needs, and greenhouse-gas emissions in a highly renewable grid. Using observed drought variation, [6] show that hydropower shortfalls in the western United States are partly replaced by fossil generation and that part of the resulting emissions burden is transferred across regions through electricity trade. Across these studies, hydrology is not a peripheral climate control; it is a determinant of the renewable regressor and of the thermal-generation response.

Industrial combustion emissions are not total CO_2 emissions

Emissions-accounting boundaries determine the economic mechanism that a model can test. Under Intergovernmental Panel on Climate Change (IPCC) inventory guidance, stationary

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fuel combustion is reported within the Energy sector, while fugitive emissions from fuels are separate and process emissions are reported under Industrial Processes and Product Use (IPPU) [7], [8]. Industry-wide mitigation assessments additionally distinguish direct on-site fuel combustion, process emissions, and indirect emissions embodied in purchased electricity and heat [1]. Consequently, 'industrial CO_2', 'industrial combustion CO_2', 'power-sector CO_2', 'territorial CO_2', and 'consumption-based CO_2' are not interchangeable labels.

Energy transition in oil- and gas-dependent economies

Recent evidence further reinforces the need to treat renewable deployment as a system-level transition rather than as a mechanical emissions-reduction input. [9], using high-frequency evidence from Uruguay, shows that wind and solar generation can displace hydro and fossil generation and reduce CO2 while still failing to eliminate fossil generation. Recent hydropower research likewise shows that climate variability and operational flexibility can materially alter the reliability and emissions consequences of renewable integration [10], [11]. For Azerbaijan specifically, [12] identifies infrastructure, investment, regulatory, and institutional constraints in the national green-energy transition, while recent work on Azerbaijan's energy politics emphasises persistent carbon lock-in associated with the country's hydrocarbon-based political economy (2026). These findings strengthen the case for a sectorally bounded, hydrology-aware empirical design: global evidence establishes the plausibility of displacement, but it does not establish that the same mechanism operates in Azerbaijan's gas-dominated system or within the industrial-combustion boundary used here.

Energy transition in a fossil-fuel exporter is a problem of political economy and structural transformation, not only technology substitution. Domestic fossil fuels may be cheap, infrastructure and skills are specialised around hydrocarbons, state-owned enterprises have multiple fiscal and social functions, and export rents shape public investment. These features can weaken the pass-through from renewable capacity to fossil retirement even when solar or wind resources are strong. They also create an opportunity-cost channel: renewable electricity can release gas for export rather than leave it unburned. Recent country-comparative ARDL (Autoregressive Distributed Lag) evidence further shows that Azerbaijan's long-run oil-price effect on real GDP (Gross Domestic Product) per capita is weak or statistically limited, while fiscal composition, demographic pressure, and structural transformation condition the welfare gains from hydrocarbon windfalls [13]. A complementary panel analysis likewise finds that oil-price shocks do not translate uniformly into welfare-related income across MENA (Middle East and North Africa) exporters and Azerbaijan, reinforcing the need to interpret energy transition within heterogeneous fiscal and structural regimes [14].

The stranded-assets literature shows why the timing and credibility of transition matter. [15] identify macroeconomic losses from fossil assets that become uneconomic as low-carbon technologies diffuse and climate policy tightens. [16] emphasise uncertainty, capital-adjustment costs, and disorderly revaluation, while [17] show that fossil-fuel-producing developing economies face region-specific choices between asset stranding and green transformation. [18] further demonstrate that anticipated climate policy can affect investment before policy implementation. For an oil-rich economy, renewable deployment therefore interacts with fiscal diversification, investment expectations, and the risk of locking in long-lived gas infrastructure.

Identification and dynamic-model limitations in a small annual sample

ARDL framework is useful for representing short-run dynamics and testing a conditional level relationship when regressors are a mixture of I(0) and I(1), provided that no included variable is I(2) and the deterministic specification is appropriate [19]. These advantages do not, however, make ARDL immune to small-sample overfitting, weak identification, structural breaks, or endogenous regressors. Cointegration is not causation, and a lagged coefficient is not automatically evidence of a delayed policy effect.

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Finite-sample inference is a second constraint. The original bounds critical values are asymptotic. [20] show that using asymptotic values can substantially oversize the bounds test in small samples; in one 30-observation design, an apparent 5% rejection based on the asymptotic upper bound corresponds to a finite-sample p-value above 0.10. [21] and [22] develop bootstrap procedures that improve size and power and help diagnose degenerate cases. These contributions imply that conventional bounds tables alone are not sufficient for a 1995–2024 application.

Most importantly, the estimand should be described correctly. An annual ARDL coefficient identifies a conditional dynamic association under the maintained specification. It does not isolate an exogenous renewable-supply shock, and it cannot show the marginal thermal plant displaced. Stronger causal identification would require a credible source of exogenous variation—such as hydrological instruments used with care, project-level commissioning, or higher-frequency dispatch data—and a design that separates supply shocks from demand and policy responses. If those data are unavailable, transparent associational language is not a weakness; it is the appropriate inference.

Azerbaijan-specific evidence and the precise research gap

Azerbaijan already has a substantive time-series literature on energy and emissions, but it addresses different outcomes and mechanisms. [23] model aggregate CO_2 and income over 1992–2013 and reject a conventional Environmental Kuznets Curve interpretation. [24] studies per-capita CO_2 and the natural-gas share over 1990–2019. [25] use consumption-based CO_2 and aggregate renewable-energy consumption for 1993–2019, while [26] model consumption-based CO_2 as a function of renewable consumption, total factor productivity, income, exports, and imports using Autometrics for 1991–2019. A complementary policy literature assesses Azerbaijan's solar and wind potential and institutional development [27]. Sectoral evidence for Azerbaijan also identifies the energy sector as the dominant emissions source and emphasizes the industrial sector's heavy reliance on crude oil and natural gas, underscoring the value of a sector-bounded emissions outcome [26]. Earlier resource and techno-economic assessment demonstrates substantial solar potential across Azerbaijan but also highlights electricity-pricing and investment barriers that can limit market deployment [28].

The precise gap has four parts. First, there is an outcome gap: evidence is limited on a transparently documented, sector-specific industrial-combustion CO_2 measure for Azerbaijan. Second, there is an exposure gap: prior work does not clearly distinguish renewable electricity generation from aggregate renewable-energy use or installed capacity. Third, there is a mechanism gap: realized fossil-generation displacement, hydrological variability, electricity trade, and technology composition are rarely evaluated jointly. Fourth, there is an inference gap: very short annual series require finite-sample critical values, aggressive parsimony, and break-robust sensitivity analysis rather than mechanically applying an unrestricted ARDL.

The literature does not justify a universal negative renewable-energy coefficient. It instead identifies a sequence of necessary links: renewable generation must be additional; it must reduce the output of emitting units rather than simply meet extra demand or increase exports; hydrology must not be mistaken for structural change; and the avoided emissions must fall inside the boundary of the dependent variable. In Azerbaijan, each link is empirically contestable because the power system is gas-dominated, historical renewable variation is hydro-sensitive, the economy is organized around hydrocarbon rents, and the annual sample is exceptionally small.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

This section develops the analytical logic linking economic scale, structural composition, energy use, and renewable-electricity composition to the bounded industrial-combustion emissions outcome, and then translates that logic into testable hypotheses.

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Analytical foundation: scale, composition, technique and boundary

The broad analytical foundation is the Impact = Population × Affluence × Technology (IPAT) and Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) view that environmental pressure reflects economic scale, affluence, and technology rather than income alone [29]. For a sectoral combustion outcome, that logic is sharpened through an emissions identity. Let Y denote aggregate real output, S_IND the industrial share of output, EI_IND industrial energy use per unit of industrial value added, and CI_IND the carbon content of the energy used by industry. Industrial combustion emissions can then be represented conceptually as:

$$CO_2_IND_t = Y_t \times S_IND_t \times EI_IND_t \times CI_IND_t \quad (1)$$

Equation (1) is an accounting decomposition, not the regression ultimately estimated. It clarifies four distinct sources of change. Output growth creates a scale effect; changes in the industrial share create a composition effect; changes in energy intensity capture efficiency and production technology; and changes in the carbon intensity of industrial energy capture fuel switching and the cleanliness of purchased electricity. Decomposition methods such as the logarithmic mean Divisia index formalise these channels when sufficiently disaggregated activity, energy, and fuel data are available [30]. The present annual dataset does not contain all four components directly. GDP per capita and the industrial share are broad proxies for scale and composition, electricity consumption mixes activity and efficiency, and the renewable generation share is only an indirect proxy for the carbon-intensity channel. This distinction prevents the empirical model from being presented as a literal decomposition identity.

Core mechanism: from renewable generation to realised fossil displacement

The second link is realised displacement. Define displacement efficiency conceptually as $\delta = -(\partial F/\partial R)$, where F is fossil electricity and R is renewable electricity. Proportional displacement implies $\delta = 1$; δ between zero and one indicates partial displacement; and δ close to zero means renewable output largely accommodates additional demand or exports rather than reducing fossil generation. Historical evidence shows that displacement is commonly incomplete and varies with demand growth, reserve margins, trade, dispatch rules, curtailment, and grid flexibility [31], [32], [33]. High-frequency studies likewise show that avoided emissions depend on the marginal thermal unit and its operating response, not on renewable megawatt-hours alone [34], [35]. The proposed annual model cannot observe the marginal plant or estimate δ directly; it estimates the reduced-form association after conditioning on available demand and structural proxies.

Transmission to industrial combustion emissions

A reduction in gas-fired generation first lowers power-sector emissions. Transmission to industrial combustion is a second step. Cleaner grid electricity may enable electrification of low- and medium-temperature heat, motors, pumps, compressors, and other industrial services; firms may also retire captive fossil generation or combine electrification with energy-efficiency investment. IPCC mitigation pathways identify electrification with low-carbon power, fuel switching, energy efficiency, and material efficiency as distinct but complementary industrial options [1]. The effect on direct combustion will therefore be smaller, slower, or absent when industrial processes remain fuel-based, electricity prices do not reward switching, or the measured series excludes the activities that electrify.

H1: conditional mitigation hypothesis. Conditional on electricity demand and structural controls, a persistent increase in the renewable share of gross electricity generation is

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associated with lower industrial combustion-related CO_2 emissions. The expected sign is negative, but the interpretation is contingent on realised fossil displacement and on a dependent-variable boundary through which cleaner electricity can plausibly affect direct combustion.

H2: cumulative dynamic hypothesis. The cumulative short-run response and, where a stable levels relationship is supported, the conditional long-run multiplier of renewable electricity are negative. No hypothesis is imposed on a unique contemporaneous or one-year-lag coefficient; timing must be evaluated through joint and cumulative effects rather than a single selected lag.

H3: component-sensitivity hypothesis. If the negative aggregate renewable-emissions association is largely reproduced by hydropower variation, M6a should retain a negative HYDRO coefficient, while M6b may yield a different and less precise NONHYDRO association. M6c evaluates both components in one equation. The HAC-robust Wald test does not reject HYDRO = NONHYDRO ($F(1, 22) = 1.5891$, $p = 0.2207$), so H3 does not receive evidence of statistically distinct component coefficients; endpoint sensitivities and direct hydrological controls remain necessary, while Newey-West HAC covariance is reported as an additional robustness check.

Translation into the empirical model

The observable relationship implied by the framework can be summarised as a conditional dynamic emissions function rather than as a structural production equation:

$$logCO2INDUST_t = f(RENERGY_t, logECONS_t, logGDPPC_t, logMANINDUST_t, URBAN_t) \quad (2)$$

In Equation (2), the renewable coefficient is the parameter of primary interest; electricity consumption and the manufacturing share within industry represent demand and composition; gross domestic product per capita and urbanisation absorb broader structural variation; and weather, hydrology, and intervention terms are identification controls. Annual mean temperature is a coarse weather control and is not interpreted as a hydrological measure. A consolidated construct-to-estimand map, including the observed proxies, expected empirical roles, and principal identification boundaries, is provided in Appendix Table A1. Heating and cooling degree days and direct hydrology indicators remain priorities for data extension rather than observed controls in the reported models.

ARDL and the conditional error-correction representation are compatible with this framework because they distinguish changes, lagged adjustment, and a possible conditional levels relationship when no series is integrated of order two [19]. They do not create causal identification. In a short sample, extensive lag searches can exhaust degrees of freedom, conventional bounds inference can be oversized, and common shocks can move renewables and emissions together. Finite-sample response-surface or bootstrap inference, tightly restricted lags, break and influence diagnostics, and cumulative effects are therefore part of the conceptual-to-empirical translation rather than optional technical embellishments [20], [21], [22]. The estimand remains a conditional dynamic association under the maintained specification.

DATA, VARIABLES AND METHODOLOGY

The empirical design distinguishes the paper's principal sectoral outcome from an economy-wide robustness outcome and separates the confirmation equation from slower-moving or potentially redundant controls. This hierarchy is essential in a 30-year annual sample: placing every available covariate and its lags in one equation would consume the residual degrees of freedom, magnify collinearity, and turn model selection into an outcome-driven exercise. The measurement protocol is therefore fixed before unit-root testing or lag selection, and every series is interpreted within its documented statistical boundary.

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Unit of observation, target period, and data lock

The unit of observation is the Azerbaijan calendar year. The dataset covers 1995–2024, giving 30 level observations; one lag reduces the effective regression sample to 1996–2024 (29 observations). Models are compared on this common effective sample so that coefficient changes are not confounded with sample changes.

The empirical role and construction of each variable are fixed before estimation. Logged variables reduce scale dispersion, whereas the renewable share enters in percentage points so that its coefficient is interpreted as a semi-elasticity. The complete variable dictionary is reported in Table 1, while the mapping between the underlying theoretical constructs, observed proxies, expected signs, and identification boundaries is presented in Appendix Table A1.

Table 1. Pre-specified variable dictionary

Variable	Operational definition	Empirical role	Source
LOGCO2INDUST	Natural log of annual CO2 from industrial fuel combustion, in one consistent mass unit.	Primary dependent variable.	https://data.worldbank.org/indicator/EN.GHG.CO2.IC.MT.CE.AR5
LOGCO2ECON	Natural log of economy-wide territorial CO2, excluding land use, land-use change and forestry and international bunkers; exact inventory boundary held constant.	Alternative dependent variable.	https://data.worldbank.org/indicator/EN.GHG.CO2.MT.CE.AR5
RENERGY	100 × renewable gross electricity generation / total gross domestic electricity generation; percentage points; not logged.	Main regressor; expected conditional sign < 0.	Authors' calculation using https://stat.gov.az/source/balance_fuel/
HYDRO	100 × hydropower gross electricity generation / total gross domestic electricity generation; percentage points; not logged.	M6a hydro-replacement and M6c joint-component regressor.	Authors' calculation using https://stat.gov.az/source/balance_fuel/ .
NONHYDRO	RENERGY − HYDRO, using the same gross-domestic-generation denominator; percentage points; not logged.	M6b non-hydro replacement and M6c joint-component regressor; never entered with RENERGY.	Authors' calculation using https://stat.gov.az/source/balance_fuel/
LOGECONS	Natural log of total final electricity consumption in GWh, from the same	Core demand-scale control.	Azerbaijan State Statistics Committee, Fuel and Energy Balance; authors' calculation

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	energy-balance lineage used for generation.		
LOGGDPPC	Natural log of real GDP per capita from one constant-price series and vintage.	Core scale/technique control; sign not imposed.	Authors' calculation by using https://stat.gov.az/source/system_nat_accounts/ and CPI
LOGMANINDUST	Natural log of 100 × manufacturing value added / total industry value added, constructed from consistent national-accounts series.	Core structural-composition control.	Authors' calculation by using https://data.worldbank.org/indicator/NV.IND.MANF.ZS and https://data.worldbank.org/indicator/NV.IND.TOTL.ZS
LOGINDUSGDP	Natural log of industry value added as a share of GDP, using a consistent classification and price basis.	Structural robustness control; replaces LOGMANINDUST.	Authors' calculation by using https://data.worldbank.org/indicator/NV.IND.TOTL.ZS
URBAN	Urban population share (%).	Separate sensitivity control.	Authors' calculation by using https://www.azstat.gov.az/portal/tblInfo/TblInfoList.do#994_001
AVERT	Area-weighted annual mean 2-m air temperature for Azerbaijan, in degrees Celsius; not logged.	Separate weather sensitivity control.	Authors' calculation by using https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download

Dependent-variable boundaries

LOGCO2INDUST is the natural logarithm of annual CO_2 emissions from industrial fuel combustion (Intergovernmental Panel on Climate Change [IPCC] 2006 category 1.A.2, Manufacturing Industries and Construction), reported in a consistent mass unit and standardised with AR5 global-warming-potential factors. Category 1.A.2 covers fuel combustion in iron and steel; non-ferrous metals; chemicals; pulp, paper and print; food processing, beverages and tobacco; non-metallic minerals; transport equipment; machinery; mining and quarrying excluding fuel extraction; wood and wood products; construction; textiles and leather; and other non-specified industry. The series excludes industrial process emissions, fugitive emissions, flaring, venting, and other gases unless explicitly included in the source metadata. It also does not by itself identify emissions from extraction, refinery own-use, captive generation, or energy-industry combustion. These boundaries govern interpretation: the article treats LOGCO2INDUST as industrial-combustion CO_2 and does not relabel it as manufacturing emissions, the hydrocarbon sector's total footprint, or national emissions. The data source, indicator code, unit, inventory category, sector coverage, and revisions are recorded in **Table 1** and the reproducibility archive. Renewable electricity and conditioning variables

RENERGY measures the share of gross domestic electricity generation supplied by renewable technologies. Accordingly, RENERGY is calculated as the ratio of renewable electricity generation to total gross domestic electricity generation, expressed in percentage points, as specified in Equation (3). The numerator and denominator are retained separately, and both use identical coverage of utility and autoproducer generation. Hydropower, wind,

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solar, bioenergy, geothermal, and marine generation are included only when consistently reported; nuclear power and non-renewable waste are excluded. Imports and exports do not enter the domestic-generation denominator. Entering the share in percentage points means that its coefficient is a semi-elasticity: a one-percentage-point increase in RENERGY is associated with approximately 100 times beta percent change in the logged outcome, conditional on the other regressors and dynamics.

$$RENERGY_t = 100 \times RENEWGEN_t \,/\, TOTALGEN_t \tag{3}$$

The 30 author-supplied HYDRO observations are aligned with the manuscript's chronological order for 1995–2024. HYDRO is calculated as the share of hydropower generation in total gross domestic electricity generation, as defined in Equation (4). NONHYDRO is subsequently derived as the difference between the aggregate renewable share and the hydropower share, as shown in Equation (5). On a ratio-of-means basis, hydropower accounts for 94.9% of the aggregate renewable share, and HYDRO is highly correlated with RENERGY (r = 0.978).

$$HYDRO_t = 100 \times HYDROGEN_t \,/\, TOTALGEN_t \tag{4}$$

$$NONHYDRO_t = RENERGY_t - HYDRO_t \tag{5}$$

As follows directly from Equations (3)–(5), RENERGY is the exact sum of HYDRO and NONHYDRO. Therefore, the aggregate share must not be entered in the same equation as both components. Pre-specified empirical hierarchy

The pre-specified hierarchy limits specification search and preserves comparability. M1 is the confirmation equation; M2-M4 assess urbanisation, weather, and structural-proxy sensitivity; M5 changes the emissions boundary. M6a replaces RENERGY with HYDRO, M6b replaces it with NONHYDRO, and M6c replaces RENERGY with both components jointly. All three component models retain the M1 outcome, core controls, sample, and restricted lag grid. M6a and M6b are separate sensitivities; M6c is the most informative joint-component robustness equation, although coefficient equality and endpoint sensitivities remain outstanding. The complete pre-specified model hierarchy, the purpose of each specification, and the corresponding rules governing interpretation are summarised in Appendix Table A2.

Methodological framework

The methodology estimates bounded conditional time-series associations rather than causal policy effects. It combines restricted ARDL models with outcome-boundary, component, and covariance sensitivities. Descriptive and integration diagnostics, the separate M6a and M6b replacement equations, and the joint M6c component equation are reported. Finite-sample residual-bootstrap inference, nonlinear long-run standard errors, cumulative dynamic simulations, direct fossil-displacement tests,M6c endpoint sensitivities remain outside the completed analysis; the HAC-robust coefficient-equality test is now reported.

Integration screening combines the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests, whose null is a unit root, with the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, whose null is stationarity [36], [37]. Test equations include an intercept and add a deterministic trend only when the plotted series and data-generating interpretation warrant it. Lag lengths are limited by the annual sample and selected with the Bayesian information criterion (BIC), subject to white-noise residuals.

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The confirmation model is estimated as an ARDL(p, q_1, ..., , q_k), where p = 1 for the dependent variable and each regressor lag , qk is restricted to zero or one. This grid captures one-year adjustment while keeping the number of candidate specifications and estimated parameters compatible with T 30.

The reported models were selected by the Akaike information criterion within a deliberately restricted zero-to-one regressor-lag grid. This restriction materially reduces the overfitting risk relative to the earlier parameter-rich specification, but it does not remove post-selection uncertainty. Bayesian and Hannan–Quinn information-criterion rankings should therefore be reported as parsimony sensitivities, together with the full candidate grid. No model with higher lags is promoted to confirmatory status solely because it increases the magnitude or significance of the renewable coefficient. Candidate models with residual serial correlation, a non-negative error-correction term, or inadequate residual degrees of freedom are excluded from substantive interpretation. The exact number of estimated coefficients and residual degrees of freedom should accompany every reported specification.

Residual and stability diagnostics are summarised for the eight reported equations. Breusch–Godfrey Lagrange multiplier (LM) tests at lags one and two, heteroskedasticity tests, the Regression Equation Specification Error Test (RESET), residual normality, cumulative-sum stability, and variance-inflation factors (VIFs) are considered jointly. The supplied M6b output does not include a residual-normality test. The updated M6c output reports heteroskedasticity- and autocorrelation-consistent (HAC) standard errors and covariance using a Bartlett kernel with Newey-West fixed bandwidth = 4.0000; M6c HAC inference is therefore treated as verified. Models with mixed serial-correlation evidence, functional-form sensitivity, recursive instability, or high collinearity are retained only as qualified robustness checks.

The tables report conventional, White heteroskedasticity-consistent type 1 (HC1), and Newey–West standard errors where independently verified. M6c is reported with conventional, White HC1, and verified Newey-West HAC inference. Because confidence intervals, influence statistics, and residual-bootstrap intervals are unavailable, covariance-sensitive significance is distinguished from coefficient stability.

RESULTS

The empirical results are presented in a staged sequence: descriptive evidence and integration diagnostics are followed by cross-model estimates and component-based robustness checks. This structure keeps the baseline inference separate from sensitivity analyses.

Descriptive Statistics and Distributional Evidence

The descriptive statistics are broadly compatible with a small-sample annual ARDL design, but the distributional evidence warns against over-reliance on normality-sensitive inference. LOGCO2INDUST and MANFGDP are clearly non-normal, while RENERGY is borderline at the 10% level. Table 2 reports descriptive statistics for all variables over 1995–2024.

The component statistics show why decomposition matters. HYDRO has a mean of 9.117 percentage points and does not reject normality (JB p = 0.246), whereas the residual NONHYDRO share averages 0.488 percentage points, is strongly right-skewed, and rejects normality (JB p < 0.001). The two components therefore represent different historical processes rather than interchangeable renewable indicators.

Table 2. Descriptive statistics of the variables, 1995–2024

Variable	Mean	Median	Min.	Max.	Std. Dev.	Skew.	Kurt.	JB p-value
AVERT	13.275	13.250	12.420	14.420	0.528	0.370	2.478	0.598
INDUSGDP	49.694	48.821	30.996	66.160	9.571	-0.006	2.167	0.648

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LOGCO2ECON	3.462	3.468	3.282	3.732	0.127	0.334	2.044	0.428
LOGCO2INDUST	0.856	0.806	0.302	2.148	0.356	1.636	7.212	<0.001
LOGECONS	9.840	9.851	9.562	10.123	0.180	-0.101	1.714	0.347
LOGGDPPC	7.134	7.584	5.642	7.968	0.769	-0.785	2.023	0.118
LOGMANINDUST	-2.119	-2.200	-2.739	-0.989	0.435	0.838	3.171	0.170
MANFGDP	6.090	5.409	3.988	11.533	1.866	1.364	4.192	0.004
RENERGY	9.605	8.934	5.469	18.495	2.927	0.933	3.920	0.067
HYDRO	9.117	8.723	4.139	18.419	3.193	0.698	3.547	0.246
NONHYDRO	0.488	0.065	0.000	2.956	0.697	1.655	6.078	<0.001
URBAN	52.802	52.927	51.108	54.911	1.097	0.280	2.572	0.733

Note: Calculated by the authors.

Stationarity diagnostics and model admissibility

Main conclusion: HYDRO is clearly I(1): level ADF, PP, and Zivot–Andrews tests fail to reject the unit-root null, while first-difference ADF, PP, and both break specifications reject it and KPSS does not reject first-difference stationarity. NONHYDRO is mixed and strongly endpoint-sensitive, so its full-sample integration order is not established with comparable confidence. M6a is ARDL-admissible. The reported full-sample M6b equation is retained only as a qualified sensitivity; a 2024 intervention and pre-2024 re-estimation remain necessary before stronger level-relationship claims (Appendix Table A3).

The retained logGDPPC series is not unambiguously classified. Conventional ADF and PP tests fail to reject a unit root in both levels and first differences, whereas KPSS rejects level stationarity but not first-difference stationarity. The level Zivot-Andrews tests reject the unit-root null with an estimated 2004 break. The series is therefore treated as mixed and break-sensitive rather than mechanically assigned to I(1) or I(2); its inclusion is conditional on break and exclusion sensitivity.

For HYDRO, the level ADF and PP statistics are −2.082 and −2.173, the intercept KPSS statistic is 0.354, and the level Zivot-Andrews tests do not reject despite candidate breaks in 2010–2011. At first difference, ADF = −4.243, PP = −4.114, KPSS = 0.085, and the break tests reject with a 2010 break; the joint evidence supports I(1). For NONHYDRO, full-sample ADF/PP and break tests fail to reject even after first differencing, although KPSS does not reject first-difference stationarity. This conflict is driven by the 2024 endpoint: through 2023, the first-difference ADF and PP statistics are −4.091 and −4.076 and KPSS is 0.245, supporting an I(1)-compatible pre-2024 sensitivity. NONHYDRO is therefore classified as mixed and endpoint-sensitive rather than mechanically assigned to I(2). Table 3 summarises the integration classifications used for model admissibility.

Table 3. Integration order and modelling implication of the candidate variables

Variable	Stationarity result	Diagnostic interpretation	ARDL implication
RENERGY	I(1)	Level tests do not give stable stationarity; first-difference evidence is sufficient.	Admissible in ARDL as the main renewable-electricity regressor.
HYDRO	I(1)	Level unit-root tests do not reject; first-difference ADF, PP and Z-A reject, while KPSS	Use in M6a or M6c by replacing aggregate RENERGY; M6c may include HYDRO with

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		does not reject first-difference stationarity.	NONHYDRO, but never with RENERGY.
NONHYDRO	Mixed; 2024 endpoint-sensitive	Full-sample ADF/PP/Z-A do not reject after first differencing, but KPSS is compatible with first-difference stationarity; pre-2024 ADF/PP/KPSS support I(1).	Use in M6b and M6c only as a qualified full-sample component; retain the 2024 intervention and pre-2024 sensitivity before stronger inference.
LOGECONS	I(1)	Mostly non-stationary at level; first difference is stationary across the main tests.	Can remain as an energy-demand/scale control, but interpret as demand-conditioned effect.
LOGCO2INDUST	I(1), level evidence mixed	ADF/PP may reject at level, but KPSS rejects stationarity; first difference is cleanly stationary.	Suitable dependent variable for the baseline ARDL/ECM; discuss level-test conflict.
LOGCO2ECON	I(1), level evidence mixed	Several level unit-root tests reject, but KPSS rejects level stationarity; first difference is stationary.	Suitable robust outcome variable; inference should be compared with industrial CO2 model.
LOGGDPPC	Mixed; break-sensitive	ADF/PP do not reject at level or first difference; KPSS rejects level stationarity but not first-difference stationarity; level Z-A tests reject with a 2004 break.	Retain only as a qualified control; report 2004-break and exclusion sensitivities and avoid an unequivocal I(1) classification.
URBAN	I(1)	Level series is slow-moving; first difference is stationary.	Use as sensitivity control because it may be collinear with income and energy demand.
INDUSGDP	I(1)	KPSS rejects level stationarity; first difference is stationary.	Use in M4 as structural robustness, replacing the manufacturing-share variable.
MANFGDP	I(1)	Level evidence is mixed, but first-difference tests support stationarity.	Acceptable as manufacturing VA (% of GDP). Do not use together with overlapping structure variables.
LOGMANINDUST	I(1), break-sensitive	Level Z-A with trend break rejects, but ADF/PP/KPSS do not support ordinary level stationarity; first difference is stationary.	Can be used as an alternative structural variable; estimate separately from MANFGDP.

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AVERT	I(0) / trend-stationary	Level tests support stationarity or trend-stationarity; first difference is also stationary.	Can enter ARDL in levels as an I(0) weather control; it should not be treated as hydrology.

Note: Calculated by the authors

Cross-model dynamic evidence

Across the five aggregate-share specifications, the renewable-energy coefficient is negative, but inferential strength is covariance-sensitive. In the baseline model, the conventional probability is 0.098, compared with 0.033 under White HC1 inference and 0.038 under Newey-West inference. In the weather model, the lagged coefficient is most clearly supported under Newey-West inference. The common sign therefore indicates directional stability, not significance under every admissible covariance estimator. The baseline industrial outcome remains the theoretical anchor; the weather, structural, urbanisation, and economy-wide equations are qualified robustness checks. The five aggregate-share specifications and three component equations are compared in Table 4.

Table 4. Model architecture and headline inference

Model	Role	Dependent variable	Selected ARDL	Long-run evidence	Article use
M1	Baseline industrial model	LOGCO2INDUST	(1,0,0,0,0)	Bounds F = 4.998; COINTEQ = -0.6228	Main anchor; report robust SE sensitivity.
M2	Urbanization robustness	LOGCO2INDUST	(1,0,0,0,0,0)	Bounds F = 4.165; COINTEQ = -0.644	Supportive check; finite-sample bounds are borderline.
M3	Weather robustness	LOGCO2INDUST	(1,1,0,0,0,1)	Bounds F = 6.153; COINTEQ = -0.6367	Strongest weather-adjusted robustness evidence.
M4	Structural-control replacement	LOGCO2INDUST	(1,0,0,0,0)	Bounds F = 4.998; COINTEQ = -0.618	Cleanest structural robustness because VIFs fall sharply.
M5	Outcome robustness	LOGCO2ECON	(1,0,1,0,1)	Bounds F = 6.578; COINTEQ = -0.617	Broader outcome consistency; not preferred due diagnostics.
M6a	Hydro-replacement sensitivity	LOGCO2INDUST	(1,0,0,0,0)	Bounds F = 5.127; COINTEQ = −0.6315	Strong component check; finite-sample 5% rejection.
M6b	Non-hydro replacement sensitivity	LOGCO2INDUST	(1,0,0,0,0)	Bounds F = 4.097; COINTEQ = −0.5445	Supplementary null result; finite-sample 5% inconclusive.
M6c	Joint componen	LOGCO2INDUST	(1,0,0,0,0,0)	Bounds F = 4.301; COINTEQ = -0.6386	Most informative joint-component check; 5% finite-

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	t robustness					sample rejection. HAC-robust Wald equality is not rejected (F(1, 22) = 1.5891, p = 0.2207); endpoint sensitivities remain outstanding.

Note: calculated by the authors.

The renewable and component coefficients under alternative covariance estimators are reported in Table 5.

Table 5. Renewable and component estimates across covariance choices

Model	Energy term	Coef.	Classical p	White type 1 p	Newey–West p	Implied LR multiplier
M1	RENERGY	-0.0269	0.098	0.033	0.038	-0.0433
M2	RENERGY	-0.0266	0.109	0.047	0.054	-0.0413
M3	RENERGY(-1)	-0.0366	0.070	0.066	0.015	-0.0695
M4	RENERGY	-0.0265	0.108	0.046	0.062	-0.0428
M5	RENERGY	-0.0058	0.057	0.008	0.010	-0.0094
M6a	HYDRO	-.028605	0.0802	0.0121	0.0131	−0.0453
M6b	NONHYDRO	0.064186	0.5761	0.4146	0.4937	0.1179 (descriptive only)
M6c	HYDRO	-.028347	0.0881	0.0042	0.0025	-0.0444 (descriptive)
M6c	NONHYDRO	0.058383	0.5949	0.4230	0.3862	0.0914 (descriptive)

Note: calculated by the authors.

Component and joint-composition results

M3's lagged coefficient is a model-specific weather-conditioned result; aggregate-share evidence is summarised in Section 5.3.

M5 corroborates the negative direction for economy-wide CO2 but remains secondary because its LM(2), RESET, CUSUMSQ, and VIF diagnostics are weaker.

M6a replaces RENERGY with HYDRO and selects ARDL(1,0,0,0,0). The HYDRO coefficient is −0.028605: conventional inference is marginal (p = 0.0802), whereas White HC1 (p = 0.0121) and Newey–West (p = 0.0131) support a negative association. A one-percentage-point increase in the hydropower share is associated with an estimated 2.82% contemporaneous reduction in industrial CO_2, holding the included controls constant. The finite-sample bounds statistic (F = 5.127) rejects no level relationship at 5% but not at 1%. The error-correction coefficient is −0.6315 (p < 0.001), and the normalised long-run HYDRO multiplier is −0.0453; because a nonlinear standard error is unavailable, that long-run value is descriptive.

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M6b replaces RENERGY with NONHYDRO and also selects ARDL(1,0,0,0,0). The NONHYDRO coefficient is 0.064186 and is not statistically supported under conventional (p = 0.5761), White HC1 (p = 0.4146), or Newey–West (p = 0.4937) inference. Its positive point estimate must therefore not be interpreted as an emissions-increasing effect. The finite-sample bounds statistic (F = 4.097) is inconclusive at 5%, even though the error-correction coefficient is negative (−0.5445, p < 0.001). The normalised long-run multiplier of 0.1179 is descriptive only because both cointegration certainty and nonlinear long-run uncertainty are insufficient.

M6c jointly replaces RENERGY with HYDRO and NONHYDRO and selects ARDL(1,0,0,0,0,0) from 32 candidates; the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan–Quinn criterion all favour this parsimonious specification. Model fit is moderate (R2 = 0.530; adjusted R2 = 0.402; model p = 0.006; Durbin–Watson (DW) = 2.123). HYDRO is negative (-0.028347): conventional inference is marginal (p = 0.0881), while White HC1 (p = 0.0042) and Newey-West HAC inference (p = 0.0025) support a negative association. The exact contemporaneous semi-elasticity is approximately -2.79% for a one-percentage-point increase. The Case-2 bounds statistic (F = 4.3006, k = 5) exceeds the finite-sample 5% I(1) critical value for N approximately 30 (4.193) but not the 1% upper bound (5.761). The error-correction coefficient is -0.6386 (p < 0.001), implying about 63.9% annual adjustment. Normalised long-run multipliers are -0.0444 for HYDRO and 0.0914 for NONHYDRO, but both are descriptive because nonlinear uncertainty is unavailable. Full fit, coefficient, long-run, and diagnostic evidence is reported in Appendix Tables A4-A7.NONHYDRO is positive but imprecise (0.058383; conventional p = 0.5949; White HC1 p = 0.4230; Newey-West HAC p = 0.3862) and is not evidence of an emissions increase. A HAC-robust Wald test of HYDRO = NONHYDRO yields a coefficient difference of -0.086731 (SE = 0.068801), F(1, 22) = 1.5891 (p = 0.2207) and chi-square(1) = 1.5891 (p = 0.2075); equality is therefore not rejected.

Taken together, M1-M5 support a negative but covariance-sensitive aggregate association; M6a shows that hydropower variation reproduces that direction, while M6b provides no statistically supported non-hydro association. M6c preserves the same qualitative pattern within one equation and is therefore the most informative component-robustness model, but it does not replace M1 as the confirmation model.The HAC-robust Wald test does not reject HYDRO = NONHYDRO (F(1, 22) = 1.5891, p = 0.2207), so the article does not claim statistically different component effects; 2024/pre-2024 sensitivities remain outstanding, while the updated Newey-West HAC covariance supports the same qualitative component pattern.

DISCUSSION

The empirical evidence points to a coherent but deliberately bounded interpretation. RENERGY retains a negative sign across the baseline and four aggregate-share robustness specifications. M6a identifies a negative robust HYDRO association, M6b identifies no supported NONHYDRO association, and M6c preserves that pattern within a joint equation. The discussion therefore rests on the hierarchy and consistency of evidence rather than on a single p-value; M1 remains primary and M6c is joint-component robustness.

Renewable electricity reduces emissions only when it displaces fossil generation or final fuel use. In Azerbaijan, the observed association depends on dispatch, grid constraints, hydrology, reserves, and whether renewable output substitutes for thermal generation rather than meeting additional demand. The negative RENERGY coefficient is therefore consistent with displacement, not proof of one-for-one substitution.

The weather-augmented model provides a useful timing sensitivity. Its lagged renewable coefficient is most clearly supported under Newey–West inference, whereas the contemporaneous term is insignificant. This result permits a delayed-adjustment interpretation within that model, but not the claim that renewable energy affects emissions only after one year.

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Annual mean temperature controls coarsely for weather-related demand variation. M6a's negative HYDRO coefficient is consistent with a hydropower-dominated aggregate association, while M6b yields no supported NONHYDRO effect. In M6c, HYDRO remains negative under both White HC1 and Newey-West HAC inference and NONHYDRO remains imprecise under both robust covariance estimators, but the model does not measure precipitation, runoff, reservoir inflow, storage, or operational water releases. The joint equation improves composition sensitivity without resolving hydrology-adjusted identification or proving that component coefficients differ.

M4 is important because Azerbaijan's industry measures mix extraction, refining, manufacturing, and construction. Replacing LOGMANINDUST with INDUSGDP preserves the negative renewable coefficient while lowering VIFs, reducing concern that the result is an artefact of one structural proxy; it does not identify a diversification channel.

The sign changes observed for some structural controls across the long-run and short-run representations should be interpreted as specification-sensitive rather than as economically contradictory effects. The annual sample is short, and urbanisation, industrial structure, electricity consumption, and income trend together. The revised model hierarchy therefore treats the urbanisation specification as supportive sensitivity and uses the alternative industry-share measure only as a replacement control; the two structural proxies are never entered simultaneously. Elevated variance-inflation factors in the urbanisation and weather models, together with borderline serial-correlation evidence in some specifications, indicate that individual control coefficients should not be interpreted as stable structural parameters. The renewable coefficient is therefore assessed primarily through sign stability and covariance-sensitive inference across the pre-specified hierarchy, not through the economic interpretation of every control coefficient.

LOGCO2INDUST is the preferred outcome because industrial-combustion CO2 is closest to the proposed mechanism. LOGCO2ECON includes transport, households, power generation, and oil-and-gas operations; M5's negative robust coefficient therefore corroborates direction at a broader boundary without replacing the sectoral model.

The results gain limited credibility from negative error-correction terms, the stable aggregate-renewable sign, component sensitivity, and alternative covariance estimates. Finite-sample bounds evidence rejects no levels relationship at 5% for M6a and M6c, whereas M6b is inconclusive at 5%.M6c's error-correction coefficient is -0.6386 ($p < 0.001$), and the HAC-robust Wald equality test is completed but does not reject equality ($F(1, 22) = 1.5891$, $p = 0.2207$); residual-bootstrap decisions and nonlinear long-run uncertainty remain unavailable.

Accordingly, the evidence is conditional and associational; it is consistent with, but does not prove, fossil-fuel displacement.

POLICY IMPLICATIONS

The first implication is that renewable-energy policy should be evaluated by actual displacement outcomes. Installed capacity and the renewable share of electricity are necessary indicators, but they are incomplete. The more relevant policy indicators are avoided fossil-fuel generation, the change in gas- or oil-fired electricity output, renewable curtailment, fossil plant capacity factors, grid losses, and CO2 emissions per unit of electricity supplied. Such indicators would connect the policy target more directly to the mitigation mechanism suggested by the ARDL results.

Because the main outcome is industrial-combustion CO2, renewable policy should be paired with industrial efficiency, electrification, cleaner heat, waste-heat recovery, and fuel switching. Emissions benefits depend on whether firms can substitute cleaner electricity for fossil fuels in production.

The empirical results support implementation measures that are specific to Azerbaijan's institutional setting. The national 'Azerbaijan 2030' framework identifies green energy as a

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strategic priority, and current government plans target a substantial increase in renewable capacity by 2030. Because electricity and natural-gas prices are regulated for important consumer categories, the transition should be assessed not only through installed renewable capacity but also through the incentives facing industrial users to electrify processes and reduce direct fossil-fuel combustion. In this setting, the State Oil Company of the Republic of Azerbaijan (SOCAR) and other state-linked energy institutions have a material role in coordinating hydrocarbon supply, energy security, investment, and low-carbon diversification. A practical monitoring framework should therefore report, by industrial sector where possible, renewable generation, fossil generation displaced, electricity consumption, direct fossil-fuel use, industrial electrification, curtailment, and associated CO2. This recommendation follows directly from the study's finding that a higher renewable share is not equivalent to verified fossil displacement and that the aggregate association is strongly influenced by hydropower. Scenario-based system-dynamics evidence from Karabakh and Eastern Zangezur similarly suggests that green investment performs best when policy sequencing, environmental safeguards, and institutional absorptive capacity are considered jointly; the simulations are policy experiments rather than empirical forecasts [38].

Hydropower variability is especially relevant because renewable electricity in Azerbaijan is not purely policy-determined; it also responds to water availability and climate conditions. The negative HYDRO association in M6a and M6c, together with the imprecise NONHYDRO estimates, supports evaluating hydro and non-hydro portfolios separately without treating the coefficients as causal or statistically different, consistent with the HAC-robust Wald test that fails to reject equality ($p = 0.2207$). Policy should combine diversified renewable portfolios, storage, flexible backup, stronger transmission planning, and climate-risk screening. A strategy that ignores hydrology may overestimate renewable-output stability and understate balancing needs.

Azerbaijan needs timely, sectorally disaggregated data on generation, dispatch, fuel input, industrial energy use, curtailment, and sectoral CO2. Higher-frequency evidence would better separate renewable integration from structural, macroeconomic, and weather effects and strengthen policy accountability.

LIMITATIONS OF THE RESEARCH

Several limitations define the strength of the claims. The evidence is best read as covariance-sensitive, conditional time-series evidence for Azerbaijan rather than definitive causal proof that renewable electricity mechanically reduces emissions one-for-one.

The 29-observation annual sample limits statistical power, admissible lags, and simultaneous break modelling; parsimonious specifications and cautious inference are therefore essential.

The revised empirical design replaces the earlier parameter-rich ARDL with a deliberately restricted lag grid in which the dependent-variable lag is one and each regressor lag is zero or one. This materially reduces overfitting risk relative to the earlier specification, but it does not eliminate post-selection uncertainty. The 29-observation annual sample therefore limits statistical power and makes finite-sample inference especially important. The reported coefficients are not treated as precise marginal causal effects, and specifications with diagnostic weaknesses are retained only as qualified robustness checks.

ARDL is suitable for short samples but cannot recover information absent from annual data. Automatic lag selection may understate post-selection uncertainty, so the coefficients are not treated as precise marginal causal effects.

RENERGY is a generation share, not measured fossil displacement. Its emissions association depends on thermal output, curtailment, demand growth, timing, and whether industrial users substitute electricity for fossil fuels.

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The study does not estimate a renewable-penetration threshold at which Azerbaijan's electricity grid becomes unstable. Such a threshold requires operational data on reserve margins, dispatch, ramping requirements, curtailment, transmission constraints, storage, and balancing resources that are not contained in the annual macroeconomic dataset. Accordingly, the reported models should not be used to infer a numerical grid-stability ceiling. Future work should estimate such a threshold using hourly dispatch and network-level data, with explicit treatment of hydrological and variable-renewable uncertainty.

The weather-augmented model includes annual average temperature, and the revised dataset contains a 1995-2024 HYDRO share. M6a and M6c report negative HYDRO coefficients supported by White HC1 and Newey-West HAC inference; M6b and the NONHYDRO term in M6c are statistically unsupported. These models improve component sensitivity, but temperature cannot proxy precipitation, river flow, reservoir storage, or operational water releases.

The limitation matters because HYDRO accounts for approximately 94.9% of the aggregate renewable share on a ratio-of-means basis and is highly correlated with RENERGY.M6c now estimates both components jointly, and the HAC-robust Wald test does not reject HYDRO = NONHYDRO ($p = 0.2207$); a complete mechanism comparison still requires a 2024 intervention and pre-2024 sensitivity, an explicit source-and-denominator audit, and direct hydrological indicators. The revision therefore distinguishes conditional component associations without separating policy-driven expansion from weather-driven hydropower variability.

LOGCO2INDUST is closest to the proposed industrial-combustion mechanism but does not permit separate estimation of extraction, refining, manufacturing, and construction effects. It excludes other national emissions channels and does not identify emissions from extraction, refinery own-use, captive generation, or energy-industry combustion. LOGCO2ECON captures broader territorial dynamics and is therefore used only as an outcome-boundary robustness check. Accordingly, the estimated renewable coefficient should not be interpreted as a sector-specific treatment effect for any single industrial subsector.

The distributed-lag and error-correction results are consistent with conditional adjustment, but they do not establish causality or a definitive structural long-run relationship. Finite-sample bounds decisions are reported for all component models, including the M6c 5% rejection and 1% inconclusive result, but residual-bootstrap decisions and endpoint sensitivities remain unavailable; the HAC-robust component-equality test is now completed and does not reject equality ($p = 0.2207$).Omitted variables, simultaneity, measurement error, hydrological confounding, and policy endogeneity therefore remain possible.

CONCLUSION

This study examined whether renewable electricity is associated with carbon mitigation in Azerbaijan, an oil- and gas-rich economy in which transition is shaped by hydrocarbon dependence, industrial structure, and weather-sensitive generation. Annual data for 1996-2024 support five aggregate-share ARDL/error-correction specifications and three component models: the HYDRO replacement (M6a), NONHYDRO replacement (M6b), and joint HYDRO-NONHYDRO equation (M6c). This hierarchy reduces reliance on a single specification while preserving the limits of a short single-country time series; M1 remains the primary confirmation model and M6c is the most informative joint-component robustness check.

The central conclusion is deliberately bounded. The aggregate renewable coefficient is negative across five specifications, but its inferential strength depends on covariance choice and diagnostics. M6a produces a negative HYDRO coefficient supported by robust standard errors. M6b produces an imprecise NONHYDRO estimate. In M6c, HYDRO is negative (-0.0283; White HC1 $p = 0.004$; Newey-West HAC $p = 0.0025$), NONHYDRO is unsupported

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(White HC1 p = 0.423; Newey-West HAC p = 0.3862), the bounds statistic rejects no levels relationship at 5%, and the error-correction coefficient is -0.6386.The HAC-robust coefficient-equality test does not reject HYDRO = NONHYDRO (F(1, 22) = 1.5891, p = 0.2207); with endpoint sensitivities still outstanding, the article does not claim statistically distinct component effects, verified fossil displacement, or hydrology-adjusted causality. Relative to earlier Azerbaijan studies based on aggregate or consumption-based CO2 measures and broader renewable-energy indicators, the contribution is the combination of a sectorally bounded industrial-combustion outcome, a generation-based renewable exposure, explicit hydro/non-hydro decomposition, and a deliberately parsimonious small-sample dynamic design. Recent international evidence reinforces the importance of this distinction, while recent Azerbaijan-focused research underscores the institutional and political-economy constraints within which renewable deployment occurs. The present study therefore contributes a mechanism-aware conditional association rather than a causal estimate of the green transition.

Overall, higher renewable-electricity shares are conditionally associated with lower reported CO2 outcomes in Azerbaijan. Decarbonisation nevertheless requires measured fossil displacement, industrial electrification, and hydrology-aware system planning, particularly in hydrocarbon-exporting economies.

DECLARATIONS

Data Availability

The underlying annual series are publicly available from the providers and series identifiers reported in Table 1.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

CRediT Author Contributions

Mayis Gulaliyev-investigation, methodology, writing-original draft; Gulsura Mehdiyeva-formal analysis, writing-review & editing; Immi Aliyeva-conceptualization, data curation, validation; Ruhiyya Huseynova- project administration;, Rasul Alakbarov- software, supervision, visualization.

Ethics Approval

This study uses aggregate country-level secondary data and involves no human participants, animals, personal data, clinical interventions, or identifiable individual records.

Using of AI

During the preparation and revision of this manuscript, the authors used OpenAI's ChatGPT software for English editing, manuscript organization, and consistency checking. The AI-powered tool was not used to generate or modify the underlying data, perform any of the reported EViews evaluations, serve as a primary reference source, or replace the authors' scientific judgment. All model specifications, numerical results, references, statistical interpretations, and conclusions have been independently verified with the original EViews outputs and source files, critically reviewed, and validated by the authors. The authors take full responsibility for the accuracy, originality, integrity, and conclusions of the manuscript.

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APPENDIX

Appendix Table A1. Construct-to-estimand map and expected empirical implications

Concept	Observed proxy	Expected role/sign	Identification boundary
Renewable transition	RENERGY aggregate share; HYDRO and NONHYDRO same-denominator components, in percentage points; M6a-M6b use separate replacements and M6c includes both components jointly	Negative under H1/H2	RENERGY is excluded from every component model. M6c includes HYDRO and NONHYDRO jointly; the HAC-robust Wald equality test does not reject equal coefficients ($p = 0.2207$), so a differential-effect claim is not supported.
Energy-demand scale	LOGECONS: log electricity consumption	Generally positive	National consumption is broader than industrial demand and can mix scale with efficiency.
Economic scale/technique	LOGGDPPC: log real GDP per capita	Ambiguous	No automatic EKC interpretation; may proxy oil cycles, efficiency, and omitted breaks.
Production composition	LOGINDUSGDP: log industry share of GDP	Generally positive	Broad industry measure does not separate extraction, refining, manufacturing, or construction.
Spatial structure	URBAN: urban population share (%)	Ambiguous	Demand and construction effects compete with density and infrastructure-efficiency effects.
Climate and hydrology	AVERT: annual mean temperature; HYDRO: hydropower generation share; direct hydrological conditions remain unobserved	Control, not a structural effect	HYDRO captures realised component output, not precipitation, inflow, reservoir storage or policy-driven additionality.
Outcome boundary	LOGCO2INDUST: log industrial	Dependent variable	Must document source, series code, unit, IPCC

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	combustion-related CO_2	category, sectors, gases, and exclusions.

Note: calculated by the authors

Appendix Table A2. Model hierarchy and interpretation rules

Model	Specification	Purpose	Claim rule
M1: confirmation	LOGCO2INDUST = f(RENERGY, LOGECONS, LOGGDPPC, LOGMANINDUST)	Primary conditional renewable-emissions association.	Central inference; parsimonious ARDL/ECM with a one-year maximum lag grid.
M2: urban	M1 + URBAN	Sensitivity to slow-moving spatial structure.	Not used to override M1; instability is reported as fragility.
M3: weather	M1 + AVERT	Sensitivity to annual mean temperature.	AVERT is unlogged and has no structural climate interpretation.
M4: structure	M1 with LOGINDUSGDP replacing LOGMANINDUST	Robustness to a broader industry-share control.	The two structure variables never enter together.
M5: outcome	LOGCO2ECON = f(RENERGY, LOGECONS, LOGGDPPC, LOGMANINDUST)	Robustness to the emissions boundary.	Same core regressors and sample; M4-style replacement may be appendix-only.
M6a: hydro replacement	LOGCO2INDUST = f(HYDRO, LOGECONS, LOGGDPPC, LOGMANINDUST)	Tests whether the aggregate RENERGY result is largely a hydropower-variation result.	Reported Priority-2 model; same sample and restricted lag grid as M1; RENERGY and NONHYDRO excluded.
M6b: non-hydro replacement	LOGCO2INDUST = f(NONHYDRO, LOGECONS, LOGGDPPC, LOGMANINDUST)	Tests whether non-hydro renewable variation reproduces the aggregate association.	RENERGY and HYDRO excluded; same sample and restricted lag grid; endpoint-sensitive and interpreted as a supplementary result.
M6c: joint component robustness	LOGCO2INDUST = f(HYDRO, NONHYDRO, LOGECONS, LOGGDPPC, LOGMANINDUST)	Evaluates hydro and non-hydro associations within one equation while excluding RENERGY.	Estimated as ARDL(1,0,0,0,0,0); report k = 5 bounds, White HC1, and verified Newey-West HAC. The HAC-robust HYDRO = NONHYDRO Wald test does not reject equality (F(1, 22) = 1.5891, p = 0.2207); D2024 and pre-2024 sensitivities remain required.

Note: calculated by the authors

Appendix Table A3. Complete ADF, PP, KPSS and Zivot-Andrews results
Panel A. Levels with intercept; Z-A intercept-break model

Variable	ADF statistic (p); lag	PP statistic (p); BW	KPSS statistic (p); BW	Z-A statistic (p); break; lag	5% decision (ADF/PP/KPSS/Z-A)
RENERGY	-2.789 (0.114); L1	-2.391 (0.159); BW3	0.240 (>0.10); BW3	-3.716 (>0.10); 2010; L1	NR/NR/NRs/NR
HYDRO	-2.082 (>0.10); L0	-2.173 (>0.10); BW3	0.354 (0.097); BW3	-4.015 (>0.10); 2010; L1	NR/NR/NRs/NR
NONHYDRO	1.636 (>0.10); L0	2.201 (>0.10); BW3	0.760 (0.010); BW3	-0.240 (>0.10); 2012; L0	NR/NR/Rs/NR
LOGECONS	-1.504 (0.545); L0	-1.763 (0.416); BW3	0.313 (>0.10); BW3	-3.826 (>0.10); 2017; L2	NR/NR/NRs/NR
LOGCO2INDUST	-4.944 (0.002); L0	-5.439 (<0.001); BW3	0.374 (0.089); BW3	-5.140 (0.025); 2002; L2	R/R/NRs/R
LOGCO2ECON	-1.059 (0.724); L0	-1.123 (0.704); BW3	0.695 (0.014); BW3	-3.894 (>0.10); 2011; L0	NR/NR/Rs/NR

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LOGGDPPC	-2.252 (0.241); L1	-1.710 (0.441); BW3	0.735 (0.010); BW3	-5.927 (<0.01); 2004; L3	NR/NR/Rs/R
URBAN	-0.615 (0.850); L0	-0.676 (0.835); BW3	0.684 (0.015); BW3	-2.472 (>0.10); 2019; L0	NR/NR/Rs/NR
INDUSGDP	-2.099 (0.293); L3	-2.068 (0.273); BW3	0.268 (>0.10); BW3	-2.488 (>0.10); 2014; L3	NR/NR/NRs/NR
MANFGDP	-3.454 (0.038); L0	-3.393 (0.020); BW3	0.562 (0.028); BW3	-5.302 (0.013); 2006; L3	R/R/Rs/R
AVERT	-3.796 (0.021); L0	-3.835 (0.008); BW3	0.697 (0.014); BW3	-6.076 (<0.01); 2017; L0	R/R/Rs/R

Panel B. Levels with intercept and trend; Z-A intercept-and-trend-break model

Variable	ADF statistic (p); lag	PP statistic (p); BW	KPSS statistic (p); BW	Z-A statistic (p); break; lag	5% decision (ADF/PP/KPSS/Z-A)
RENERGY	-2.822 (0.283); L1	-2.340 (0.434); BW3	0.115 (>0.10); BW3	-3.756 (>0.10); 2011; L3	NR/NR/NRs/NR
HYDRO	-2.817 (>0.10); L1	-2.340 (>0.10); BW3	0.130 (0.080); BW3	-4.006 (>0.10); 2011; L3	NR/NR/NRs/NR
NONHYDRO	-0.335 (>0.10); L0	0.309 (>0.10); BW3	0.220 (0.010); BW3	-4.413 (>0.10); 2015; L2	NR/NR/Rs/NR
LOGECONS	-1.785 (0.728); L0	-2.099 (0.571); BW3	0.092 (>0.10); BW3	-7.946 (<0.01); 2006; L2	NR/NR/NRs/R
LOGCO2INDUST	-4.333 (0.028); L0	-4.626 (0.006); BW3	0.185 (0.022); BW3	-5.009 (0.064); 2010; L2	R/R/Rs/NR
LOGCO2ECON	-4.657 (0.016); L0	-4.624 (0.006); BW3	0.156 (0.041); BW3	-6.024 (<0.01); 2008; L0	R/R/Rs/R
LOGGDPPC	-1.842 (0.706); L1	-0.717 (0.964); BW3	0.198 (0.017); BW3	-8.138 (<0.01); 2004; L1	NR/NR/Rs/R
URBAN	-2.823 (0.283); L0	-2.816 (0.215); BW3	0.076 (>0.10); BW3	-4.017 (>0.10); 2014; L3	NR/NR/NRs/NR
INDUSGDP	-1.677 (0.772); L3	-1.328 (0.883); BW3	0.200 (0.016); BW3	-5.008 (0.064); 2004; L1	NR/NR/Rs/NR
MANFGDP	-3.287 (0.153); L1	-2.733 (0.243); BW3	0.165 (0.035); BW3	-8.745 (<0.01); 2009; L3	NR/NR/Rs/R
AVERT	-5.958 (<0.001); L0	-6.063 (<0.001); BW3	0.141 (0.060); BW3	-7.306 (<0.01); 2001; L0	R/R/NRs/R

Panel C. First differences with intercept; Z-A intercept-break model

Variable	ADF statistic (p); lag	PP statistic (p); BW	KPSS statistic (p); BW	Z-A statistic (p); break; lag	5% decision (ADF/PP/KPSS/Z-A)
RENERGY	-4.119 (0.012); L3	-3.905 (0.007); BW3	0.100 (>0.10); BW3	-4.719 (0.068); 2010; L3	R/R/NRs/NR
HYDRO	-4.243 (0.008); L3	-4.114 (0.004); BW3	0.085 (>0.10); BW3	-5.228 (0.018); 2010; L3	R/R/NRs/R
NONHYDRO	-1.568 (>0.10); L0	-1.021 (>0.10); BW3	0.437 (0.061); BW3	-2.323 (>0.10); 2012; L0	NR/NR/NRs/NR
LOGECONS	-4.826 (0.004); L0	-4.866 (<0.001); BW3	0.073 (>0.10); BW3	-5.058 (0.031); 2010; L0	R/R/NRs/R
LOGCO2INDUST	-5.808 (<0.001); L0	-6.353 (<0.001); BW3	0.363 (0.093); BW3	-6.085 (<0.01); 2018; L0	R/R/NRs/R
LOGCO2ECON	-6.452 (<0.001); L0	-6.937 (<0.001); BW3	0.245 (>0.10); BW3	-6.891 (<0.01); 2010; L0	R/R/NRs/R
LOGGDPPC	-2.007 (0.333); L0	-2.101 (0.274); BW3	0.316 (>0.10); BW3	-3.683 (>0.10); 2007; L0	NR/NR/NRs/NR
URBAN	-5.111 (0.002); L0	-5.109 (<0.001); BW3	0.147 (>0.10); BW3	-5.543 (<0.01); 2001; L0	R/R/NRs/R
INDUSGDP	-4.357 (0.008); L1	-4.463 (0.002); BW3	0.414 (0.071); BW3	-6.492 (<0.01); 2008; L1	R/R/NRs/R

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MANFGDP	-5.777 (<0.001); L3	-3.544 (0.015); BW3	0.272 (>0.10); BW3	-6.892 (<0.01); 2011; L3	R/R/NRs/R
AVERT	-7.180 (<0.001); L1	-13.696 (<0.001); BW3	0.089 (>0.10); BW3	-8.703 (<0.01); 2003; L0	R/R/NRs/R

Panel D. First differences with intercept and trend; Z-A intercept-and-trend-break model

Variable	ADF statistic (p); lag	PP statistic (p); BW	KPSS statistic (p); BW	Z-A statistic (p); break; lag	5% decision (ADF/PP/KPSS/Z-A)
RENERGY	-3.964 (0.061); L3	-3.794 (0.032); BW3	0.093 (>0.10); BW3	-5.692 (<0.01); 2010; L3	NR/R/NRs/R
HYDRO	-4.171 (0.038); L3	-3.990 (0.022); BW3	0.087 (>0.10); BW3	-6.433 (<0.01); 2010; L3	R/R/NRs/R
NONHYDRO	-2.101 (>0.10); L0	-0.545 (>0.10); BW3	0.097 (>0.10); BW3	-2.814 (>0.10); 2021; L0	NR/NR/NRs/NR
LOGECONS	-4.734 (0.015); L0	-4.779 (0.004); BW3	0.071 (>0.10); BW3	-6.359 (<0.01); 2010; L0	R/R/NRs/R
LOGCO2INDUST	-5.896 (0.002); L0	-6.637 (<0.001); BW3	0.101 (>0.10); BW3	-6.096 (<0.01); 2016; L0	R/R/NRs/R
LOGCO2ECON	-6.274 (<0.001); L0	-6.728 (<0.001); BW3	0.087 (>0.10); BW3	-6.706 (<0.01); 2010; L0	R/R/NRs/R
LOGGDPPC	-2.511 (0.408); L0	-2.554 (0.317); BW3	0.102 (>0.10); BW3	-4.468 (>0.10); 2007; L0	NR/NR/NRs/NR
URBAN	-5.121 (0.006); L0	-5.119 (0.002); BW3	0.076 (>0.10); BW3	-7.447 (<0.01); 2019; L0	R/R/NRs/R
INDUSGDP	-4.942 (0.009); L1	-4.873 (0.003); BW3	0.075 (>0.10); BW3	-6.970 (<0.01); 2008; L1	R/R/NRs/R
MANFGDP	-6.053 (<0.001); L3	-3.730 (0.037); BW3	0.060 (>0.10); BW3	-6.376 (<0.01); 2011; L3	R/R/NRs/R
AVERT	-7.020 (<0.001); L1	-13.547 (<0.001); BW3	0.069 (>0.10); BW3	-8.627 (<0.01); 2003; L0	R/R/NRs/R

Note: calculated by the authors

Appendix Table A4. Specification, fit and long-run adjustment

Model	Specification	Fit	Bounds/ECM result	Interpretive decision
M1	LOGCO2INDUST = f(RENERGY, LOGECONS, LOGGDPPC, LOGMANINDUST); ARDL(1,0,0,0,0)	R2 = 0.517; adj. R2 = 0.412; F p = 0.003	Bounds F = 4.998; COINTEQ = -0.6228, p < 0.001	Preferred baseline industrial model.
M2	M1 + URBAN; ARDL(1,0,0,0,0,0)	R2 = 0.522; adj. R2 = 0.391; F p = 0.007	Bounds F = 4.165; COINTEQ = -0.644, p < 0.001	Urbanization control robustness; finite-sample bounds caution.
M3	M1 + AVERT; ARDL(1,1,0,0,0,1)	R2 = 0.717; adj. R2 = 0.603; F p = 0.0004	Bounds F = 6.153; COINTEQ = -0.6367, p < 0.001	Strongest weather-adjusted robustness model.
M4	M1 with INDUSGDP replacing LOGMANINDUST; ARDL(1,0,0,0,0)	R2 = 0.517; adj. R2 = 0.412; F p = 0.003	Bounds F = 4.998; COINTEQ = -0.618, p < 0.001	Clean structural-control replacement.
M5	LOGCO2ECON outcome; ARDL(1,0,1,0,1)	R2 = 0.944; adj. R2 = 0.925; F p < 0.001	Bounds F = 6.578; COINTEQ = -0.617, p < 0.001	Outcome extension; diagnostic limitations.
M6a	HYDRO + core controls; ARDL(1,0,0,0,0)	R^2 = 0.524; adj. R^2 = 0.421; F p = 0.0028	Bounds F = 5.127; COINTEQ = −0.6315, p < 0.001	Strong hydro-replacement check; finite-sample 5% rejection.
M6b	NONHYDRO + core controls; ARDL(1,0,0,0,0)	R^2 = 0.462; adj. R^2 = 0.346; F p = 0.0098	Bounds F = 4.097; COINTEQ = −0.5445, p < 0.001	Supplementary null; finite-sample 5% bounds inconclusive.

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M6c	HYDRO + NONHYDRO + core controls; ARDL(1,0,0,0,0,0)	R2 = 0.530; adj. R2 = 0.402; F p = 0.0062	Bounds F = 4.301; COINTEQ = -0.6386, p < 0.001	Joint component robustness; 5% finite-sample rejection and 1% inconclusive.

Note: calculated by the authors

Appendix Table A5. Renewable and component coefficient evidence

Model	Term	Coefficient	Classical SE (p)	White HC1 SE (p)	HAC SE (p)	Interpretation
M1	RENERGY	-0.0269	0.0156 (0.098)	0.0119 (0.033)	0.0123 (0.038)	Negative; significant under White and Newey–West inference but marginal conventionally.
M2	RENERGY	-0.0266	0.0159 (0.109)	0.0126 (0.047)	0.0130 (0.054)	Negative after adding urbanization; HAC evidence is borderline.
M3	RENERGY	-0.0076	0.0154 (0.627)	0.0151 (0.620)	0.0115 (0.515)	No immediate effect in the weather model.
M3	RENERGY(-1)	-0.0366	0.0191 (0.070)	0.0188 (0.066)	0.0138 (0.015)	Delayed negative effect; strongest under HAC.
M4	RENERGY	-0.0265	0.0158 (0.108)	0.0126 (0.046)	0.0135 (0.062)	Negative after structure replacement; White-significant, HAC-borderline.
M5	RENERGY	-0.0058	0.0029 (0.057)	0.0020 (0.008)	0.0020 (0.010)	Negative in the economy-wide outcome model under robust SE.
M6a	HYDRO	−0.028605	0.015629 (0.0802)	0.010504 (0.0121)	0.010641 (0.0131)	Negative association supported by both robust covariance estimators.
M6b	NONHYDRO	0.064186	0.113172 (0.5761)	0.077246 (0.4146)	0.092280 (0.4937)	Imprecise and unsupported; the positive point estimate is not substantive evidence.
M6c	HYDRO	-0.028347	0.015883 (0.0881)	0.008886 (0.0042)	0.008304 (0.0025)	Negative; White-supported, conventionally marginal.
M6c	NONHYDRO	0.058383	0.108199 (0.5949)	0.071511 (0.4230)	0.066034 (0.3862)	Imprecise and unsupported; not evidence of an increase.

Note: calculated by the authors

Appendix Table A6. Long-run multipliers and dynamic interpretation

Model	Adjustment speed	Energy-term LR multiplier	Other long-run evidence	Decision
M1	62.3% per year	-0.0433	Other controls not statistically supported; LOGGDPPC and LOGMANINDUST mainly condition the equation.	Renewable-energy mitigation signal is baseline-consistent.
M2	64.4% per year	-0.0413	URBAN LR multiplier = 0.0596 but not significant.	Urbanization does not explain away the renewable-energy effect.
M3	63.7% per year	-0.0695	AVERT has short-run relevance; no stable long-run temperature effect.	Weather-adjusted model supports a delayed renewable channel.
M4	61.8% per year	-0.0428	INDUSGDP LR multiplier = -0.0007 and insignificant.	Cleaner structural control preserves the result.
M5	61.7% per year	-0.0094	LOGECONS LR multiplier = 0.3898; income weakly positive.	Broader CO2 outcome corroborates direction with caveats.
M6a	63.2% per year	HYDRO: −0.0453	Nonlinear long-run standard error and confidence interval unavailable.	Directionally supportive; finite-sample 5% bounds evidence, but LR magnitude is descriptive.
M6b	54.4% per year	NONHYDRO: 0.1179	Finite-sample 5% bounds decision is inconclusive; nonlinear LR uncertainty unavailable.	Descriptive only; do not infer a positive long-run effect.

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M6c	63.9% per year	HYDRO: -0.0444; NONHYDRO: 0.0914	Nonlinear long-run SEs/CIs unavailable; HAC inference verified. Wald equality is not rejected (F(1, 22) = 1.5891, p = 0.2207).	Joint qualitative pattern only; the HAC-robust Wald test does not reject coefficient equality, so a component difference is not established.

Note: calculated by the authors

Appendix Table A7. Diagnostic profile by model

Model	Passed checks	Cautions	Reporting implication
M1	Normality, heteroskedasticity, RESET and CUSUM/CUSUMSQ pass; LM(1) passes.	LM(2) is close to 10%; small-sample automatic selection.	Report White and HAC estimates; retain as baseline.
M2	Normality, heteroskedasticity, RESET and stability pass.	High VIFs; LM(2) mixed; finite-sample bounds are borderline.	Use as supportive urbanization robustness, not decisive evidence.
M3	Normality, serial correlation, heteroskedasticity and stability pass.	RESET F p = 0.099 and LR p = 0.039; VIFs close to 10.	Strong robustness model, but avoid overclaiming functional-form certainty.
M4	Normality, heteroskedasticity, RESET and stability pass; VIF profile is clean.	LM(2) is near 10%; HAC RENERGY p is borderline.	Important structural robustness model.
M5	Normality and heteroskedasticity pass; LM(1) passes.	LM(2) mixed; RESET sensitive; CUSUMSQ breach; high VIFs.	Use as outcome consistency, not as preferred model.
M6a	Normality, heteroskedasticity, RESET, CUSUM/CUSUMSQ and LM(1) pass.	LM(2) Obs*R^2 p = 0.0648; LOGGDPPC and LOGMANINDUST VIFs are 7.675 and 7.792; post-selection inference.	Strong component check; report conventional, White HC1 and HAC inference together.
M6b	Heteroskedasticity, RESET, CUSUM/CUSUMSQ and LM(1) pass.	Residual normality output was not supplied; LM(2) Obs*R^2 p = 0.0763; LOGGDPPC VIF = 10.787 and LOGMANINDUST VIF = 9.700.	Supplementary null result only; normality and endpoint sensitivities remain outstanding.
M6c	Normality, BPG heteroskedasticity, RESET, LM(1), and CUSUM/CUSUMSQ pass at 5%.	LM(2) Obs*R2 p = 0.0697 is borderline at 10%; LOGGDPPC VIF = 11.004 and LOGMANINDUST VIF = 9.888; CUSUMSQ approaches the upper endpoint; HAC inference is verified, and the Wald equality test does not reject equality (p = 0.2207).	Most informative joint-component robustness; report White HC1 and verified HAC inference. The Wald equality test does not support distinct component effects; endpoint sensitivities remain outstanding.

Note: calculated by the authors

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