International Journal of Sustainable Development and Planning
Vol. 21, No. 9, September, 2026, pp. 4319-4328
Journal homepage: http://iieta.org/journals/ijsdp

Assessing the Long-Run Role of Renewable Electricity Generation in Reducing CO_2 Emissions and Supporting Industrial Labour Absorption in Morocco

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https://doi.org/10.18280/ijsdp.210929

Received: 27 June 2026
Revised: 19 August 2026
Accepted: 26 August 2026
Available online: 30 September 2026

Keywords:
Autoregressive Distributed Lag bounds testing, error correction model, Granger causality, CO_2 emissions, electricity decarbonisation, industrial labour absorption, Morocco, renewable electricity generation

ABSTRACT

This study examines long-run associations between renewable electricity generation (REN), CO_2 emissions and industrial employment in Morocco over 1990–2023. REN is measured as the share of renewables in total electricity generation and serves as an indicator of electricity decarbonisation. The study applies the Autoregressive Distributed Lag (ARDL) bounds-testing approach to two models and a Granger causality test to examine whether past changes in Morocco's dependence on coal-fired electricity provide predictive information about the future evolution of REN. Bounds tests confirm cointegration in both models. In the CO_2 emissions model, REN has a significant long-run coefficient of −0.068928, indicating that a 1% increase in REN is associated with a 0.069% reduction in CO_2 emissions per capita. In the industrial-employment model, its positive and significant coefficient of 0.053054 indicates that higher REN is associated with a higher industrial-employment share. Error-correction and stability results support the robustness of both models. Granger results support H4 by showing that past changes in coal-based electricity generation provide predictive information about the future evolution of REN. Overall, REN plays an important role in reducing CO_2 emissions and supporting industrial labour absorption in Morocco.

1. INTRODUCTION

The Paris Agreement has increased pressure on countries to align economic development with low-greenhouse-gas and climate-resilient pathways [1]. In Morocco, this commitment gained greater visibility through the hosting of COP22 in Marrakech in 2016, which highlighted the country's climate-policy position and renewable-energy ambitions [2]. Morocco's energy decarbonisation strategy has progressively become an important component of its long-term sustainable-development agenda, linking climate mitigation, electricity-system transformation, renewable-energy deployment and industrial-sector involvement [3]. Electricity occupies a central position in this strategy because Morocco's power system remains strongly dependent on fossil fuels. In 2018, the electricity sector accounted for approximately 40% of energy-related CO_2 emissions, while fossil fuels supplied about 81% of electricity generation, including 59% from coal, compared with around 19% from renewable sources [3].

Morocco aims to increase the renewable share of installed electricity capacity to 52% by 2030, while its long-term strategy considers renewable shares of 70% by 2040 and 80% by 2050, together with carbon neutrality by 2050. Large-scale projects such as the Noor Ouarzazate Solar Complex illustrate the progressive implementation of these objectives. Electricity accounted for 19% of Morocco's total final energy consumption in 2023 [4]. Consequently, electricity-sector decarbonisation cannot be fully achieved without progressively substituting coal and other fossil-fuel-based electricity generation with renewable sources. Renewable electricity generation, denoted as renewable electricity generation (REN), is therefore measured as the share of renewables in total electricity generation and used as a realised production-based indicator of Morocco's electricity decarbonisation pathway.

Beyond its environmental dimension, Morocco's decarbonisation process raises an industrial-employment question. Industrial employment represented approximately 23% of total employment in 2023, confirming the importance of industry in the national employment structure [5]. In this study, industrial employment is used as a broad indicator of industrial labour absorption, activity expansion and sector participation in decarbonisation. It does not measure direct green-job creation, but helps assess whether renewable-electricity expansion supports industrial labour absorption and industrial-sector involvement.

Figure 1 presents the evolution of electricity generation by source in Morocco over 1990–2023. Renewable electricity generation has expanded progressively, reflecting the growing contribution of hydro, wind and solar power to the national electricity system. However, coal continues to occupy an important position in the electricity mix and remains a major source of electricity supply. This coexistence between renewable expansion and persistent fossil-fuel dependence

shows that Morocco's electricity-decarbonisation pathway should be understood in relation to changes in both renewable and non-REN. It also raises the question of whether Morocco's dependence on coal-fired electricity acts as a predictive driver of the future evolution of REN. Coal-based electricity generation is therefore included as a control variable in the CO_2-emissions model and examined in the complementary Granger causality analysis.

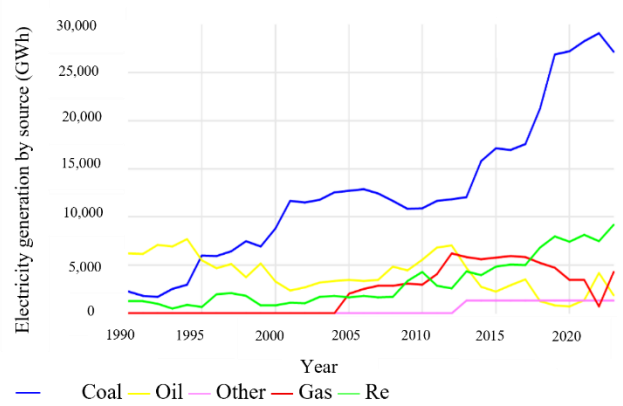


Figure 1. Electricity generation by energy source
Note: Coal, Oil and Gas represent fossil-fuel electricity generation; Other denotes other sources; and Re denotes renewable electricity generation (REN). All values are in GWh.
Source: Authors' elaboration based on IEA data [4].

Despite growing research on renewable energy, CO_2 emissions and employment, three gaps remain. First, many studies rely on renewable-energy consumption, installed capacity or individual technologies rather than REN as a realised share of total generation.

Second, environmental and employment outcomes are generally examined separately, limiting understanding of their joint relationship with electricity decarbonisation.

Third, limited analysis examines whether renewable-electricity expansion is associated with industrial labour absorption, used as a broad indicator of the expansion of industrial activity and its capacity to generate employment. This study addresses these gaps through two complementary models centred on REN. Model 1 examines the long-run association between REN and CO_2 emissions within an Environmental Kuznets Curve (EKC)-based specification, in which income and its squared term capture income nonlinearity, while coal-based electricity generation is included as a control variable. Model 2 examines the long-run association between REN and industrial employment, considering productive and digital conditions, while education expenditure and broad money are included as control variables. The Autoregressive Distributed Lag (ARDL) bounds-testing approach estimates long-run relationships and short-run adjustments, while the Granger causality analysis examines whether past changes in Morocco's dependence on coal-fired electricity provide predictive information about the future evolution of REN. The following hypotheses are tested:

H1: Renewable electricity generation is negatively associated with CO_2 emissions per capita in the long run.

H2: Renewable electricity generation is positively associated with industrial-employment share in the long run.

H3: Long-run cointegration exists among the dynamic variables of both models.

H4: Past changes in Morocco's dependence on coal-fired electricity provide predictive information about the future evolution of REN.

The remainder of the article is organised as follows: Section 2 reviews the relevant literature, Section 3 presents the methodology, Section 4 reports and discusses the empirical results, Section 5 provides the conclusions, and Section 6 outlines the study's limitations and areas for future research.

2. LITERATURE REVIEW

The literature review examines three dimensions: REN and CO_2 emissions, REN and industrial employment, and the relationship between coal dependence and the future evolution of REN. Together, these dimensions examine the environmental and industrial roles of REN while considering whether changes in coal-based electricity generation precede and help predict its development.

The CO_2 emissions model adopts an EKC-based specification to capture a possible nonlinear relationship between per capita income and emissions by including GDP per capita and its squared term [6, 7]. REN may also reduce emissions by replacing fossil-based electricity generation [8].

Studies using electricity-generation indicators generally show that renewable electricity reduces CO_2 emissions when it replaces fossil-based generation. D'Agosti [8] reported that renewable electricity lowers power-sector emissions by displacing carbon-based sources, while Yang and Wang [9] and Silva et al. [10] identified similar negative effects. However, these environmental benefits may remain limited when dependence on fossil fuels persists [11, 12]. These findings support the joint inclusion of REN and fossil-based electricity generation in Model 1 and the formulation of H1.

Beyond its environmental effects, renewable-electricity expansion may support employment through equipment production, construction, installation, technical services, operation and maintenance. Hlongwane and Khobai [13] and Silva et al. [10] identified positive employment effects, although their magnitude depends on the type of renewable technology. Employment outcomes also depend on domestic renewable-energy production capacity, technological capabilities and workforce skills. Pham et al. [14] showed that employment effects vary across sectors and skill requirements, while Rutovitz et al. [15] identified distinct labour needs in electricity generation, storage, transmission and construction. Financial development may stimulate investment and employment creation [16], whereas digital technologies can either support economic activity or replace routine labour [17]. In Morocco, the employment effects of renewable-electricity expansion depend on the economy's productive capacity and its ability to absorb labour [18]. EMP is therefore used as a broad indicator of industrial labour absorption rather than a direct measure of green jobs [19], supporting H2 and the specification of Model 2.

Renewable-energy development also depends on institutional and economic conditions [20]. Environmental policies may support renewable substitution [21], while financial development can facilitate renewable-energy expansion [22]. Fiscal decentralization [23] and digital enablers [24] have also been examined in relation to renewable electricity. Continued coal dependence may reinforce Morocco's need to expand REN [11, 12]. H4 examines whether past coal changes predict REN.

3. METHODOLOGY

3.1 Model specification

The empirical analysis uses two complementary models to examine whether REN is associated with lower CO_2 emissions and greater industrial labour absorption in Morocco. This structure addresses the environmental and industrial-employment dimensions of electricity decarbonisation within the empirical framework.

Model 1 adopts an EKC-based control specification following Grossman and Krueger [6] and Panayotou [7]. Following Danish et al. [25], $LNCO_2$ is used as the dependent variable and represents the natural logarithm of CO_2 emissions per capita from OWID [26]. LNREN is the main explanatory variable, and its coefficient is expected to be negative because renewable electricity may displace carbon-intensive generation [8-12, 27, 28]. LNGDPPC represents the effect of per capita income on emissions, while LNGDPPC2, calculated as the square of LNGDPPC, captures nonlinearity in the income–emissions relationship [25]. LNCOAL is included as a control variable because coal-based electricity generation is an important source of CO_2 emissions and its inclusion helps reduce omitted-variable bias [28, 29]. The Model 1 specification is adapted from Danish et al. [25].

$$\mathrm{LNCO}_{2_t} = \beta_0 + \beta_1 \mathrm{LN}REN_t + \beta_2 \mathrm{LNG}DPPC_t + \beta_3 \mathrm{LN}GDPPC2_t + \beta_4 \mathrm{LNCOAL}_t + \varepsilon_t \quad (1)$$

Model 2 examines the long-run association between REN and industrial employment. LNEMP is the dependent variable and reflects industrial labour absorption rather than direct green-job creation [18]. LNREN is the main explanatory variable, and its coefficient is expected to be positive because renewable-energy expansion may support employment through construction, installation, operation, maintenance and related industrial activities [13, 18]. LNPROD represents industrial labour productivity [30], while LNCEL measures mobile-cellular subscriptions as an indirect proxy for digital connectivity and technology adoption [17]. LNEDUC captures human-capital development [31], while LNM2 captures financial conditions [16]; both are included as fixed control regressors [29]. The coefficient on LNCEL may be negative if technology adoption reduces industrial labour absorption by substituting for certain tasks. The Model 2 specification is adapted from Bajja et al. [18].

$$\mathrm{LNEMP}_t = \alpha_0 + \alpha_1 \mathrm{LN}REN_t + \alpha_2 \mathrm{LN}PROD_t + \alpha_3 \mathrm{LN}CEL_t + \alpha_4 \mathrm{LNEDUC}_t + \alpha_5 \mathrm{LNM2}_t + \varepsilon_t \quad (2)$$

All variables are transformed into natural logarithms, while LNGDPPC2 is constructed as $(\mathrm{LNGDPPC})^2$. Annual data cover the period 1990–2023, providing a maximum of 34 observations. Table 1 presents the variable definitions, measurement units and data sources.

3.2 Econometric strategy

The analysis begins with descriptive statistics. The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit-root tests are then applied to determine whether the variables are stationary at level, I(0), or after first differencing, I(1) [32-34]. An ADF breakpoint unit-root test is then used to account for a structural break in each series [35, 36].

Table 1. Description of the study variables, measurement units, and data sources

Indicator	Acronym	Unit	Source
CO_2 emissions	CO_2	Metric tonnes per capita	OWID
Employment in industry	EMP	% of total employment	WDI
Share of renewables in power generation	REN	% of total electricity generation	IEA
Electricity production from coal sources	COAL	% of total electricity generation	WDI
Industry (including construction), value added per worker	PROD	Constant 2015 US$	WDI
Education expenditure	EDUC	% of Gross National Income	WDI
Mobile cellular subscriptions	CEL	Subscriptions per 100 people	WDI
Broad money	M2	Broad money % of GDP	WDI
GDP per capita (constant 2015 US$)	GDPPC	Constant 2015 US$	WDI
Squared GDP per capita to capture nonlinearity.	GDPPC2	Squared natural logarithm	Constructed from GDPPC

Note: In the unit column, t denotes metric tonnes. LNGDPPC2 is constructed as $(\mathrm{LNGDPPC})^2$ to capture the potential nonlinear effect of economic growth on CO_2 emissions. OWID [26] denotes Our World in Data, WDI denotes World Development Indicators, and IEA denotes the International Energy Agency.

The breakpoint test includes an intercept and trend, allows for a break in the intercept, selects the break date using the minimum Dickey–Fuller t-statistic and determines the lag length using the Schwarz Information Criterion [37]. These tests also confirm that none of the variables is integrated of order two, I(2). The ARDL bounds-testing approach developed by Pesaran et al. [38] is then used because it is suitable for small samples and accommodates variables integrated at I(0) and I(1).

Given the annual dataset of 34 observations, one lag is retained to capture the maximum available information while maintaining an effective sample of 33 observations. Within this restriction, the final lag structure of each model is selected using the Akaike Information Criterion [39]. Cointegration is assessed by comparing the calculated F-statistic with the corresponding asymptotic critical values reported by Pesaran et al. [38]. A long-run relationship is confirmed when the F-statistic exceeds the upper-bound critical value [38]. When cointegration is confirmed, the conditional ARDL error-correction model (ECM) is estimated to distinguish short-run changes from long-run relationships [38].

The conditional ARDL specifications of the CO_2 emissions and industrial-employment models are formulated following Pesaran et al. [38], expressed in natural logarithmic form following Wooldridge [29], and presented in Eqs. (3) and (4), respectively:

$$\Delta\mathrm{LNCO}_{2_t} = \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta\mathrm{LNCO}_{2_{t-i}} + \sum_{j=0}^{q-1} \beta_{2j} \Delta\mathrm{LNREN}_{t-j} + \sum_{j=0}^{q-1} \beta_{3j} \Delta\mathrm{LNGDPPC}_{t-j} \quad (3)$$

$$+\sum_{j=0}^{q-1}\beta_{4j}\Delta LNGDPPC2_{t-j}+\gamma_1 LNCO_{2_{t-1}}$$
$$+\gamma_2 LNREN_{t-1}+\gamma_3 LNGDPPC_{t-1}$$
$$+\gamma_4 LNGDPPC2_{t-1}+\theta_1 LNCOAL_t+\varepsilon_t$$

$$\Delta LNEMP_{t=}\alpha_0+\sum_{i=1}^{p-1}\alpha_{1i}\Delta LNEMP_{t-i}$$
$$+\sum_{j=0}^{q-1}\alpha_{2j}\Delta LNREN_{t-j}+\sum_{j=0}^{q-1}\alpha_{3j}\Delta LNPROD_{t-j}$$
$$+\sum_{j=0}^{q-1}\alpha_{4j}\Delta LNCEL_{t-j}+\delta_1 LNEMP_{t-1}+ \quad (4)$$
$$\delta_2 LNREN_{t-1}+\delta_3 LNPROD_{t-1}+\delta_4 LNCEL_{t-1}$$
$$+Z_1 LNEDUC_t+Z_2 LNM2_t+\varepsilon_t$$

In Eqs. (3) and (4), Δ denotes the first-difference operator, while β_0 and α_0 are the constant terms. The coefficients β_{1i} and α_{1i} capture the short-run persistence of the dependent variables, whereas $\beta_{2j}-\beta_{4j}$ and $\alpha_{2j}-\alpha_{4j}$ measure the short-run effects of changes in the explanatory variables. The coefficients $\gamma_1-\gamma_4$ and $\delta_1-\delta_4$ are associated with the lagged-level variables and are jointly tested to determine the existence of long-run relationships.

The coefficient θ_1 is associated with the fixed control regressor $LNCOAL_t$, while Z_1 and Z_2 are associated with the fixed control regressors $LNEDUC_t$ and $LNM2_t$, respectively. Cointegration is confirmed when the bounds-test F-statistic exceeds the relevant upper critical bound. In the corresponding ECM, a negative and statistically significant error-correction coefficient indicates convergence toward long-run equilibrium and measures the speed of adjustment. A pairwise Granger causality test is subsequently conducted between coal-based and REN using one lag. Following Granger [40], the general specification is expressed as follows:

$$Y_t=\alpha_0+\sum_{i=1}^{p}\alpha_i Y_{t-i}+\sum_{j=1}^{q}\beta_j X_{t-j}+\varepsilon_t \quad (5)$$

where, Y_t denotes the dependent variable, X_{t-j} denotes the explanatory variable, p and q represent their respective lag lengths, and ε_t is the error term. The hypotheses are specified as follows: H_0: $\beta_1=\beta_2=\cdots=\beta_q=0$; H_1: at least one $\beta_j\neq 0$, for j = 1, …, q. Rejecting H_0 when the p-value is below 5% indicates that past values of X_t provide useful information for predicting Y_t [40]. To satisfy the stationarity requirement of the conventional Granger causality test, variables integrated of order one, I(1), were expressed in first differences, while I(0) variables were retained in levels [40, 41].

Finally, model validity and robustness are assessed using diagnostic and stability tests. The Breusch–Godfrey LM test examines serial correlation [42, 43], while the Breusch–Pagan–Godfrey test assesses heteroskedasticity [44].

Residual normality is evaluated using the Jarque–Bera test [45], and parameter stability is examined through the CUSUM and CUSUM of Squares tests [46]. Together, these tests assess the robustness of the estimated models by determining whether they satisfy the principal econometric assumptions and whether their coefficients remain stable throughout the study period.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 Preliminary analysis

In Model 1, LNCOAL has a higher mean than LNREN (3.917625 compared with 2.371699), reflecting the relatively high presence of coal over the sample period (Table 2). LNREN shows greater variability, with a standard deviation of 0.449951 compared with 0.388186 for LNCOAL, indicating greater variation in REN. The Jarque–Bera probabilities show that most variables do not reject normality at the 5% level, whereas LNCOAL departs significantly from a normal distribution. In Model 2, LNEMP has lower variability than LNREN and LNCEL, with a standard deviation of 0.041125 compared with 0.449951 and 3.382855, respectively. This low dispersion suggests that industrial labour absorption evolved more gradually, whereas LNREN and LNCEL experienced greater fluctuations. Normality is not rejected for most variables, although LNEDUC shows a significant departure from normality.

Table 2. Descriptive statistics of the variables included in Model 1 and Model 2

Model 1						
Variables	$LNCO_2$	LNGDPPC	LNGDPPC2	LNREN	LNCOAL	
Mean	0.343855	7.799618	60.89339	2.371699	3.917625	
Median	0.428762	7.830098	61.31054	2.523838	4.008157	
Maximum	0.642735	8.137752	66.223	3.029557	4.34842	
Minimum	-0.089084	7.426972	55.15991	1.49744	2.842713	
Std. Dev.	0.22795	0.247273	3.8495	0.449951	0.388186	
Skewness	-0.387617	-0.132831	-0.110196	-0.361694	-1.440553	
Kurtosis	1.70136	1.499966	1.493943	1.754193	4.177735	
Jarque-Bera	3.240562	3.28763	3.282105	2.940043	13.72442	
Probability	0.197843	0.193241	0.193776	0.229921	0.001047	
Model 2						
Variables	LNEMP	LNREN	LNPROD	LNEDUC	LNCEL	LNM2
Mean	3.063816	2.371699	9.278651	1.651218	14.91841	4.405867
Median	3.062667	2.523838	9.281302	1.648659	16.58839	4.499571
Maximum	3.136191	3.029557	9.472364	1.943525	17.75386	4.858751
Minimum	2.987217	1.49744	9.070338	1.526056	7.31322	3.865
Std. Dev.	0.041125	0.449951	0.120997	0.066194	3.382855	0.314319
Skewness	0.075943	-0.361694	-0.028384	2.538304	-1.010847	-0.325344
Kurtosis	2.114639	1.754193	1.735882	13.8108	2.507468	1.567204
Jarque-Bera	1.042289	2.940043	2.06824	184.2502	5.592703	3.198552
Probability	0.59384	0.229921	0.355539	0	0.061032	0.202043

Note: All variables are presented in natural logarithms; LNGDPPC2 is constructed as $(LNGDPPC)^2$ to capture the nonlinear effect of economic growth.

4.2 Stationarity, breakpoint unit-root tests and AIC-based lag selection

The ADF and PP tests in Table 3 show mixed orders of integration, I(0) and I(1), with no variable integrated of order two, I(2). This confirms the suitability of the ARDL bounds-testing approach for examining relationships between REN, CO_2 emissions and industrial employment. LNREN and LNEDUC are stationary at level, whereas the remaining variables are classified as I(1) based on first-difference evidence from at least one conventional test. The breakpoint unit-root test in Table 4 complements these results by allowing for structural changes over 1990–2023. After accounting for breaks, $LNCO_2$, LNCOAL, LNPROD and LNM2 remain I(1), while the other variables are stationary at level. The break dates suggest that Morocco's environmental, electricity, income, productive, employment, educational, digital and financial indicators were affected differently by economic, energy and institutional changes. Accounting for breaks reduces the risk of mistaking structural change for non-stationarity. The AIC-based lag-selection results in Figure 2 retain a parsimonious structure for both models. Given the annual frequency and the limited sample of 34 observations, the maximum lag order is restricted to one to preserve degrees of freedom and available information. This structure captures the adjustment of CO_2 emissions and industrial employment to changes in REN and the explanatory variables.

Table 3. Results of the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit-root tests

Variables	ADF Intercept and Trend		PP Intercept and Trend		Chosen Order of Integration
	Level	Difference	Level	Difference	I(0) or I(1)
$LNCO_2$	-0.979508	-8.128641***	-1.58242	-8.326907***	I(1)
LNGDPPC	-1.326399	-10.48229***	-2.520545	-9.859527***	I(1)
LNGDPPC2	-1.471184	-10.32115***	-2.577645	-9.745554***	I(1)
LNCOAL	-1.736511	-6.308746***	-1.691664	-6.285510***	I(1)
LNEMP	-1.83675	-4.730644***	-2.006022	-4.687501***	I(1)
LNREN	-3.790306**	-5.990769***	-3.310306*	-14.84052***	I(0)
LNPROD	-3.029621	-5.734759***	-3.029621	-5.765573***	I(1)
LNEDUC	-4.449226***	-6.010765***	-4.454284***	-17.43266***	I(0)
LNCEL	-1.460518	-3.906114**	-0.975139	-2.976059	I(1)
LNM2	-1.467165	-8.424518***	-1.057535	-8.203003***	I(1)

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Source: Authors' elaboration.

Table 4. Breakpoint Augmented Dickey–Fuller (ADF) unit-root test results with structural breaks

Break Specification with Intercept and Trend	Test Statistic	Break Year	Test Statistic	Break Year	
Variables	I(0)		I(1)		Decision
LNCO2	-4.152744	2003	-9.031600***	2003	I(1) with break
LNGDPPC	-5.738336***	2019	-11.89869***	1994	I(0) with break
LNGDPPC2	-5.826472***	2019	-11.64149***	2000	I(0) with break
LNCOAL	-4.508966	2004	-7.761373***	1995	I(1) with break
LNEMP	-5.700202***	2012	-6.957995	2005	I(0) with break
LNREN	-4.693508*	1998	-7.813737***	2008	I(0) with break
LNPROD	-3.485366	2021	-7.160028***	1997	I(1) with break
LNEDUC	-8.229473***	2005	-9.591981	2007	I(0) with break
LNCEL	-5.605952***	2004	-8.87038	2006	I(0) with break
LNM2	-2.870104	2004	-9.524743***	2000	I(1) with break

Note: I(0) and I(1) denote level and first-difference stationarity; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

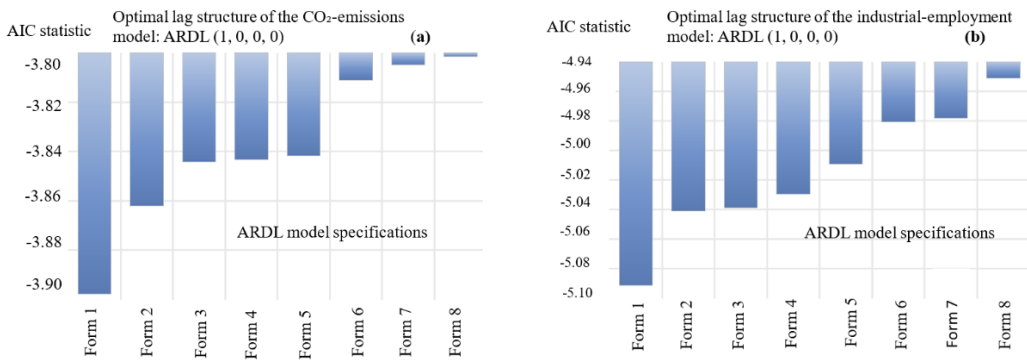


Figure 2. Optimal lag selection based on the AIC. Panels (a) and (b) report the optimal lag choices for Model 1 and Model 2, respectively

4.3 Autoregressive Distributed Lag bounds-testing results

The bounds-test results reported in Table 5 confirm long-run cointegration in both models. In Model 1, the F-statistic of 4.881382 exceeds the 1% upper critical bound of 4.66. The null hypothesis of no long-run relationship is therefore rejected, showing that CO_2 emissions, REN and the income variables move together over time despite short-run changes.

In Model 2, the F-statistic of 5.584864 also exceeds the 1% upper bound of 4.08, confirming a stable long-run relationship among industrial employment, REN, industrial productivity and digital connectivity. These findings support H3 and show that the estimated relationships are not limited to short-term movements. Economically, changes in REN in Morocco remain connected over the long term to CO_2 emissions and industrial labour absorption. Although short-run shocks may temporarily move the variables away from equilibrium, they remain linked by stable long-run relationships. Cointegration therefore justifies estimating the long-run coefficients and the ECM to assess the speed of adjustment toward equilibrium in both models.

Table 5. Results of the Autoregressive Distributed Lag (ARDL) bounds test for cointegration

Asymptotic Critical Values			
F-Bounds Test	**Value of F-Statistic**	**I(0)**	**I(1)**
Model 1	4.881382		
10%		2.79	3.67
5%		3.15	4.08
1%		3.65	4.66
Model 2	5.584864		
10%		2.37	3.2
5%		2.79	3.67
1%		3.15	4.08

Note: Bounds-test critical values are based on Pesaran et al. [38].

4.4 Long-run estimation results

The long-run results reported in Table 6 show that, in Model 1, LNREN has a negative and statistically significant coefficient of −0.068928 at the 5% level (p = 0.0239). Because cointegration is confirmed in both models, these coefficients represent stable long-run associations rather than temporary short-run movements. Since the variables are expressed in natural logarithms, the coefficient is interpreted as an elasticity: a 1% increase in the REN share is associated with a 0.069% decrease in CO_2 emissions per capita in the long run. Econometrically, this supports H1. Economically, renewable-electricity expansion is associated with lower CO_2 emissions in Morocco. However, the small coefficient indicates only a limited reduction, highlighting the need to examine other factors that may continue to sustain emissions.

LNGDPPC and LNGDPPC2 are included in the EKC-based model to capture possible nonlinearity in the income–emissions relationship rather than to validate the EKC hypothesis. Neither coefficient is statistically significant at the 5% level, with p-values of 0.4207 and 0.5489, respectively. Therefore, no conclusion can be drawn regarding the effects of income on CO_2 emissions. As a fixed control regressor, LNCOAL is not included among the estimated long-run coefficients; therefore, no numerical long-run interpretation is provided.

In Model 2, LNREN has a positive and statistically significant coefficient of 0.053054 at the 5% level (p = 0.0157). A 1% increase in the REN share is therefore associated with a 0.053% increase in the industrial-employment share. Econometrically, this supports H2. Economically, renewable-electricity expansion is associated with greater industrial labour absorption in Morocco. However, the small coefficient reflects the industrial sector's gradual engagement in decarbonisation through labour absorption and should not be interpreted as automatic green-job creation. Local employment benefits may nevertheless arise through construction, cabling, metal structures, installation, grid connection, operation and maintenance. LNCEL has a negative and statistically significant coefficient of −0.018091 at the 5% level (p = 0.0200), indicating that a 1% increase in mobile-cellular subscriptions is associated with a 0.018% decrease in the industrial-employment share. This may reflect labour substitution by technology and Morocco's limited industrial and technological capacity. Because advanced renewable-energy technologies are largely imported, domestic production of technologically advanced equipment remains limited, reducing labour absorption in these activities.

LNPROD has a negative but statistically insignificant coefficient (−0.208947; p = 0.3100), so no clear conclusion can be drawn regarding its long-run association with industrial employment. As fixed control regressors, LNEDUC and LNM2 are not included among the estimated long-run coefficients; therefore, no numerical long-run interpretation is provided. Overall, REN is associated with lower CO_2 emissions and greater industrial labour absorption in Morocco.

Table 6. Long-run estimation results for the CO_2 emissions and industrial employment models using Autoregressive Distributed Lag (ARDL)

Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Model 1				
LNGDPPC	3.523344	4.308639	0.817739	0.4207
LNGDPPC2	-0.167878	0.276521	-0.607108	0.5489
LNREN	-0.068928**	0.028803	-2.393091	0.0239
Constant	-16.87528	16.73467	-1.008402	0.3222
Model 2				
LNREN	0.053054**	0.020336	2.608886	0.0157
LNPROD	-0.208947	0.201271	-1.03814	0.31
LNCEL	-0.018091**	0.007234	-2.500736	0.02
Constant	4.035285***	1.405592	2.87088	0.0086

Note: LNCOAL in Model 1 and LNEDUC and LNM2 in Model 2 are included as fixed control regressors and are therefore not reported among the estimated long-run coefficients. LNGDPPC2 is constructed as $(LNGDPPC)^2$ to capture the potential nonlinear effect of economic growth on CO_2 emissions.

4.5 Error-correction, diagnostic and stability results

Tables 7 and 8 and Figure 3 report the adjustment, diagnostic and stability results for both models. The error-correction term, ECT (−1), is negative and statistically significant at the 1% level, with coefficients of −0.678598 in Model 1 and −0.544529 in Model 2 (Table 7). This confirms that short-run deviations are corrected over time. About 67.9% of the disequilibrium is corrected each year in Model 1, compared with 54.5% in Model 2 (Table 7). The CO_2-

emissions model therefore returns more quickly to its long-run equilibrium after a shock. Economically, CO_2 emissions can respond rapidly to changes in the electricity mix, whereas industrial employment adjusts more slowly because labour absorption requires investment, skills and time. In Model 2, LNM2 has a positive and statistically significant short-run coefficient of 0.144415 ($p < 0.001$), indicating that greater liquidity may support productive activity and labour demand (Table 7). By contrast, LNEDUC has a negative coefficient of −0.054464 ($p = 0.036$), which may reflect delayed returns to education or skill mismatches (Table 7). The diagnostic tests support the robustness of both models. The Breusch–Godfrey LM probabilities of 0.4994 and 0.9080 indicate no serial correlation, while the Breusch–Pagan–Godfrey probabilities of 0.1274 and 0.1318 indicate no heteroskedasticity (Table 8). The Jarque–Bera probabilities of 0.587980 and 0.531196 confirm normal residuals (Table 8). The CUSUM and CUSUMSQ statistics remain within the 5% critical bounds, showing parameter stability over 1990–2023 (Figure 3).

These results confirm the robustness of the estimated relationships involving REN, as they are not driven by residual problems and the parameters remain stable in both models.

Table 7. Short-run error-correction model (ECM) estimation results for Model 1 and Model 2

	Variables	Coefficient	Std. Error	t-Statistic	Prob.
Model 1	LNCOAL	0.021350***	0.003314	6.443294	0
	ECT (-1)	-0.678598***	0.104767	-6.477239	0
Model 2	LNM2	0.144415***	0.024537	5.885591	0
	LNEDUC	-0.054464**	0.024467	-2.226014	0.036
	ECT (-1)	-0.544529***	0.090136	-6.041187	0

Note: LNCOAL and LNEDUC/LNM2 are fixed control regressors in Models 1 and 2, respectively. ECT (−1) denotes the lagged error-correction term. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

Table 8. Robustness diagnostics for Models 1 and 2

	Test	*p*-Value	Result
Model 1	Breusch-Godfrey LM test	0.4994	No serial correlation
	Breusch-Pagan-Godfrey	0.1274	No heteroskedasticity
	Jarque-Bera normality test	0.58798	Normal residuals
Model 2	Breusch-Godfrey LM test	0.908	No serial correlation
	Breusch-Pagan-Godfrey	0.1318	No heteroskedasticity
	Jarque-Bera normality test	0.531196	Normal residuals

Note: This table summarises the diagnostic-test results for both models.

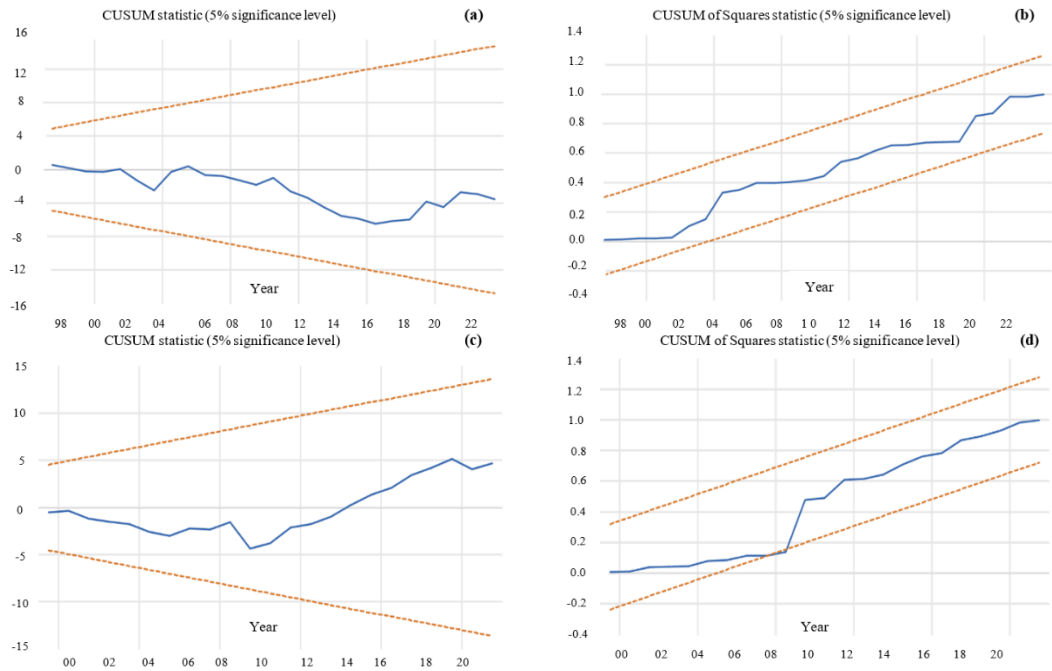


Figure 3. Panels (a) and (b) present the CUSUM and CUSUMSQ stability diagnostics for Model 1, while panels (c) and (d) present the corresponding stability diagnostics for Model 2

4.6 Granger causality results

The Granger causality analysis complements the ARDL results by examining whether past changes in the share of coal in electricity generation help predict the future evolution of REN. Table 9 shows that the null hypothesis that ΔLNCOAL does not Granger-cause LNREN is rejected at the 5% level, with an F-statistic of 4.32457 and a probability of 0.0465. Econometrically, this result shows that past changes in the share of coal in electricity generation provide significant predictive information about the future evolution of REN. Economically, the increasing importance of coal in Morocco's

electricity mix has reinforced the need to develop REN to progressively reduce the country's dependence on carbon-intensive energy sources. This orientation also responds to the need to adapt Morocco's electricity system to evolving international environmental requirements, by limiting exposure to carbon-related taxes, emissions-pricing mechanisms and stringent environmental standards affecting international trade. The expansion of REN constitutes a central instrument of the decarbonisation strategy, enabling the substitution of carbon-intensive electricity with renewable generation and reducing the carbon intensity of the electricity mix. It contributes to strengthening the implementation of Morocco's climate commitments under the Paris Agreement, in line with the momentum reinforced by COP22 held in Marrakech. Combined with the long-run results showing that REN is associated with lower CO_2 emissions and greater industrial labour absorption, this result opens the way to an integrated interpretation of the environmental and social dimensions of decarbonisation: dependence on coal reinforces the need to accelerate REN, which contributes to reducing emissions and supporting industrial employment. The result highlights the strategic contribution of decarbonisation for Morocco, as a response to coal dependence, as a means of strengthening its environmental commitments and as a lever supporting industrial development. However, the estimated relationship remains predictive causality in the Granger sense and does not imply that changes in the share of coal constitute, on their own, the sole determinant of REN.

Table 9. Granger causality tests for Model 1

Model 1		
Null hypothesis	Probability	Causality outcome
ΔLNCOAL⇏ LNREN	0.0465	Causality at 5%

Note: "⇏" denotes no Granger causality. Δ denotes the first-difference operator applied to I(1) variables in the conventional Granger causality test. Only null hypotheses rejected at the 5% level are reported.

5. CONCLUSIONS

The results show that REN is associated with lower CO_2 emissions and greater industrial labour absorption in Morocco. The bounds tests confirm cointegration in both models, supporting H3.

First, REN is negatively and significantly associated with CO_2 emissions in the long run, with an elasticity of –0.068928, supporting H1. Renewable-electricity expansion is therefore associated with lower CO_2 emissions. However, the small coefficient indicates that this effect remains limited while fossil fuels, particularly coal, continue to occupy an important position in the electricity mix.

Second, REN is positively and significantly associated with industrial employment, with an elasticity of 0.053054, supporting H2. This relationship reflects the industrial sector's engagement in electricity decarbonisation through labour absorption rather than automatic green-job creation. Local employment benefits may arise through construction, equipment supply, cabling, metal structures, installation, grid connection, technical services, operation and maintenance. However, dependence on imported technologies limits domestic production of high-technology renewable-energy equipment and reduces employment in these activities.

Third, the Granger result shows that past changes in coal-based electricity generation provide predictive information about the future evolution of REN, supporting H4. Economically, Morocco's dependence on coal-fired electricity emerges as a significant predictor of the future evolution of REN. This finding reinforces the fundamental rationale for decarbonisation: progressively reducing reliance on carbon-intensive electricity through the development of REN, limiting potential exposure to pollution-related taxes and carbon costs, strengthening Morocco's contribution to global environmental protection, and supporting the fulfilment of its international climate commitments. When considered together with the long-run results, the finding shows that Morocco's renewable-electricity strategy responds to persistent coal dependence while contributing to lower CO_2 emissions and greater industrial labour absorption. The error-correction, diagnostic and stability results support the robustness of both models.

Overall, the findings underline the importance of reducing fossil-fuel dependence, strengthening domestic renewable-equipment production, developing workforce skills and aligning renewable expansion with employment-oriented industrial policies.

6. LIMITATIONS AND AREAS FOR FUTURE RESEARCH

Although this study examines the long-run associations of REN with CO_2 emissions and industrial employment in Morocco, several limitations should be acknowledged. First, Model 1 primarily assesses REN, while coal-based electricity production is included only as a control variable. Consequently, it does not provide clear evidence of the independent long-run effect of coal use on CO_2 emissions. Future research could examine interactions between renewable-electricity expansion, coal dependence and emissions reduction by disaggregating REN into wind, solar and hydropower to identify their specific effects. Second, industrial employment is used as a broad indicator of the industrial sector's capacity to support electricity decarbonisation through labour provision.

However, it does not fully capture the wider productive effects of renewable-electricity development. Further studies could analyse industrial value added to determine whether renewable expansion contributes to industrial production, domestic value creation and structural transformation. The analysis could also extend to the overall economy to assess the broader employment and wealth-creation benefits of participation in the decarbonisation process.

ACKNOWLEDGMENT

We are grateful to Mohammed V University in Rabat, the Faculty of Legal, Economic and Social Sciences-Agdal (FSJES-Agdal), and the Laboratory of Applied Economics for their institutional support.

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NOMENCLATURE

ADF	Augmented Dickey–Fuller unit-root test
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag model
CUSUM	Cumulative sum stability test
CUSUMSQ	Cumulative sum of squares stability test
ECM	Error correction model
ECT	Error-correction term
ECT (−1)	Lagged error-correction term
EKC	Environmental Kuznets Curve
GDPPC	Gross domestic product per capita
GDPPC2	Squared natural logarithm of GDP per capita
GWh	Gigawatt-hour
I(0)	Stationary at level
I(1)	Stationary after first differencing
IEA	International Energy Agency
LN	Natural logarithm
OWID	Our World in Data
p	Number of lags of the dependent variable
PP	Phillips–Perron unit-root test
q	Number of lags of the explanatory variable
WDI	World Development Indicators

Greek symbols

$\alpha_0 - \beta_0$	Constant term
$\alpha_i - \beta_j$	Short-run coefficients
θ_1	Coefficient of the control variable in Model 1
$Z_1 - Z_2$	Coefficients of the control variables in Model 2
$\gamma_j - \delta_j$	Coefficients of lagged-level variables
ε_t	Error term at time t
Δ	First-difference operator
H_0	Null hypothesis
H_1	Alternative hypothesis
$\nRightarrow$	No Granger causality
$\sum$	Summation operator

Subscripts

i	Lag index of the dependent variable
j	Lag index of the explanatory variable
t	Time period