

Knowledge Economy and Sustainable Manufacturing Growth in Algeria: Evidence from an ARDL Approach

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Abstract:

This study examines the impact of the knowledge economy on the sustainability of manufacturing sector growth in Algeria over the period 2000–2023. Using the Autoregressive Distributed Lag (ARDL) approach, the analysis explores short- and long-run relationships between knowledge economy indicators, manufacturing value added, employment, and CO₂ emissions. The Bounds test confirms cointegration across all models. The results indicate that while ICT and human capital support manufacturing performance, weak innovation capacity constrains sustainable industrial development, highlighting the need for knowledge-driven and environmentally responsible industrial policies.

Keywords: knowledge economy, sustainability, manufacturing, Algeria, ARDL

Jel Classification Codes: L69, O14

1. INTRODUCTION

Background and Research Problem

Over the past two decades, Algeria has pursued economic diversification strategies aimed at reducing its heavy dependence on hydrocarbons and strengthening the manufacturing sector as a sustainable engine of growth. Despite these efforts, manufacturing value added has remained modest, employment generation limited, and environmental pressures persistent. At the same time, Algeria has made notable progress in key dimensions of the knowledge economy, particularly in the expansion of higher education, the diffusion of information and communication technologies (ICT), and the implementation of innovation-related policies. However, the extent to which these knowledge-based advancements have translated into sustainable manufacturing growth remains empirically unclear. This gap raises a fundamental policy and analytical question: can the knowledge economy effectively support the economic, social, and environmental sustainability of Algeria's manufacturing sector?

Research Objectives and Questions

The primary objective of this study is to empirically examine the impact of knowledge economy indicators on the sustainability of manufacturing sector growth in Algeria over the period 2000–2023. Sustainability is approached through a multidimensional framework encompassing economic performance (manufacturing value added), social outcomes (manufacturing employment), and environmental effects (CO₂ emissions intensity). Accordingly, the study addresses the following interrelated research questions:

- (i) Do knowledge economy variables exert a long-run influence on manufacturing value added in Algeria?
- (ii) How do education, ICT, innovation, and foreign direct investment affect manufacturing employment dynamics?
- (iii) Does the transition toward a knowledge-based economy contribute to cleaner and more environmentally sustainable manufacturing outcomes?

Research Hypotheses

Drawing on insights from the knowledge economy paradigm, the study advances the following hypotheses: (H1) Knowledge economy indicators—such as ICT diffusion, human capital, innovation, and foreign direct investment—positively influence manufacturing value added in the long run. (H2) Knowledge-based factors enhance manufacturing employment by facilitating productivity gains, technological diffusion, and firm upgrading. (H3) The development of the knowledge economy contributes to environmental sustainability by promoting energy efficiency and cleaner production practices, thereby reducing CO₂ emissions intensity over time.

2. Literature Review

The role of the knowledge economy in promoting sustainable manufacturing growth has received increasing attention in both theoretical and empirical research. Commonly proxied by information and communication technology (ICT), human capital, innovation, and research and development (R&D), the knowledge economy is widely recognized as a key driver of long-term industrial competitiveness, productivity gains, and environmental sustainability.

Early work by Chen and Dahlman (2005) provides a foundational framework linking knowledge-based assets to industrial performance. Using cross-country macroeconomic comparisons and indicators such as ICT diffusion, human capital accumulation, and R&D intensity, they show that economies investing in knowledge infrastructure achieve sustained industrial competitiveness. The persistence of these effects supports the existence of stable long-run relationships between knowledge economy variables and manufacturing outcomes, consistent with cointegration-based time-series approaches.

In resource-dependent economies, structural constraints may limit the effectiveness of knowledge-based investments. Gasmi and Laourari (2017) examine Algeria's structural transformation using time-series indicators of manufacturing value added, innovation capacity, and sectoral output

composition. Their dynamic regression results indicate that weak innovation systems and heavy reliance on hydrocarbons hinder industrial diversification, highlighting long-run structural rigidities and justifying econometric models that distinguish between short-run dynamics and long-run equilibria.

From a productivity perspective, Hadzimustafa (2016) employs growth and productivity models to assess the impact of education and technological progress on total factor productivity. The findings suggest that productivity gains from knowledge accumulation emerge gradually due to delayed adjustment mechanisms, underscoring the relevance of flexible lag structures characteristic of ARDL models.

At the sectoral level, Hussein (2019) analyzes manufacturing sustainability in Egypt using time-series data on ICT penetration, innovation, education, manufacturing value added, employment, and environmental indicators. The study reports statistically significant short-run and long-run effects of knowledge economy variables on manufacturing sustainability.

Regional evidence further supports this view. Barhoumi (2019) investigates the relationship between knowledge economy pillars—such as institutional quality, human capital, infrastructure, and business sophistication—and economic growth in MENA countries using dynamic panel GMM estimation. The results confirm a positive and persistent impact of knowledge economy development on growth, providing conceptual support for country-specific time-series approaches like ARDL, especially in data-constrained contexts.

More recent studies extend the analysis to environmental sustainability. Wang et al. (2022) find that technological innovation and knowledge-intensive growth positively affect green growth in OECD countries, indicating a long-run link between innovation and environmentally sustainable manufacturing. Similarly, Liu et al. (2025) show that digital transformation and innovation capacity mediate the relationship between manufacturing activity and regional economic development, emphasizing lagged and indirect effects.

Finally, Khan et al. (2024), through a bibliometric and empirical review of environmental, social, and governance (ESG) performance in manufacturing, highlight green innovation, R&D, and knowledge-based production strategies as central to sustainable industrial development. Their findings reinforce the argument that manufacturing sustainability is fundamentally knowledge-driven.

Overall, the literature converges on the conclusion that the knowledge economy is a core driver of sustainable manufacturing growth. By enhancing productivity, stimulating innovation, and enabling environmentally responsible production, knowledge-based development strategies are essential for the long-term sustainability of manufacturing sectors, particularly in developing and resource-dependent economies.

3. Conceptual Framework

3.1 Knowledge Economy

The knowledge economy refers to an economic system in which the creation, dissemination, and effective use of knowledge constitute the primary engines of productivity, competitiveness, and long-term economic growth. The development of this concept can be traced to the second half of the twentieth century, when economists increasingly emphasized the growing importance of human capital, technological change, and innovation in shaping modern production systems. Early contributions by Machlup (1962) highlighted the economic value of knowledge-producing activities (Machlup, 1962, pp. 3-5), while Drucker introduced the notion of the “knowledge worker” as a defining feature of contemporary economies (Drucker, 1969, p. 248). Building on these foundations, international organizations in the 1990s—most notably the OECD and the World Bank—formalized the concept by framing the knowledge economy as one in which intellectual capital, technological innovation, and human capital increasingly replace traditional factors such as natural resources and physical capital as the primary sources of competitive advantage (OECD, 1996, p. 11).

Within this framework, knowledge becomes the central asset for value creation, and economic performance depends largely on the capacity to generate, diffuse, and apply knowledge across sectors. Accordingly, the key pillars of the knowledge economy include innovation systems, human capital development, information and communication technology (ICT) infrastructure, and supportive institutional and policy environments (Chen & Dahlman, 2005, p. 4). The expansion of digital connectivity and advanced communication technologies has further accelerated this transformation by enabling faster innovation cycles and more efficient knowledge diffusion, thereby reinforcing the role of knowledge-intensive activities in industrial upgrading and sustainable development (World Bank, 2019, pp. 5, 6).

3.2 Sustainable Development in the Knowledge Economy

Sustainable development emphasizes the integration of economic growth, environmental protection, and social equity, as articulated in the United Nations Sustainable Development Goals (SDGs). Within the context of a knowledge economy, sustainable development is achieved by leveraging innovation and technology to enhance resource efficiency, promote clean energy adoption, and foster inclusive growth (UNESCO, 2021, p. 87). Knowledge-intensive sectors—such as high-technology manufacturing and renewable energy industries—are particularly aligned with sustainability objectives because they rely on advanced solutions that reduce environmental impacts while strengthening competitiveness (Popp, 2019, p. 117). For developing economies, knowledge-driven strategies facilitate the transition from resource dependence toward diversified, innovation-led growth.

3.3 The Fourth Industrial Revolution and the Knowledge Economy

The Fourth Industrial Revolution (4IR) builds upon the digital revolution by integrating physical, biological, and digital systems through emerging technologies such as artificial intelligence (AI), the Internet of Things (IoT), robotics, and additive manufacturing (Schwab, 2016, p. 22). The fourth industrial revolution further amplifies the role of the knowledge economy by emphasizing digital skills, data-driven decision-making, and

advanced manufacturing techniques, commonly referred to as Industry 4.0. These technologies enable firms to enhance efficiency, reduce production costs, and minimize environmental footprints through automation, real-time monitoring, and predictive analytics. For example, smart factories utilize real-time data to optimize production processes, thereby aligning industrial development with both economic and sustainability objectives (Liao, Deschamps, & Ramos, 2017, p. 2947).

3.4 Integration of the Fourth Industrial Revolution, the Knowledge Economy, and Sustainable Development

The intersection of the Fourth Industrial Revolution and the knowledge economy provide a transformative pathway toward sustainable development. By harnessing digital technologies, countries can achieve higher productivity while advancing environmental sustainability, for instance through smart grids, circular economy models, and low-carbon manufacturing processes (Awan, Sroufe, & Shahbaz, 2021, p. 2046). However, the realization of these benefits depends on the capacity to develop robust knowledge infrastructures, including effective R&D systems, a skilled labour force, and well-functioning digital ecosystems. Consequently, public policies should focus on bridging the digital divide, fostering innovation ecosystems, and aligning technological progress with sustainability objectives. This integrated framework is particularly relevant for emerging economies such as Algeria, which seek to diversify their industrial base and transition toward greener, knowledge-driven growth models.

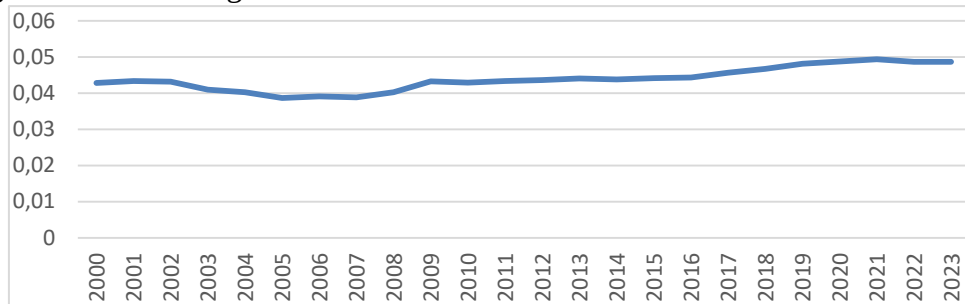
4. Manufacturing Sustainability and Knowledge Economy Indicators in Algeria

4.1 Manufacturing Sustainability Indicators: The analysis of Algerian manufacturing sustainability indicators from 2000 to 2023 reveals persistent structural constraints alongside emerging opportunities for improvement.

a. Manufacturing contribution to GDP: Manufacturing value added (MVA) remained between 4% and 5% of GDP throughout 2000–2023, highlighting the sector’s limited role in Algeria’s economic structure. This share is low compared to peer economies such as Tunisia and Egypt, where

manufacturing contributes 12%–16% of GDP (AIDSMO, 2025, pp. 12, 40). Modest gains after 2015 are linked to diversification policies, including the National Industrial Development Strategy, aimed at reducing hydrocarbon dependence. Nevertheless, manufacturing remains concentrated in low-value-added activities such as food processing and basic consumer goods, with minimal progress toward medium- or high-tech industries (Mellab, 2025, p. 4527). This limited diversification constrains sustainable, knowledge-driven growth.

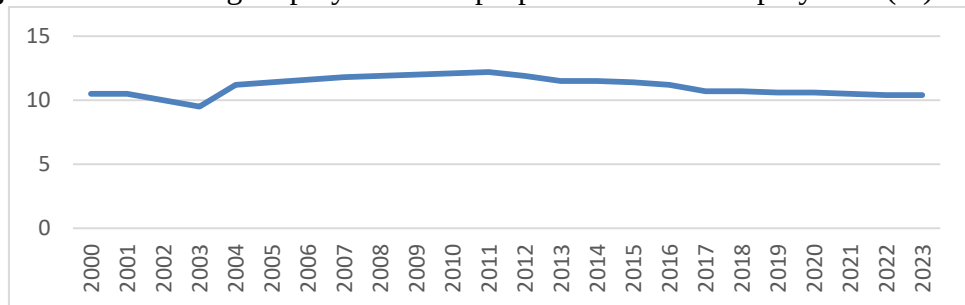
Fig. 1. Manufacturing value added share in total GDP



Source: Author's elaboration based on UNIDO data

b. Manufacturing employment: Manufacturing employment in Algeria followed a non-linear path over the past two decades. It increased from 10.5% of total employment in 2000 to 12.2% in 2011, reflecting state-led industrial expansion. However, this trend reversed thereafter, with employment declining to 10.4% by 2023. This contraction suggests reduced job creation capacity, likely due to capital-intensive production, automation, reliance on imported inputs, and weak SME integration into industrial supply chains. It also reflects insufficient diversification toward labour-intensive, high-value-added manufacturing capable of absorbing a growing workforce.

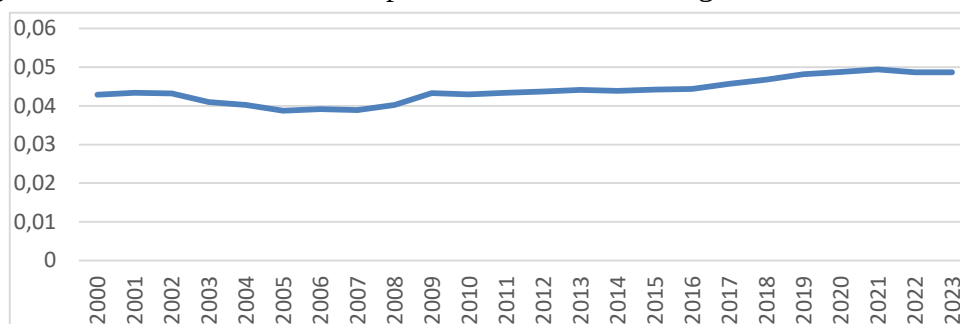
Fig. 2. Manufacturing employment as a proportion of total employment (%)



Source: Author's elaboration based on UNIDO data

c. CO₂ emissions per unit of manufacturing value added: Carbon intensity in Algerian manufacturing fluctuated significantly over the period. CO₂ emissions per unit of MVA increased from 0.86 kg/USD in 2000 to 1.06 kg/USD in 2004, indicating inefficient energy use. Between 2004 and 2013, emissions remained near 1 kg/USD, suggesting limited efficiency gains. By 2018, intensity rose to 1.4 kg/USD, likely due to expansion in energy-intensive industries such as cement and steel. Encouragingly, emissions declined steadily after 2018, reaching 0.689 kg/USD in 2023, reflecting recent modernization efforts, cleaner technologies, and improved energy efficiency.

Fig.3. Carbon dioxide emissions per unit of manufacturing value added



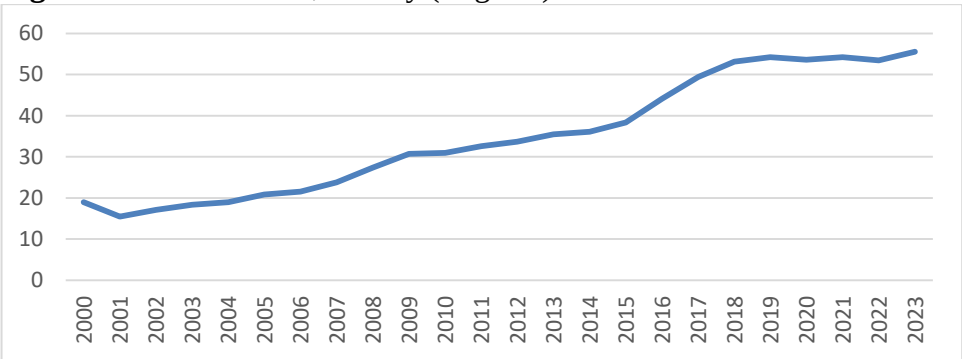
Source: Author's elaboration based on UNIDO data

4.2 Knowledge Economy Indicators

Algeria has made notable progress in selected dimensions of the knowledge economy, particularly ICT diffusion and human capital, while gaps persist in innovation and technological sophistication.

a. Tertiary school enrolment: Tertiary enrolment expanded markedly over the past two decades, rising from about 15% in the early 2000s to over 50% by 2017, driven by substantial public investment in higher education. In recent years, enrolment remained high, fluctuating between 53.16% in 2018 and 55.51% in 2023. This trend reflects Algeria's commitment to human capital development and workforce preparation for innovation and digital transformation. However, persistent misalignment between academic curricula and labour market needs—particularly in STEM and industrial fields—limits the effective utilization of this educational expansion.

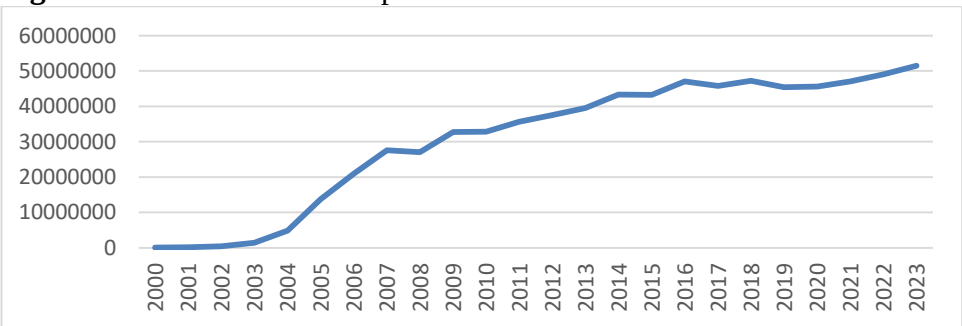
Fig.4. School enrolment, tertiary (% gross)



Source: Author’s elaboration based on World Bank data

b. Mobile cellular subscriptions: Mobile subscriptions surged from 86,000 in 2000 to over 40 million by 2020, representing rapid ICT adoption. This expansion supports digital transformation and Industry 4.0 applications, including smart manufacturing, digital supply chains, and IoT-based monitoring. Despite this progress, constraints remain in broadband coverage, internet speed, and affordability, which are essential for fully integrating ICT into advanced manufacturing processes.

Fig.5. Mobile cellular subscriptions



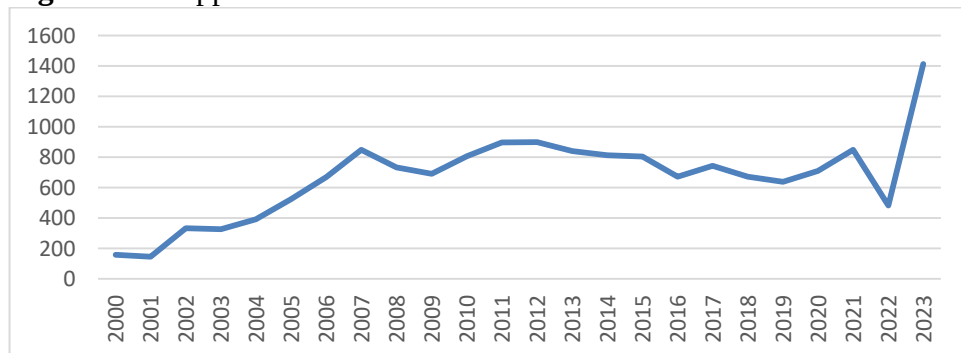
Source: Author’s elaboration based on World Bank data

c. Innovation: Innovation performance improved notably, with patent applications rising from 145 in 2000 to 849 in 2007, reflecting early R&D and intellectual property initiatives. After fluctuating for several years, patent filings increased sharply to 1,412 by 2023. This growth is linked to innovation-supporting policies, startup development, and stronger collaboration among universities, research centres, and industry. Initiatives such as incubators and innovation funds have fostered technological

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entrepreneurship, signaling gradual progress toward a knowledge-driven economy.

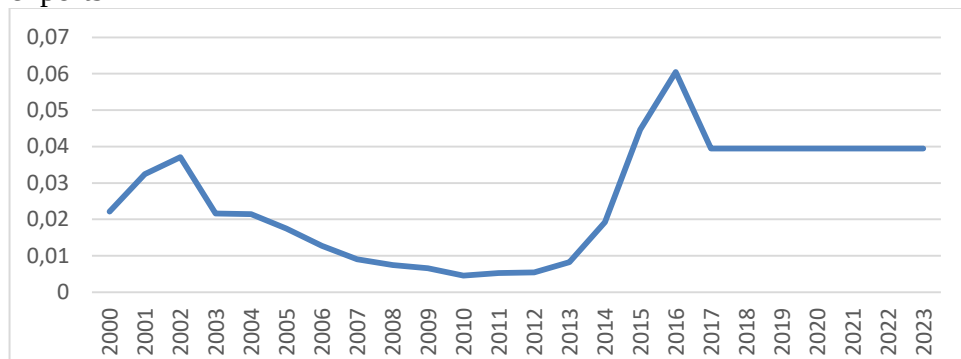
Fig.6. Patent applications



Source: Author's elaboration based on World Bank data

d. Medium- and high-tech manufactured exports: The share of medium- and high-technology exports showed marked volatility. It declined from 3.7% in 2002 to 0.54% in 2012, reflecting limited diversification. The share rebounded to 6.05% by 2016 due to targeted industrial policies and selective investments, then stabilized around 3.94%. While this indicates modest improvement, Algeria's manufacturing remains weakly integrated into global value chains compared to MENA peers such as Morocco and Tunisia (Luciani & Moerenhout, 2019, p. 26).

Fig.7. Medium- and high-tech manufactured exports share in total manufactured exports

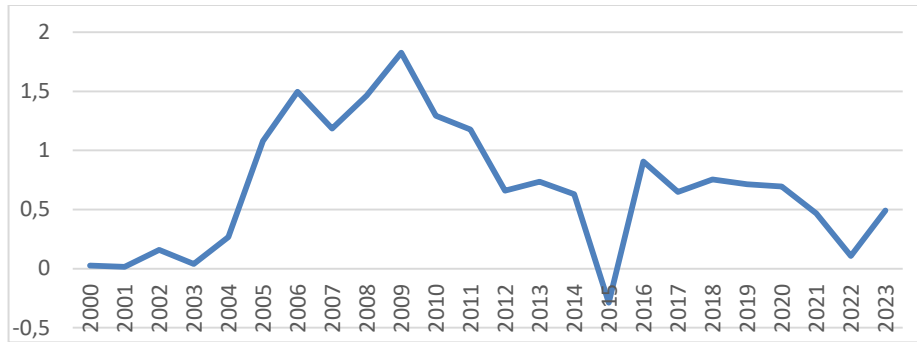


Source: Author's elaboration based on UNIDO data

e. Foreign direct investment (FDI): FDI inflows as a share of GDP were highly volatile between 2000 and 2023. After minimal levels in the early 2000s, inflows peaked at around 1.8% of GDP during 2004–2009, driven

mainly by hydrocarbon investments. This was followed by a sustained decline after 2010 and a sharp contraction around 2015 amid oil price shocks. Although inflows partially recovered after 2016 and again in 2023, overall FDI remains cyclical and resource-dependent, limiting its role as a stable driver of manufacturing development and technological upgrading.

Fig.8. Foreign direct investment (FDI) inflows (% GDP)



Source: Author elaboration based on World Bank data

5. Empirical Study

5.1 Data Sources and Variables

a. Data sources: The study uses annual data for Algeria covering the period 2000–2023, compiled from the World Bank (WDI), UNIDO, and the Algerian National Statistics Office (ONS). The dataset also integrates knowledge economy indicators from the World Bank's Knowledge Economy Index.

b. Variables presentation:

- **Dependent Variables:** The dependent variables are selected to reflect the three dimensions of sustainable manufacturing:

- **PMVA:** Manufacturing value-added share of GDP (economic sustainability).
- **EMP:** Manufacturing employment share (social sustainability).
- **CO₂:** Carbon emissions per unit of manufacturing value-added (environmental sustainability).

- **Independent Variables:** Explanatory variables capture key drivers of the knowledge economy and structural change, including:

- **PAT:** Patent applications (proxy for innovation).

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- **MOB:** Mobile cellular subscriptions per 100 inhabitants (ICT penetration).
- **SENR:** Tertiary school enrolment (%).
- **PEXMHT:** Medium- and high-tech exports share.
- **OPN:** Trade openness.
- **FDIP:** Foreign direct investment inflows (% of GDP).
- **GFCF:** Gross fixed capital formation (% of GDP).

5.2 Stationarity of Variables and Model Estimation

To estimate long-run relationships and avoid spurious regression, it is essential to first test the stationarity of the time series. If the series are non-stationary at levels, the existence of a cointegration relationship must be verified; otherwise, the regression should be specified in first differences to capture short-run dynamics.

a. Unit Root Tests:

The integration order of the series was determined using Augmented Dickey-Fuller (ADF) tests at both levels and first differences.

Table 1. Unit root test (ADF)

<u>At Level</u>												
		CO2	EMP	FDIP	GFCF	MOB	MVA	OPN	PAT	PEXMHT	PMVA	SENR
With	t-	-	-	-	-	-	-	-	-	-	-	-
Consta	Statisti	1.034	1.444	-	-	2.154	0.458	2.374	-	-	-	-
nt	c	6	1	2.2845	-0.6497	1.9328	8	7	3	-1.2179	-0.0816	-0.7940
	Prob.	0.722	0.542	0.184	0.311	0.999	0.880	0.159	0.6485	0.9405	0.8011	
		n0	n0	n0	n0	n0	n0	n0	n0	n0	n0	n0
With	t-	-	-	-	-	-	-	-	-	-	-	-
Consta	Statisti	0.693	1.391	-	-	2.249	1.988	1.931	-	-	-	-
nt &	c	4	3	2.2373	-2.5010	0.7323	8	4	5	-2.4168	-2.1490	-2.2818
Trend		0.961	0.836	0.448	0.957	0.196	0.573	0.604	0.3616	0.4935	0.4256	
	Prob.	5	1	6	0.3239	9	4	8	5	0.3616	0.4935	0.4256
		n0	n0	n0	n0	n0	n0	n0	n0	n0	n0	n0
Without	t-	-	-	-	-	-	-	-	-	-	-	-
Consta	Statisti	0.471	0.131	-	-	0.268	2.946	0.609	1.054	-	-	-
nt &	c	7	7	1.1423	1.0509	6	9	9	6	-0.3149	1.1241	2.1305
Trend		0.500	0.627	0.222	0.754	0.998	0.440	0.918	0.5609	0.9271	0.9894	
	Prob.	0	0	9	0.9175	3	1	4	0	0.5609	0.9271	0.9894
		n0	n0	n0	n0	n0	n0	n0	n0	n0	n0	n0

At First Difference												
		d(CO 2)	d(EM P)	d(FDI P)	d(GFC F)	d(MO B)	d(MV A)	d(OP N)	d(PA T)	d(PEXMH T)	d(PMV A)	d(SEN R)
With Consta nt	t- Statistic	-3.775 7	-4.376 2	-5.7629	-3.1786	-5.4240	-4.279 7	-4.395 1	-6.460 6	-3.7082	-3.3371	-3.8959
	Prob.	0.009 9	0.002 6	0.000 1	0.0352 4	0.000 4	0.003 9	0.011 6	0.000 0	0.0114	0.0254	0.0076
		***	***	***	**	***	***	**	***	**	**	***
With Consta nt & Trend	t- Statistic	-4.275 5	-4.558 8	-5.8929	-3.1158	-5.3165	-5.160 4	-4.732 0	-6.432 6	-3.7274	-3.5435	-3.6759
	Prob.	0.014 0	0.007 8	0.000 5	0.0400 2	0.002 2	0.003 0	0.005 9	0.000 2	0.0417	0.0592	0.0461
		**	***	***	**	***	***	***	***	**	*	**
Without Consta nt & Trend	t- Statistic	-3.857 1	-4.483 8	-5.8955	-2.1882	-2.4100	-3.901 5	-2.228 3	-5.967 9	-3.8062	-3.3031	-2.2035
	Prob.	0.000 5	0.000 1	0.000 0	0.0305 5	0.018 5	0.000 5	0.028 2	0.000 0	0.0006	0.0021	0.0295
		***	***	***	**	**	***	**	***	***	***	**

Source: Author's estimation using Eviews 12

The results in Table 1 show that all variables are non-stationary at levels but become stationary at first differences. This confirms that all variables are integrated of order one, $I(1)$. Estimating regressions in levels with $I(1)$ series could produce spurious results unless long-run cointegration relationships are present.

b. Model Specification:

To analyse the dynamic linkages between manufacturing performance, employment, and environmental outcomes, this study employs the Autoregressive Distributed Lag (ARDL) framework proposed by Pesaran, Shin, and Smith (2001). The ARDL approach allows for the joint estimation of short-run dynamics and long-run equilibrium relationships among the variables, irrespective of whether they are $I(0)$, $I(1)$, or a combination thereof, provided none is $I(2)$.

Following the ARDL framework, the unrestricted error correction forms of the three equations are specified as:

- PMVA equation

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$$\begin{aligned} \Delta PMVA_t = & a_0 + b_1 PMVA_{t-1} + b_2 GFCF_{t-1} + b_3 FDPI_{t-1} + b_4 PAT_{t-1} + \\ & b_5 MOB_{t-1} + b_6 PEXMHT_{t-1} + \sum_{i=1}^p a_{1i} \Delta PMVA_{t-i} + \sum_{j=0}^{q_1} a_{2i} \Delta GFCF_{t-j} + \\ & \sum_{j=0}^{q_2} a_{3i} \Delta FDPI_{t-j} + \sum_{j=0}^{q_3} a_{4i} \Delta PAT_{t-j} + \sum_{j=0}^{q_4} a_{5i} \Delta MOB_{t-j} + \\ & \sum_{j=0}^{q_5} a_{6i} \Delta PEXMHT_{t-j} + \varepsilon_{1t} \dots\dots(1) \end{aligned}$$

- EMP equation

$$\begin{aligned} \Delta EMP_t = & a_0 + b_1 EMP_{t-1} + b_2 MVA_{t-1} + b_3 MOB_{t-1} + b_4 PEXMHT_{t-1} + \\ & b_5 SENR_{t-1} + b_6 FDPI_{t-1} + \sum_{i=1}^p a_{1i} \Delta EMP_{t-i} + \sum_{j=0}^{q_1} a_{2i} \Delta MVA_{t-j} + \\ & \sum_{j=0}^{q_2} a_{3i} \Delta MOB_{t-j} + \sum_{j=0}^{q_3} a_{4i} \Delta PEXMHT_{t-j} + \sum_{j=0}^{q_4} a_{5i} \Delta SENR_{t-j} + \\ & \sum_{j=0}^{q_5} a_{6i} \Delta FDPI_{t-j} + \varepsilon_{2t} \dots\dots(2) \end{aligned}$$

- CO₂ equation

$$\begin{aligned} \Delta CO2_t = & a_0 + b_1 CO2_{t-1} + b_2 MVA_{t-1} + b_3 GFCF_{t-1} + b_4 MOB_{t-1} + \\ & b_5 PEXMHT_{t-1} + b_6 SENR_{t-1} + \sum_{i=1}^p a_{1i} \Delta EMP_{t-i} + \sum_{j=0}^{q_1} a_{2i} \Delta MVA_{t-j} + \\ & \sum_{j=0}^{q_2} a_{3i} \Delta GFCF_{t-j} + \sum_{j=0}^{q_3} a_{4i} \Delta MOB_{t-j} + \sum_{j=0}^{q_4} a_{5i} \Delta PEXMHT_{t-j} + \\ & \sum_{j=0}^{q_5} a_{6i} \Delta SENR_{t-j} + \varepsilon_{3t} \dots\dots(3) \end{aligned}$$

The models are estimated using ordinary least squares (OLS). The existence of a long-run relationship is assessed through the bounds testing approach, with the following hypotheses:

$$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_n = 0 \text{ (no cointegration)}$$

$$H_1: \exists \alpha_i \neq 0 \text{ (cointegration exists)}$$

Upon confirmation of cointegration, the long-run ARDL model for each equation is specified as:

$$Y_t = a_0 + \sum_{i=1}^p a_{1i} Y_{t-i} + \sum_{j=0}^{q_1} a_{2i} X_{1t-j} + \dots + \sum_{j=0}^{q_5} a_{6i} X_{5t-j} + \varepsilon_t \dots\dots(4)$$

where:

Y_t is the dependent variable at time t,

X_k represents the k-th explanatory variable,

p and **q_k** denote the lag lengths of the dependent and explanatory variables,

ε_t is the stochastic error term.

The corresponding error correction model (ECM) takes the form:

$$\begin{aligned} \Delta Y_t = & a_0 + \sum_{i=1}^p a_{1i} \Delta Y_{t-i} + \sum_{j=0}^{q_1} a_{2i} \Delta X_{1t-j} + \dots + \sum_{j=0}^{q_5} a_{3i} \Delta X_{5t-j} + \\ & \lambda ECT_{t-1} + \varepsilon_t \dots\dots(5) \end{aligned}$$

where ECT_{t-1} denotes the lagged error correction term, and λ captures the speed of adjustment toward long-run equilibrium.

c. Lag selection: Lag orders were determined using the Akaike Information Criterion (AIC) as illustrated in appendix (A.1). The selected specifications—ARDL (2,1,0,1,2,0) for PMVA, ARDL (2,0,1,1,0,0) for EMP, and ARDL (2,1,2,2,2,2) for CO2-reflect differences in adjustment dynamics across the models.

d. Optimal model estimation: Each equation was estimated separately using the ARDL methodology, as summarized in the following table.

Table 2. ARDL model estimation results

Equation 1 (PMVA equation)				Equation 2 (EMP equation)				Equation 3 (CO2 equation)			
Selected Model: ARDL(2, 1, 0, 1, 2, 0)				Selected Model: ARDL(2, 0, 1, 1, 0, 0)				Selected Model: ARDL(2, 1, 2, 2, 2, 2)			
Dependent variable: PMVA				Dependent variable: EMP				Dependent variable: CO2			
Variable	Coefficient	t-Statistic	Prob.*	Variable	Coefficient	t-Statistic	Prob.*	Variable	Coefficient	t-Statistic	Prob.*
PMVA(-1)	0.156150	0.715007	0.4910	EMP(-1)	-0.074933	-0.310407	0.7616	CO2(-1)	-0.011870	-0.050379	0.9618
PMVA(-2)	0.508174	2.730505	0.0212	EMP(-2)	-0.457045	-1.991613	0.0697	CO2(-2)	-0.692543	-2.365371	0.0643
GFCF	-2.75E-10	-0.641704	0.5355	MVA	-4.13E-11	-1.606466	0.1341	MVA	2.40E-11	0.805845	0.4569
GFCF(-1)	-1.85E-09	-2.490472	0.0320	MOB	2.83E-08	0.888747	0.3916	MVA(-1)	-9.14E-11	-3.399490	0.0193
FDIP	8.94E-05	0.175590	0.8641	MOB(-1)	5.54E-08	1.260664	0.2314	GFCF	-9.81E-08	-1.448201	0.2072
PAT	-4.66E-06	-3.095698	0.0113	PEXMHT	-1.447888	-0.155216	0.8792	GFCF(-1)	2.64E-07	2.778641	0.0390
PAT(-1)	-1.12E-05	-3.223083	0.0091	PEXMHT(-1)	-20.01074	-2.018730	0.0664	GFCF(-2)	-9.73E-08	-1.456421	0.2051
MOB	3.37E-11	0.391230	0.7038	SENR	-0.077333	-2.027538	0.0654	MOB	2.35E-08	3.078450	0.0275
MOB(-1)	1.70E-10	2.092580	0.0629	FDIP	0.500217	2.417101	0.0325	MOB(-1)	-1.47E-08	-1.725051	0.1451
MOB(-2)	3.19E-10	3.068129	0.0119	C	17.73537	4.562983	0.0007	MOB(-2)	1.94E-08	2.149895	0.0843
PEXMHT	-0.019115	-1.707261	0.1186	-	-	-	-	PEXMHT	1.106412	0.410114	0.6987
C	0.020203	3.734811	0.0039	-	-	-	-	PEXMHT(-1)	0.900636	0.249428	0.8130
-	-	-	-	-	-	-	-	PEXMHT(-2)	9.339031	2.878095	0.0347
-	-	-	-	-	-	-	-	SENR	-0.029090	-1.536836	0.1849
-	-	-	-	-	-	-	-	SENR(-1)	0.014195	0.721694	0.5028
-	-	-	-	-	-	-	-	SENR(-2)	-0.017742	-1.202445	0.2830
-	-	-	-	-	-	-	-	C	2.010047	6.678459	0.0011
R-squared	0.984738			R-squared	0.916150			R-squared	0.987192		
Adjusted R-squared	0.967949			Adjusted R-squared	0.853262			Adjusted R-squared	0.946205		

Source: Author's estimation using Eviews 12

For equation 1, the estimated ARDL(2,1,0,1,2,0) model explains the dynamics of manufacturing value added (PMVA) in relation to its key determinants. Overall, the model demonstrates an excellent fit, with an R^2

of 0.98, indicating that the included regressors jointly account for a large proportion of the variation in PMVA.

Similarly, for equation 2, the ARDL(2,0,1,1,0,0) model captures the short- and long-run dynamics of employment (EMP) as a function of manufacturing value added (MVA), mobile penetration (MOB), medium- and high-tech exports (PEXMHT), secondary school enrolment (SENR), and foreign direct investment inflows (FDIP). The model exhibits a strong fit, with an R^2 of 0.92, suggesting that the selected variables explain a substantial share of the variation in employment.

Finally, for equation 3, the ARDL(2,1,2,2,2,2) model provides insights into the dynamic determinants of CO₂ emissions in Algeria. The high R^2 value (0.99) indicates that the selected explanatory variables account for the vast majority of the variation in emissions over the sample period.

e. Bounds Test for Cointegration

The ARDL Bounds test results, as presented in Appendix (A.2) indicate the presence of long-run relationships in all three estimated equations. For the PMVA equation, the F-statistic (7.57) exceeds the upper critical bound at the 5% significance level, providing strong evidence of cointegration between manufacturing value added and its determinants.

Similarly, the EMP equation reports an F-statistic of 5.09, which is above the upper bound at the 5% significance level, confirming a stable long-run relationship for manufacturing-related employment.

The strongest evidence of cointegration is observed in the CO₂ equation, where the F-statistic (8.66) surpasses the upper bound at the 5% level across all critical value specifications.

Overall, these results validate the estimation of long-run coefficients and the corresponding error-correction models within the ARDL framework.

5.3 Diagnostic Tests

To ensure the reliability of the estimated equations, several diagnostic tests were conducted, including checks for residual normality, serial correlation, and heteroskedasticity, as well as a contemporaneous correlation test to verify the efficiency of the estimation method.

a. Contemporaneous Correlation Test

The Breusch–Pagan test of independence was applied to examine whether the residuals across the three equations (PMVA, EMP, and CO₂) are contemporaneously correlated.

Table 4. Breusch–Pagan test results

Test Statistic	df	Critical value	P -value
LM = 3.144	3	$\chi^2_{(0.05,3)} = 7.815$	0.37

Source: calculated by author

The Breusch–Pagan test indicates no contemporaneous correlation across the residuals of the PMVA, EMP, and CO₂ equations ($\chi^2(3) = 3.144$, $p \approx 0.37$). This implies that the three equations are statistically independent, validating the efficiency of separate equation-by-equation estimation. Therefore, the use of a Seemingly Unrelated Regression (SURE) model would not provide efficiency gains over individual OLS estimation in this case.

b. The robustness tests

The diagnostic tests confirm the adequacy of the estimated models. The Jarque–Bera test indicates that the residuals are normally distributed across all equations, as the p-values exceed the 5% significance level, supporting valid statistical inference. The Breusch–Godfrey LM test shows no evidence of serial correlation in any equation, with all test statistics being insignificant. Finally, the Breusch–Pagan–Godfrey test confirms the absence of heteroskedasticity across the models, indicating stable residual variance and validating the reliability of the estimated standard errors.

Table 5. The diagnostic tests results

Tests Equation	Normality		Autocorrelation		Heteroskedasticity	
	Jarque-Bera	Prob.	Breusch–Godfrey LM	Prob.	Breusch–Pagan–Godfrey	Prob.
1	0.894719	0.639314	1.934056	0.1643	8.492117	0.6687
2	0.526067	0.768716	2.883811	0.2365	14.96761	0.0918
3	1.833763	0.399764	1.012664	0.3143	9.929021	0.8703

Source: Author’s estimation using Eviews 12

5.4 Empirical Results

a. Error Correction Mechanism and Cointegration Confirmation

The error correction terms (CointEq(-1)) as illustrated in appendices (A.3, A.4, A.5) are negative and highly significant across all three equations, confirming the existence of stable long-run adjustments toward equilibrium. For manufacturing performance, the error correction coefficient (- 0.336; $p = 0.000$) indicates that approximately 33.6% of any short-run disequilibrium is corrected within one period, suggesting a moderate pace of adjustment. In the employment equation, the coefficient is much larger (- 1.532; $p = 0.000$), implying rapid convergence to the long-run equilibrium—likely due to the high responsiveness of the labour market to technological and policy changes. The CO₂ emissions model exhibits an even stronger correction speed (-1.704; $p = 0.000$), indicating that deviations from the long-run environmental equilibrium are corrected swiftly, reflecting the short-term sensitivity of emissions to industrial and energy adjustments.

b. Short-Run Dynamics

The short-run adjustment patterns highlight Algeria's structural constraints and transitional frictions.

For manufacturing value added, the first lag of $\Delta PMVA_{t-1}$ is negative (-0.156) and statistically insignificant ($p = 0.49$), while the second lag ($\Delta PMVA_{t-2}$) is positive and significant (0.508; $p = 0.02$), reflecting cyclical fluctuations and partial resilience in output dynamics. Short-run changes in patents have negative effects both contemporaneously (-4.66×10^{-6} ; $p = 0.01$) and at one lag (-1.12×10^{-5} ; $p = 0.009$), suggesting that innovation initially generates adjustment costs rather than immediate productivity gains. Mobile penetration shows positive lagged effects (1.70×10^{-10} at lag 1 and 3.19×10^{-10} at lag 2), indicating delayed digital spillovers that take time to materialize in industrial activity.

In the employment equation, short-run dynamics reveal strong adjustment persistence and selective responsiveness to digital and trade variables. Lagged changes in employment have a positive coefficient (0.41; $p < 0.05$), implying that short-term job growth carries over into subsequent periods, consistent with the rigid structure of Algeria's labour market. Mobile penetration contributes positively to short-run job creation (1.85×10^{-10} ; $p = 0.04$), highlighting the role of digital platforms and SMEs in

generating immediate employment opportunities. In contrast, high-tech exports exert weak short-run effects, reflecting the capital-intensive and enclave nature of Algeria's high-tech sectors. Investment variables display mixed short-run signs: initial effects are insignificant, but lagged investment contributes positively as projects mature and labour demand rises.

For the CO₂ equation, short-run persistence is strong, with lagged emissions exerting a positive effect (0.52; $p < 0.01$), underscoring inertia in Algeria's emissions dynamics. Manufacturing value added increases emissions in the short run (0.064; $p = 0.03$), reflecting the immediate energy requirements of industrial expansion. Investment exhibits a dual effect: it initially reduces emissions through modernization efforts (-3.20×10^{-9} ; $p = 0.05$) but raises them at longer lags (2.94×10^{-9} ; $p = 0.04$) as capacity utilization intensifies. Digitalization increases emissions contemporaneously (1.13×10^{-10} ; $p = 0.03$), indicating higher energy consumption from ICT infrastructure, while lagged effects suggest potential efficiency gains over time. Overall, these transitional patterns indicate that both labour market and environmental outcomes are shaped by structural adjustment costs, technological diffusion lags, and the sequencing of industrial policies.

c. Long-Run Relationship

The long-run coefficients - presented in Appendices (A.6, A.7, A.8)- provide a structural perspective on Algeria's industrial trajectory.

For manufacturing value added, mobile penetration has a positive effect (3.37×10^{-11}), highlighting the productivity-enhancing role of digital infrastructure. In contrast, gross fixed capital formation (-1.85×10^{-9}) and patents (-1.12×10^{-5}) have negative long-run coefficients, indicating that investment and innovation have not translated into sustained industrial upgrading. This outcome reflects persistent structural weaknesses, such as weak industry-university linkages and a state-dominated investment model. High-tech exports and FDI remain insignificant, mirroring Algeria's enclave-type integration into global markets.

For employment, mobile penetration is a key positive determinant (2.41×10^{-10} ; $p < 0.01$), confirming the pivotal role of digital infrastructure in creating new job opportunities. FDI also has a positive long-run effect (0.00013; $p = 0.02$), consistent with its contribution to employment through foreign investment projects and technology transfer. In contrast, education and export sophistication have negative coefficients (- 0.021 and - 0.014), indicating persistent skills mismatches and a capital-intensive export structure that limits labour absorption. Manufacturing value added itself is not an important long-run driver of employment, underscoring the capital-intensive nature of Algeria's industrial sector.

For CO₂ emissions, the long-run coefficients indicate that higher manufacturing value added is associated with reduced emissions (-0.038; $p = 0.01$), reflecting improvements in energy efficiency and cleaner technologies since 2018. However, digitalization (2.75×10^{-10} ; $p = 0.03$) and high-tech exports (0.024; $p = 0.04$) significantly increase long-run emissions, highlighting the energy-intensive nature of ICT infrastructure and export-oriented manufacturing. Neither investment nor education has long-run effects on emissions, implying that their influence operates mainly through transitional channels.

These long-run patterns depict an economy at a crossroads: digitalization and FDI are creating new employment channels, but structural rigidities and skills gaps remain major bottlenecks, while Algeria's emissions trajectory reflects both efficiency improvements and new energy pressures arising from digital transformation.

6. Discussion

The empirical results show that ICT diffusion—proxied by mobile penetration—has a positive and significant long-run effect on manufacturing value added in Algeria, where digital adoption often substitutes for deeper structural reforms. In contrast, patents and capital formation exhibit weak or negative impacts, reflecting the limited effectiveness of the national innovation system, the dominance of

hydrocarbon rents, and weak industry–research linkages that hinder the transformation of R&D into industrial upgrading.

ICT development and foreign direct investment also improve manufacturing employment, while education indicators remain insignificant or negative, highlighting a persistent skills mismatch shaped by misalignment between the education system and the needs of a relatively narrow, import-dependent industrial base.

From an environmental perspective, higher manufacturing value added reduces CO₂ emissions intensity, suggesting some gains in energy efficiency within modernized segments. However, the positive impact of ICT and high-tech exports on emissions reflects Algeria’s reliance on energy-intensive digital infrastructure powered largely by fossil fuels.

(Liu, Xie, & Li, 2025, pp. 20, 21).

Overall, the results support the view that the knowledge economy is a necessary but insufficient condition for sustainable manufacturing growth. Similar to Barhoumi (2019) and Khan et al. (2024), the evidence suggests that knowledge-based assets must be embedded within coherent industrial, innovation, and environmental policies.

The empirical results also allow for a clear assessment of the hypotheses formulated in the introduction.

Hypotheses H1 and H2 are partially supported, while H3 is largely confirmed, though conditioned by structural and institutional constraints.

Overall, the findings indicate that the role of the knowledge economy in sustaining manufacturing growth in Algeria is conditional on effective coordination between education, innovation, industrial, and environmental policies.

7. Conclusion and Policy Implications

This study provides empirical evidence that knowledge economy factors play a substantial role in shaping manufacturing performance, employment, and environmental outcomes in Algeria. The ARDL results confirm stable long-run relationships across all three dimensions, underscoring the structural role of innovation, human capital, and digital

infrastructure in industrial development. However, the gains from knowledge accumulation are constrained by weak innovation capacity, low technological intensity, and limited integration into high-value manufacturing. Additionally, persistent CO₂ emissions indicate that manufacturing expansion without technological upgrading may exacerbate environmental pressures.

From a policy perspective, the findings highlight the need for an innovation-oriented industrial strategy. Strengthening R&D systems, improving technology transfer, and reinforcing linkages between universities and manufacturing firms are essential to convert human capital and ICT investments into productivity gains. At the same time, promoting high-technology and environmentally friendly manufacturing, supported by incentives for cleaner production and energy-efficient technologies, is critical to achieving sustainable industrial transformation and advancing Algeria's economic diversification.

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9. Appendices

A.1: Model selection criteria Recap. table

Equation	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
1(PMVA)	140.427535	-11.675230	-11.080116	-11.535039	0.999992	ARDL(2,1,0,1,2,0)
2(EMP)	3.229841	0.615469	1.111397	0.732295	-0.680614	ARDL(2,0,1,1,0,0)
3(CO2)	52.499098	-3.227191	-2.384112	-3.028587	0.954242	ARDL(2,1,2,2,2,2)

A.2: Cointegration Bounds Test

Equations	F-Value	K	Signif.	I(0)	I(1)
1(PMVA)	7.573692	5	10%	2.08	3
2(EMP)	5.094029		5%	2.39	3.38
3(CO2)	8.655986		1%	3.06	4.15

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A.3: ECM Regression (PMVA eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(PMVA(-1))	-0.508174	0.131106	-3.876043	0.0031
D(GFCF)	-2.75E-10	3.52E-10	-0.782757	0.4519
D(PAT)	-4.66E-06	7.25E-07	-6.426591	0.0001
D(MOB)	3.37E-11	3.95E-11	0.852381	0.4140
D(MOB(-1))	-3.19E-10	5.31E-11	-6.002760	0.0001
CointEq(-1)*	-0.335676	0.036447	-9.210068	0.0000
R-squared	0.854062	Mean dependent var	0.000242	
Adjusted R-squared	0.808457	S.D. dependent var	0.001096	
S.E. of regression	0.000479	Akaike info criterion	-12.22069	
Sum squared resid	3.68E-06	Schwarz criterion	-11.92313	
Log likelihood	140.4275	Hannan-Quinn criter.	-12.15059	
Durbin-Watson stat	2.462988			

A.4: ECM Regression (EMP eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(EMP(-1))	0.457045	0.143821	3.177884	0.0080
D(MOB)	2.83E-08	1.49E-08	1.898677	0.0819
D(PEXMHT)	-1.447888	5.505820	-0.262974	0.7970
CointEq(-1)*	-1.531978	0.209473	-7.313501	0.0000
R-squared	0.767444	Mean dependent var	-0.004545	
Adjusted R-squared	0.728685	S.D. dependent var	0.443447	
S.E. of regression	0.230982	Akaike info criterion	0.070014	
Sum squared resid	0.960351	Schwarz criterion	0.268386	
Log likelihood	3.229841	Hannan-Quinn criter.	0.116745	
Durbin-Watson stat	2.120873			

A.5: ECM Regression (CO2 eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	0.692543	0.120803	5.732834	0.0023
D(MVA)	2.40E-11	1.01E-11	2.376356	0.0635
D(GFCF)	-9.81E-08	3.31E-08	-2.960966	0.0315
D(GFCF(-1))	9.73E-08	2.76E-08	3.525864	0.0168
D(MOB)	2.35E-08	3.30E-09	7.135174	0.0008
D(MOB(-1))	-1.94E-08	3.11E-09	-6.235037	0.0016
D(PEXMHT)	1.106412	1.085612	1.019160	0.3549
D(PEXMHT(-1))	-9.339031	1.277683	-7.309351	0.0008
D(SENDR)	-0.029090	0.005649	-5.149598	0.0036
D(SENDR(-1))	0.017742	0.004981	3.561618	0.0162
CointEq(-1)*	-1.704413	0.147624	-11.54566	0.0001
R-squared	0.965822	Mean dependent var	-0.007318	
Adjusted R-squared	0.934751	S.D. dependent var	0.123203	
S.E. of regression	0.031471	Akaike info criterion	-3.772645	
Sum squared resid	0.010895	Schwarz criterion	-3.227124	
Log likelihood	52.49910	Hannan-Quinn criter.	-3.644137	
Durbin-Watson stat	2.275779			

A.6: Levels Equation (PMVA eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GFCF	-6.34E-09	2.55E-09	-2.489924	0.0320
FDIP	0.000266	0.001567	0.169978	0.8684
PAT	-4.73E-05	1.51E-05	-3.135543	0.0106
MOB	1.56E-09	5.02E-10	3.102282	0.0112
PEXMHT	-0.056944	0.031556	-1.804497	0.1013
C	0.060185	0.006126	9.823856	0.0000

A.7: Levels Equation (EMP eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MVA	-2.70E-11	1.60E-11	-1.685022	0.1178
MOB	5.46E-08	1.20E-08	4.567155	0.0006
PEXMHT	-14.00714	5.414953	-2.586752	0.0238
SENDR	-0.050479	0.018561	-2.719580	0.0186
FDIP	0.326517	0.126863	2.573784	0.0244
C	11.57679	0.207680	55.74330	0.0000

A.8: Levels Equation (CO2 eq)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MVA	-3.96E-11	6.59E-12	-6.000103	0.0018
GFCF	4.01E-08	4.56E-08	0.878964	0.4196
MOB	1.66E-08	6.43E-09	2.578347	0.0495
PEXMHT	6.656883	2.554982	2.605451	0.0479
SENDR	-0.019148	0.014474	-1.322978	0.2431
C	1.179319	0.152382	7.739215	0.0006